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USING A CLASSIFIER FOR BEHAVIOR ASSESSMENT OF REFRIGERATION SYSTEM

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Abstract. *In recent years, the change in eating habits of the population caused an increase in demand for food ready for consumption. This phenomenon has greatly increasing the use of refrigeration systems and food conditioning through the cold. It is clear also that the vapor compression refrigeration systems are big energy consumers, especially in secondary and tertiary sectors, and in recent years, mathematical and computational models have been applied to these systems to analyze their operating conditions and improve their efficiency. Thus, using a mathematical model of a refrigeration system will be obtained operating data with and without the presence of degradation of their main components (compressor, condenser, expansion device and evaporator). The objective of this study is to test a classifier based on computational intelligence about its performance in diagnosing the state of the refrigeration system under analysis. Through this work, it is expected to have a way to establish a prognosis of the refrigeration system behavior, which can be used as a tool to assist in the monitoring of refrigeration facilities, as well as conducting an operational analysis of the entire system.*

Keywords: *Refrigeration System; Thermodynamic Diagnosis; Computational Model; Computational Intelligence and Components Degradation.*

1. INTRODUCTION

Vapor compression refrigeration systems are one of the main consumers of electrical energy and are applied in the domestic, commercial and industrial sectors. According to Omer (2008), the demand for energy in the world in 2020 will be, at least, 50% superior to the demand of the 90’s.

Problems associated to the operation of refrigeration systems are related with physical degradation to its components, incorrect installation or even sensor failure. These problems result in higher energy consumption for these systems (Rocha et al., 2010). Even small degradations can lead to substantial energy waste, increasing the maintenance costs, higher inactivity periods and reduction of the quality of the system function (Kocyigit et al., 2014). Some breakdown could promote even a complete collapse of the system. The possibilities of degradations in the main components of a refrigeration system in a determined reference condition are broad. Considering only the individual breakdown on the components (compressor, condenser, expansion device and evaporator), a wide pattern of degradations can be defined, when compared with a referential operating condition.

The application of techniques of degradation detection and diagnosis are introduced to point out the abnormal operational behavior of the system, in order to identify the faults in an effective and timely manner. The monitoring systems aim to correlate the variables obtained, emitting trends, diagnoses, prognostics and recommendations (Isermann 2005). A technique that automatically detects degradations in components of refrigeration systems leads to a reduction in energy consumption, as well as assisting in the maintenance activities of such facilities.

The diagnosis and detection of degradations can be conducted through a model of the system being analyzed. This model is used to generate system operating data that correspond to situations with and without the presence of degradations. Mathematical and computational modeling has been widely used to predict the performance and functioning of refrigeration systems (Winkler 2008; Shao et al., 2008; Qiao et al., 2010; Mendes et al., 2012 e Rasmussen e Shenoy, 2012). This modeling also makes it possible to obtain historical data from the analyzed system for a diagnostic process (Ding, 2007). In diagnosis and detection of degradations in systems in general, the objective is to identify the faults in their initial state. This fact confers a difficulty in obtaining success through the analysis of small variations in the quantities read in the analyzed. Logging data manually obtains sufficient clues about system performance. However, according to Isermann (2005), this way of obtaining data ends up being inefficient in helping the diagnosis and the detection of degradations. This inefficiency is often related to the large time lag between recorded data and to obtaining recommendations through them.

Once the refrigeration system has been modeled, the effects caused by degradations in its components can be simulated and properly computed under a variety of operating conditions. With this data an automated tool can be used to identify patterns with respect to data that is free of degradation. Computational intelligence techniques are timely to identify these patterns. If properly structured, a learning algorithm can be drawn from previously known situations, performing predictions and generalizations with high speed and reliability (Kocyigit, 2015). Through this monitoring, the management of maintenance activities is improved. Rapid reaction to degradation reduces refrigeration system downtime as well as improves energy consumption.

This study will discuss the timely use of classification techniques based on computational intelligence in diagnosis and detection of degradations. The computational model of the refrigeration system presented in this paper has the role of providing the data used for the analysis of this utility. The analysis involves a classification problem where in addition to identifying the presence or not of degradation, the degraded component will also be identified. This analysis is a multiclass classification problem where a computational intelligence technique will be used to solve this problem.

2. MATHEMATICAL AND COMPUTATIONAL MODEL FOR THE REFRIGERATION SYSTEM

The operation of a refrigeration system depends on the behavior of its individual components, which are: compressor, condenser, expansion device and evaporator. Each of these components must be in balance with each other, for the perfect functioning of the system as a whole (Qiao et al. 2010).

In this work, the analysis will be conducted through the development of a case study. Thus, a plant with a cooling capacity of 27.5 TR (~ 96.7 kW) was considered. In order to calculate the thermal load and the design of the system, the following parameters were considered: 32.0 °C for the external ambient temperature, T_{ext}, and -2.0 °C inside the refrigerated space (chamber temperature), T_{int}. The refrigerant used was HCFC-22. Figure 1 shows the idealized system with its main components.

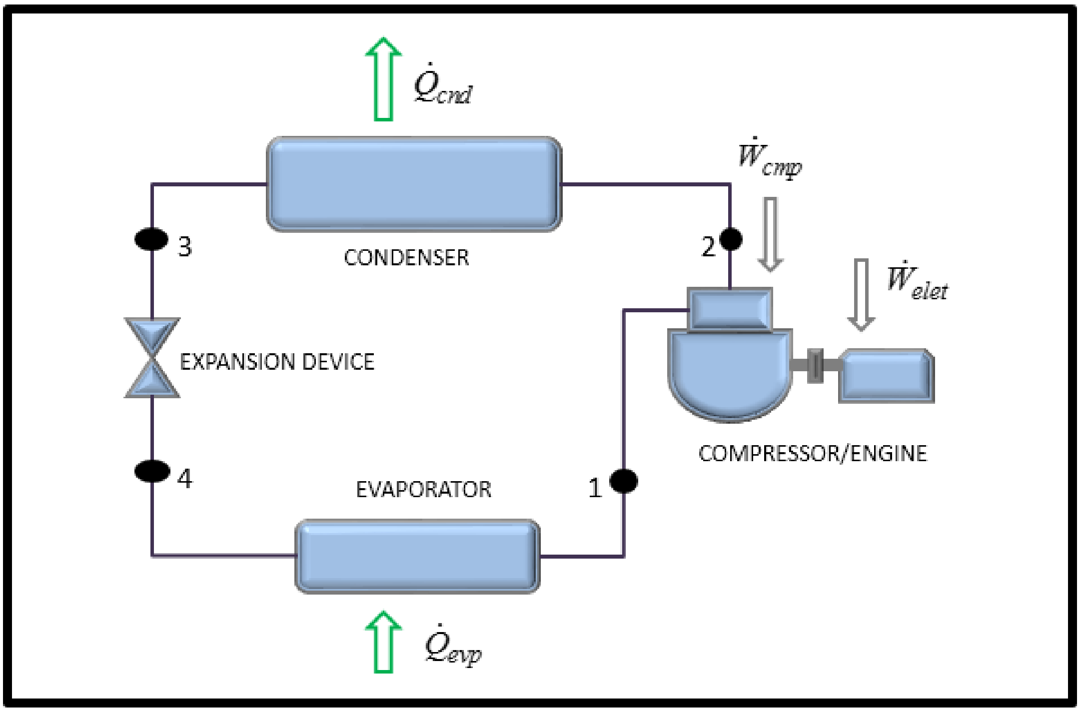

Figure 1 - Representation of the refrigeration system. Adapted from Mendes et al. (2016).

The simulation of the refrigeration system is obtained through the solution of a set of non-linear equations that govern the operation of the system. With this model the behavior of the system can be obtained for the various temperature conditions of the external environment and the refrigerated space.

The information required for the preparation of the set of equations mentioned above (design parameters) were obtained from the manufacturer's catalog data of each of the components. The parameters are as follows:

- Volumetric displacement of the compressor, $\dot{V}_{desl}$;
- Rated compressor motor voltage, U;
- Compressor motor power factor, FP;
- Compressor volumetric efficiency, η_{vol}, depending on the pressure ratio, RP;
- Capacity per unit of temperature difference, C, for the condenser, C_{cnd}, and evaporator, C_{evp}, as a function of the air flow rate through their fans;
- Characteristic coefficient of thermostatic valve, Ka, used as an expansion device;

The parameters mentioned above were used to characterize each component of the system, with the objective of simulating the behavior of the same working together. The system of nonlinear equations, obtained through the mathematical modeling and the First Law of Thermodynamics applied for the compressor, condenser, expansion device and evaporator was solved with the aid of EES Engineering Equation Solver software (Klein, 2015).

The bisection method is used for the convergence of the results of these equations for the evaporation temperature, T_{evp}, condensation temperature, T_{cnd}, superheating degree $DTSA$ and subcooling degree $DTSR$. For each condition considered, the solution of the system formed by the governing equations of each component corresponds to a condition of equilibrium of the system, that is, corresponds to a point where the system can be considered to be operating in a steady state, that is, it is considered Quasi-static regime (Qiao et al., 2010).

The First Law analysis requires a mathematical formulation based on principles of thermodynamics and mass conservation, in addition to the establishment of boundary conditions. The following considerations were adopted for the analysis in question:

- "Heat loss" except the compressor (non-isentropic compression) are neglected;
- Variations of kinetic and potential energy are neglected;
- Pressure loss on pipes, condenser and evaporator are neglected.

Subscripts in the form of numbers relate to the points shown in Fig. 1. From the above mentioned considerations, together with the principle of mass conservation and with the First Law of Thermodynamics, applied to the control volume formed by the evaporator, the cooling capacity of the system, $\dot{Q}_{evp}$, given by Eq. (1).

$$\dot{Q}_{evp} = \dot{m}_f \cdot (h_1 - h_4) \tag{1}$$

The evaporator is modeled according to that presented by Khan and Zubair (1999). The modeling is based on the definition of its heat transfer capacity per unit of temperature difference, Eq. (2). This methodology is satisfactory to represent this component in engineering applications, since the overall coefficient is not normally provided by the manufacturers of such equipment.

$$\dot{Q}_{evp} = C_{evp} \cdot (T_{AEE} - T_{evp}) \tag{2}$$

where:
C_{evp}: heat transfer capacity per unit of temperature difference;
T_{AEE}: air temperature at the inlet of the evaporator;
T_{evp}: Vaporization temperature.

The compression power consumption $\dot{W}_{12} = \dot{W}_{cmp}$ is given by Eq. (3).

$$\dot{W}_{12} = \dot{W}_{cmp} = \dot{m}_f \cdot (h_2 - h_1) \tag{3}$$

According to Qiao et al. (2010), the volumetric, η_{vol}, and isentropic efficiency, η_{isent}, can be calculated as a function of the pressure ratio, RP, , in Eq. (4) and superheating degree, $DTSA$. The volumetric efficiency of the compressor is given by Eq. (5) and the isentropic efficiency is given by Eq. (6), both for a given $DTSA$ value. The coefficients of this equations are determined through a regression process using the catalog data of the component manufacturer and are different for each superheating degree value.

$$RP = \frac{P_{cnd}}{P_{evp}} \quad (4)$$

$$\eta_{vol} = a \cdot RP^2 + b \cdot RP + c \quad (5)$$

$$\eta_{isent} = d \cdot RP^2 + e \cdot RP + f \quad (6)$$

where:
P_{cnd}: condensation pressure;
P_{evp}: evaporation pressure;
a, b, c, d, e, f: Coefficients of polynomials of second degree.

With the volumetric displacement of the compressor, $\dot{V}_{desl}$, obtained from the manufacturer's catalog data, together with the specific volume of the refrigerant in the suction of this component, v_{suc}, the mass flow rate of the refrigerant ($\dot{m}_f$) can be calculated by Eq. (7) (Venturini et al., 1999).

$$\dot{m}_f = \frac{\dot{V}_{desl} \cdot \eta_{vol}}{v_{suc}} \quad (7)$$

Using the global efficiency, η_{global}, that is composed of the mechanical, η_{mec}, and isentropic, η_{isent}, efficiencies and electrical efficiency, η_{elet}, of the electric motor, it is possible to determine the electric power, $\dot{W}_{elet}$, consumed by the compressor (Richardson et al., 2002) by Eq. (8).

$$\dot{W}_{elet} = \frac{\dot{W}_{cmp}}{\eta_{global} \cdot \eta_{elet}} \quad (8)$$

With the electric voltage, U, and the power factor, FP, obtained through the compressor catalog, it is possible to calculate the electric current consumed by the electric motor, I_{cmp}, through Eq. (9).

$$I_{cmp} = \frac{\dot{W}_{elet}}{\sqrt{3} \cdot U \cdot FP} \quad (9)$$

For the condenser, applying the principles of mass conservation and the First Law of Thermodynamics, it is possible to determine its heat rejection rate $\dot{Q}_{cnd}$, as shown in Eq. (10).

$$\dot{Q}_{cnd} = \dot{m}_f \cdot (h_2 - h_3) \quad (10)$$

Using the same method adopted to model the evaporator (Khan and Zubair, 1999), it is possible to determine the heat rejection rate in the condenser as a function of operating temperatures, as shown in Eq. (11):

$$\dot{Q}_{cnd} = C_{cnd} \cdot (T_{cnd} - T_{AEC}) \quad (11)$$

where:
C_{cnd}: heat transfer capacity per unit of temperature difference;
T_{AEC}: air temperature at the condenser inlet (in general is equal to the ambient temperature);
T_{cnd}: condensation temperature.

The residence time of the refrigerant inside the condenser establishes the degree of subcooling, $DTSR$. Thus, it is modeled as a function of the difference between the temperature of the external environment, T_{ext} and the condensation temperature, T_{cnd}, as in Eq. (12).

$$\begin{aligned}
&(T_{cnd} - T_{ext}) < 4 \rightarrow DTSR = 0 \\
&4 \leq (T_{cnd} - T_{ext}) \leq 12 \rightarrow DTSR = (T_{cnd} - T_{ext}) - 4 \\
&(T_{cnd} - T_{ext}) > 12 \rightarrow DTSR = 8
\end{aligned} \quad (12)$$

The expansion process in the valve can be considered isentalpic, which can also be verified using the principles of mass conservation and the First Law of Thermodynamics, resulting in Eq. (13).

$$h_3 = h_4 \quad (13)$$

The expansion device used in the refrigeration system under analysis was a thermostatic external equalization expansion valve. From the data provided by the manufacturer, one can determine the characteristic coefficient of the valve, Ka, as a function of the evaporation temperature, as shown in Eq. (14). The coefficients of this equation are determined by a regression process using the catalog data of the component manufacturer. This coefficient is equivalent to the product between the discharge coefficient and the valve bore diameter, which values are most often not provided by the manufacturer's catalogs (Koury et., 2001). Through Eq. (15), it is possible to determine the maximum flow of refrigerant supplied by the valve, $\dot{m}_{fmax}$. The characteristic coefficient and the maximum refrigerant flow, together with Eq. (16), can be used to simulate the operation of the valve in any other operational condition, thus obtaining the degree of superheating, $DTSA$. The dynamic super heating degree, $DTSA_{OS}$, and static super heating degree, $DTSA_{SS}$, are states for evaporation temperature of 0 °C according to manufacturer’s catalog of thermostatic valve (Yassuda et al., 1983).

$$Ka = g \cdot T_{evp}^2 + h \cdot T_{evp} + i \tag{14}$$

$$Ka = \frac{\dot{m}_{fmax}}{\sqrt{2 \cdot \rho_3 \cdot (P_{cnd} - P_{evp})}} \tag{15}$$

$$DTSA = \left(\frac{\dot{m}_{fmax}}{\dot{m}_f}\right) \cdot DTSA_{OS} + DTSA_{SS} \tag{16}$$

where:
g, h, i: Coefficients of polynomials of second degree;
ρ_3: refrigerant density at the inlet;
$DTSA$: superheating degree;
$DTSA_{OS}$: dynamic superheating degree;
$DTSA_{SS}$: static superheating degree.

Equation (17) presents the coefficient of performance of the refrigeration system, COP:

$$COP = \frac{\dot{Q}_{evp}}{\dot{W}_{cmp}} \tag{17}$$

The present work focuses on the detection and diagnosis of degradations in the vapor compression refrigeration systems using models and computational intelligence techniques. The refrigeration system for detection and diagnosis of degradations is shows in Fig. (2). From the mathematical model presented, the presence of individual degradations in each component will be represented by:

- Reduction of the heat transfer capacity per unit of temperature difference of the heat exchangers. The objective is to simulate the presence of fouling in the condenser and ice formation in the evaporator, both on the outer surface of these components, thereby reducing the heat transfer area;
- Reduction of the isentropic efficiency of the compressor, η_{isent}. The inefficiency in compression simulates, for example, a greater heat dissipation from the cylinders due to friction loss;
- Reduction in the coefficient characteristic of the thermostatic valve, Ka, used as expansion device. Inefficiency in the valve, for example, may be due to the obstruction in the flow of the refrigerant fluid there through.

The degradations presented above are related to the capacities of the compressor, condenser, evaporator and expansion device. The behavior of these degradations, individually, will be assessed by measuring the following quantities of the refrigeration system, shown schematically in Fig. 2:

- External ambient temperature (T_{ext});
- Refrigerated compartment temperature (T_{int});
- Electrical current consumed by the compressor drive motor (I_{cmp});
- Discharge pressure ($P_2 = P_{desc}$);
- Suction pressure ($P_1 = P_{suc}$);
- Refrigerant mass flow rate ($\dot{m}_f$);
- Superheating degree ($DTSA$).

These read quantities are used as input data for a classifier. With various degradation data and reference situations it is possible to train a classifier to detect the presence of degradations in the components of the refrigeration system. The classifier used in this work will be detailed in the next section.

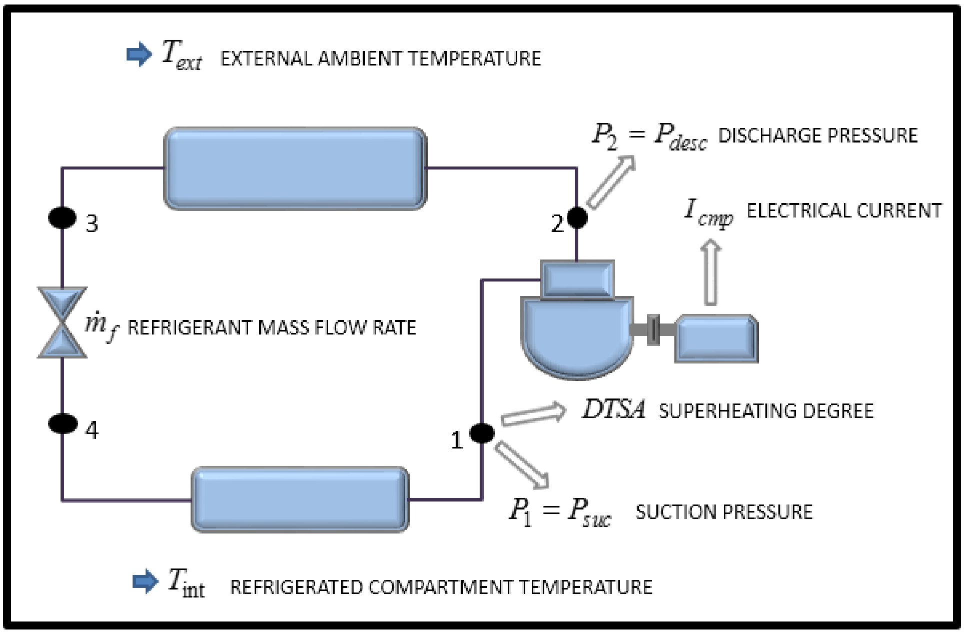

Figure 2 - Representation of the measurements obtained in the refrigeration system. Adapted from Mendes et al. (2016).

3. EXTREME LEARNING MACHINE - ELM

The ELM classifier is a machine learning technique developed for the training of feedfoward neural networks that have only one hidden layer (Huang et al., 2006). For networks with this topology, the parameters of the hidden layer can be defined at random, leaving only the weights of the output layer to be determined during the training, where such weights can be obtained analytically, with the solution of a system of linear equations (Horta, 2015). The particular topology for the problem of thermodynamic diagnosis of the refrigeration system is shown in Fig. 3.

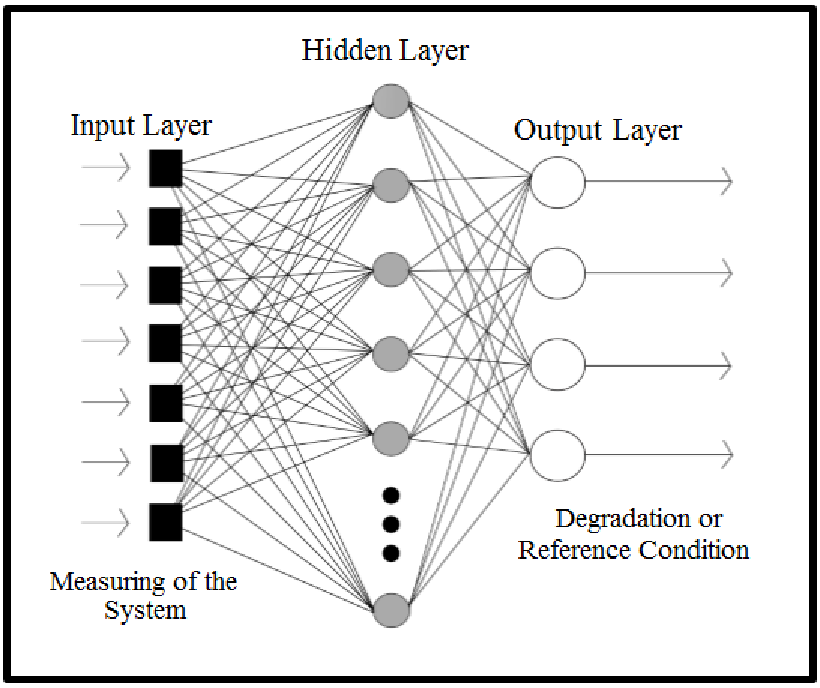

Figure 3. Topology of the ELMs and particularized topology for the thermodynamic diagnosis.

One of the characteristics of the ELM's, it is determined that the parameters of the hidden layer are randomly determined, and that the weights of the output layer are obtained directly using the pseudoinverse method, without the iterations (Horta, 2015).

The input matrix X has "N" rows and "n" columns, where "N" is the number of patterns and "n" is the size of the input space, given by Eq. (18).

$$X = \begin{bmatrix} X_1^T \\ \vdots \\ X_N^T \end{bmatrix} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nn} \end{bmatrix} \tag{18}$$

$$H = \begin{bmatrix} g \cdot (w_1 X_1 - b_1) & \cdots & g \cdot (w_p X_1 - b_p) \\ \vdots & \ddots & \vdots \\ g \cdot (w_1 X_N - b_1) & \cdots & g \cdot (w_p X_N - b_p) \end{bmatrix} \tag{19}$$

The matrix X is then propagated in a feedfoward network with single layer hidden with "p" neurons and activation function $g(x)$. Once the hidden layer parameters, weights "w" and bias "b", are randomly defined, the matrix H, Eq. (19) can be calculated at the output of the hidden neurons. The output of the network T can be expressed by the linear system of Eq. (20).

$$H\beta = T \tag{20}$$

Thus, we have β defined in Eq. (21), where "r" is the number of neurons in the output layer.

$$\beta = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1r} \\ \vdots & \ddots & \vdots \\ \beta_{p1} & \cdots & \beta_{pr} \end{bmatrix} \tag{21}$$

Also T, as presented in Eq. (22).

$$T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix} = \begin{bmatrix} t_{11} & \cdots & t_{1r} \\ \vdots & \ddots & \vdots \\ t_{N1} & \cdots & t_{Nr} \end{bmatrix} \tag{22}$$

The training process consists of propagating all the training patterns in the ELM hidden layer, obtaining the matrix H and solving the resulting linear system. According to Huang et al. (2006), the solution to the linear system in which β has the lowest norm and gives the least training error is presented by Eq. (23). In this equation $\widehat{H}$ is the Moore-Penrose pseudoinverse.

$$\beta = \widehat{H}T \tag{23}$$

After the training step and obtaining all the parameters of the network w, b and β, the response Y to new input patterns X_{test} is obtained by propagating X_{test} through the hidden layer, obtaining a new matrix H, called H_{test}. Performing the multiplication $H_{test} \cdot \beta$ yields an output value for each neuron. The response Y will correspond to the neuron index that has the highest activation value (Huang et al., 2006).

4. RESULTS AND DISCUSSION

Figure 4 shows the influence of the degradations on the coefficient of performance of the refrigeration system. For the degradation in the compressor occurs increase of the compression power, according to Eq. (8). The degradation in the valve results in a reduction of the mass flow of refrigerant fluid, Eq. (15), causing a reduction of the evaporation pressure, which results in an increase in the compression power. The condensation and evaporator degradations result in increased condensation temperature and reduced evaporation, according to Eq. (11) and Eq. (2), respectively. Therefore, these effects result in an increase in the compression power of the system. Thus, for the same refrigeration capacity, the reduction in the *COP*, for all these modes of degradation, occurs.

With the objective of using the ELM classifier to identify degradations in a refrigeration system, a database was generated using the model of the refrigeration system presented in this work. The inputs are: external ambient temperature

(T_{ext}); temperature of the refrigerated chamber (T_{int}); electric current consumed by the compressor drive motor (I_{cmp}); compressor discharge pressure (P_{desc}); compressor suction pressure (P_{suc}); refrigerant mass flow rate ($\dot{m}_f$); degree of superheating ($DTSA$).

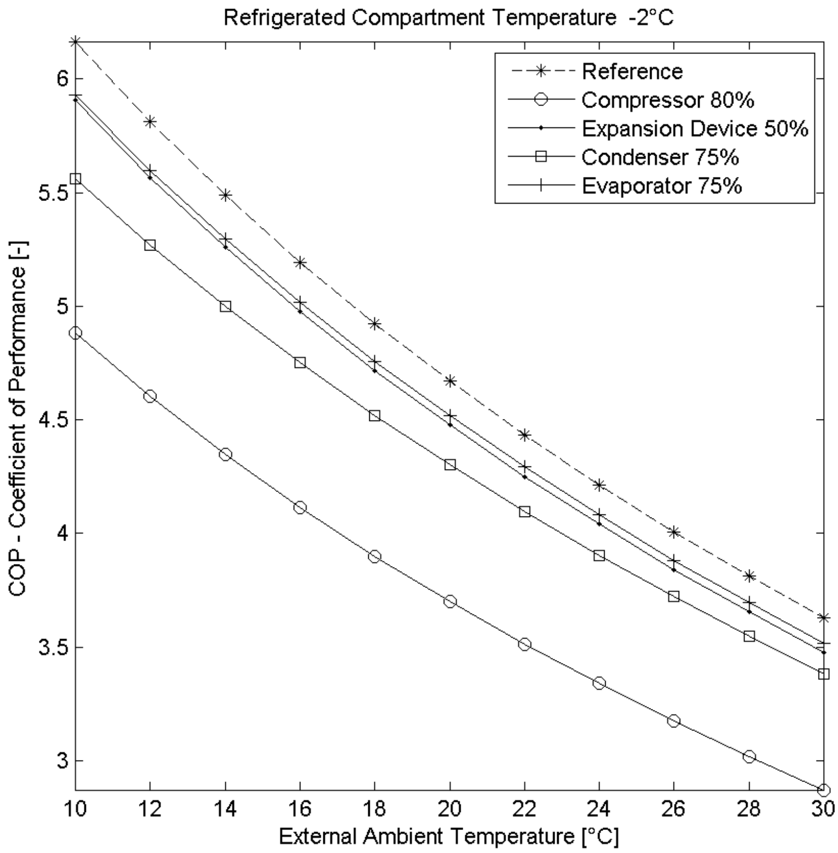

Figure 4 - Coefficient of Performance for Conditions with and without Degradations in System Components.

All data were normalized to have mean 0 and standard deviation 1. Training data were presented for an ELM with 100 hidden neurons. The source codes used are available on the author's website (Huang, 2016). Five situations are simulated: degradation in the compressor; degradation in condenser; degradation in the expansion device; degradation in the evaporator and system without degradation. The test data were presented to the trained network to verify the accuracy of the classification.

Two experiments were performed. The first experiment consists in using data obtained with degradation intensities of 2%, 4%, 6%, 8% and 10% in the capacities of the refrigeration system components. Thus, a database of 1050 patterns were obtained, 210 of each class. For the training set are used 2/3 of the database and for the test set 1/3 of the same database. The order of the patterns was defined in a random way. This procedure was repeated 100 times, and the mean and standard deviation of the training and test accuracy were collected.

Table 1: Classifier Accuracy for the First Experiment.

Accuracy of the Training Set	0.958+/-0.006
Accuracy of the Test Set	0.947+/-0.011

As observed in Tab. (1), the classifier correctly identified approximately 95% of the patterns presented in the test phase. The second experiment consists in using the same information used in the previous experiment, but without refrigerant mass flow rate as input data for the classifier. This is justified by the fact that the measurement of the refrigerant mass flow rate in the refrigeration systems is very imprecise. The Table (2) shows that the classifier correctly identified approximately 92 % of the patterns presented in the test phase. It can be observed that the refrigerant mass flow rate has negligible interference in the detection of the operation conditions.

Table 2: Classifier Accuracy for the Second Experiment.

Accuracy of the Training Set	0.955+/-0.005
Accuracy of the Test Set	0.923+/-0.013

5. CONCLUSIONS

In this work, we presented a model of a refrigeration system that allowed the simulation of operational situations with and without the presence of degradation in its main components. Two experiments were carried out with the objective of training a classifier capable to identify whether degradation occurs and in which component. In the second experiment, we observed that the refrigerant mass flow rate is irrelevant to the scenario analyzed in this work. The model presents inaccuracies that can be reduced through the more elaborate modeling of its components, instrumentation and external conditions that could modify the operation of the installation. Thus, if refined models are used it could be possible to generate more representative data degradation conditions. The use of a classifier can lead repairs and contribute to system performance in terms of operating quality and energy consumption.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Ding, G., 2007. “Recent developments in simulation techniques for vapour-compression refrigeration systems”, International Journal of Refrigeration, Vol.30, pp. 1119-1133.

Horta, E., G., 2015 “Aplicação De Máquinas De Aprendizado Extremo Ao Problema De Aprendizado Ativo”. 87 f. Tese (Doutorado). Escola de Engenharia. Universidade Federal de Minas Gerais. Belo Horizonte. 2015.

Huang, G., B., 2016. “Basic ELM Algorithms”. Available: <http://www.ntu.edu.sg/home/egbhuang/elm_codes.html/>.

Huang, G., B.; Zhu, Q., Y.; Siew, C., K., 2006 “Extreme Learning Machine: Theory And Applications”. Neurocomputing, V. 70, P. 489–501.

Isermann, R. (2005). "Model-based fault-detection and diagnosis–status and applications." Annual Reviews in control 29(1): 71-85.

Khan, J., Zubair,S.,M., 1999 “Design and performance evaluation of reciprocating refrigeration systems”, International Journal of Refrigeration, Vol. 22, pp. 235–243.

Klein, S., A., 2015. Engineering Equation Solver - Academic Professional V9.902. F-Chart Software.

Kocyigit, N., 2015 “Fault and sensor error diagnostic strategies for a vapor compression refrigeration system by using fuzzy inference systems and artificial neural network”, International Journal of Refrigeration, Vol.50, pp. 69-79.

Kocyigit, N., Bulgurcu, H., Lin C., 2014 “Fault diagnosis of a vapor compression refrigeration system with hermetic reciprocating compressor based on p-h diagram”. International Journal of Refrigeration, Vol. 45, pp. 44-54.

Koury, R., N., N., Machado L., Ismail K., A., R., 2001“Numerical simulation of a variable speed refrigeration system”, International Journal of Refrigeration, Vol. 24, pp.192-200.

Mendes, T., Horta, E., G., Pereira, J., F., Guzella, M., S., Venturini, O., J., Pirani, M., J. 2016. Diagnóstico Termodinâmico em um Sistema de Refrigeração por Compressão Mecânica de Vapor Utilizando Modelos e Técnicas de Inteligência Computacionais. SIMMEC XII Simpósio de Mecânica Computacional 23 a 25 de maio (2016), Diamantina, MG, Brasil.

Mendes, T., Venturini, O., J., Pirani, M., J., 2012 “Thermodynamic Diagnosis Techniques to Assess the Bahavior of Vapour Compression Refrigeration Systems” ENCIT - 14th Brazilian Congress of Thermal Sciences and Engineering, Novenber 18-22 2012, Rio de Janeiro, Brazil.

Omer A., M., Energy, environment and sustainable development. Renewable and Sustainable Energy Reviews, Vol. 12, pp. 2265–2300, 2008.

Qiao, H.; Radermacher, R.; Aute, V. A Review for Numerical Simulation of Vapor Compression Systems. International Refrigeration and Air Conditioning Conference at Purdue, West Lafayette, USA, 2010.

Rasmussen, B., P., Shenoy, B., 2012 "Dynamic modeling for vapor compression systems-Part II: Simulation tutorial, HVAC&R Research, Vol.18 (No.5), pp. 956-973.

Rocha, C., R., Bajay, S., and Gorla, F., D., Gorla, "Oportunidades de eficiência energética para a indústria: Relatório setorial: alimentos e bebidas,"Brasília: CNI, p. 58, 2010.

Shao, S., Shi, W., Li, X., Yan Q., 2008 " Simulation model for complex refrigeration systems based on two-phase fluid network – Part I: Model development." International Journal of Refrigeration, Vol. 31, pp. 490-499.

Venturini, O., J., Almeida, M., S., V.; Silva, E., 1999. "Modelo Computacional Para La Simulacion de Sistemas de Aire Acondicionado Con Termoacumulacion", Información Tecnológica, La Serena - Chile, Vol. 10, No. 2, pp. 273-278.

Winkler, J., Aute, V., Radermacher, R. 2008 "Comprehensive Investigation of Numerical Methods in Simulating a Steady-State Vapor Compression System." International Journal of Refrigeration, Vol. 31, pp. 930-942.

Yassuda, H., Touber, S., Machielsen, C., H., M., 1983 "Simulation Model of Vapour Compression Refrigeration System", ASHARE Transactions, part 2a, pp. 408-425.

8. RESPONSIBILITY NOTICE

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