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DEVELOPMENT OF A COMMITTEE OF ARTIFICIAL NEURAL NETWORKS FOR THE PERFORMANCE TESTING OF COMPRESSORS FOR THERMAL MACHINES IN VERY REDUCED TIMES

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Abstract

This paper presents a new test method able to infer – in periods of less than 7 seconds – the refrigeration capacity of a compressor used in thermal machines, which represents a time reduction of approximately 99.95% related to the standardized traditional methods. The method was developed aiming at its application on compressor manufacture lines and on 100% of the units produced. Artificial neural networks (ANNs) were used to establish a model able to infer the refrigeration capacity based on the data collected directly on the production line. The proposed method does not make use of refrigeration systems and also does not require using the compressor oil.

Keywords: refrigeration compressor, artificial neural networks, performance test.

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1. Introduction

The market for compressors to be used in refrigeration thermal machines imposes the development of new technologies to achieve increasingly high levels of the energy efficiency. This can be verified by the fact that the compressors currently produced by the global market leader in this sector consume half the energy in relation to those produced two decades ago. In this context, the compressor performance test has become an important activity in the development and improvement of these products, and to ensure that the efficiency parameters established through contracts are respected.

The compressor performance parameters include the refrigeration capacity, which is one of the main variables in the refrigeration systems design. Thus, this is one of the parameters given most consideration by the clients of companies which manufacture compressors for thermal machines.

Different methods can be used to obtain the refrigeration capacity of a compressor. Typically, the well-established methods used are described in the main standards, notably, ANSI/ASHRAE 23 [1], DIN EN 13771 [2] and ISO 917 [3]. All of the standards are very similar, often differentiated only by the allowable measurement uncertainty and operation limits. The ISO 917 standard requires measuring the refrigeration capacity under steady-state conditions in special refrigeration circuits. This condition is characterized by the measured quantities being within established limits for a period of 1 hour [3]. However, the overall test time is much longer and on average is over 4 hours due to an unsteady state operation [4−6].

Additionally to a long time required to run the tests, the compressor production volume at factories is high, reaching tens of thousands units per day in a single production plant. These two factors combined make using standardized tests as a quality control tool during the

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production process impracticable, so the refrigeration capacity can only be determined for a small sample of each lot of compressors produced.

In this context, this paper describes a new test method which does not make use of refrigeration systems and can be used to infer the refrigeration capacity of compressors during the production process. In this test method a committee of artificial neural networks is used to infer the performance characteristics.

2. A traditional test rig for the performance test

The refrigeration capacity of a compressor (Q_{rf}) is defined as the product of the mass flow rate of the refrigerant fluid through the compressor and the difference between the specific enthalpy of the refrigerant at inlet conditions and the specific enthalpy of the saturated liquid at the temperature corresponding to the discharge pressure of the compressor (1). In other words, the refrigeration capacity is a measure of the compressor capability to generate a mass flow of the refrigerant fluid when a pressure difference is imposed between its suction inlet and discharge outlet [7].

$$Q_{rf} = q_{mf} \cdot \frac{V_{ga}}{V_{gl}} \cdot \left(h_{g1} - h_{f1}\right), \tag{1}$$

where q_{mf} is the mass flow rate of the refrigerant, V_{ga} is the specific volume of the refrigerant fluid entering the compressor during the test, V_{gl} is the specific volume of the refrigerant entering the compressor at standard test conditions, h_{g1} is the specific enthalpy of the refrigerant entering the compressor under basic conditions specified in the test and h_{f1} is the specific enthalpy of the liquid refrigerant at the pressure corresponding to the compressor discharge.

Currently, the ISO 917 standard [3] describes nine methods for obtaining the refrigeration capacity of a compressor. The standard also determines that a test must be conducted simultaneously applying two different methods and that the results are considered acceptable when the deviation between the results is less than 4%, as detailed in (2).

$$\frac{2 \cdot \left(Q_{rfx} - Q_{rfy}\right)}{Q_{rfx} + Q_{rfy}} \cdot 100\% < 4\%, \tag{2}$$

where Q_{rfx} is the result for the refrigeration capacity of the compressor obtained by a method X and Q_{rfy} is the result for the refrigeration capacity of the compressor obtained by a method Y.

Flesch and Normey-Rico [5] described a test rig model, shown in Fig. 1, to measure the refrigeration capacity of a compressor according to the ISO 917 standard. The main components and measurement points of interest for the determination of the refrigeration capacity are presented. Two methods are presented: one involving the measurement of the mass flow rate in the liquid phase and the other employing the calorimetry in the suction line. In both methods the enthalpies are obtained using temperature and pressure measurements at points specified by the standard, and the mass flow rate is obtained directly from the meter in the first method and estimated by (3) in the dry system refrigerant calorimetry method.

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$$q_{mf} = \frac{P_i + F_l \cdot (T_a - T_g)}{h_{g2} - h_{f2}}, \tag{3}$$

where q_{mf} is the mass flow of the refrigerant fluid, P_i is the electrical power applied to the heater, F_l is the calorimeter heat leakage factor; T_a is the average ambient temperature, T_g is the average calorimeter surface temperature, h_{g2} is the specific enthalpy of evaporated refrigerant leaving the calorimeter, and h_{f2} is the enthalpy of the refrigerant in the liquid state entering the expansion valve.

The test rig is comprised of refrigeration circuits, measuring instruments, controllers and data acquisition systems. For the topology presented – with the application of advanced control methods and a high performance instrumentation – the level of measurement uncertainty for the capacity can reach values about ±1%.

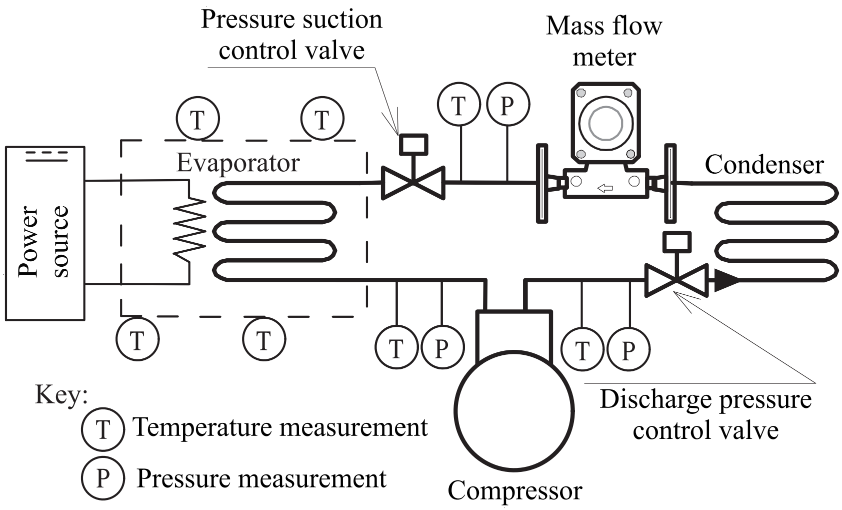

Fig. 1. A general scheme of the test rig for measuring the refrigeration capacity of a compressor.

The standards describe the state-of-the-art test methods for the measurement of the refrigeration capacity. All of them make use of the refrigeration fluid and have test durations of about 4 hours, requiring using the compressor oil according to the compressor design. These factors prohibit the application of the methods on the production line, given the high costs involved in recycling the refrigerant fluid and the extensive test duration considering the lead time, which can reach 7 seconds between two units produced consecutively. Also, due to contractual clauses, not all of the produced compressors can have a contact with the compressor oil. In this study, the standardized test rigs were used to obtain training and test data sets for developing the proposed artificial neural network method.

3. Committees of artificial neural networks

ANNs make direct use of data from the real world, allowing the network to learn from the data and provide an implicit model for the case under analysis. Thus, for complex problems, where the traditional mathematical modelling of physical phenomena becomes unfeasible, the use of ANNs presents a practical solution when integrated with a consistent engineering approach [8]. This enables efficient modelling of complex problems with satisfactory results [9−13].

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The theory related to ANNs presents different types of networks and learning algorithms suitable for implementation. In this study, multilayer feedforward ANNs with back-propagation learning are used. This type of ANNs has one or more intermediate, or hidden, layers between its inputs and outputs. These hidden layers allow the ANN to extract high-order statistics, enabling its use in non-linear applications.

Due to the randomness related to the learning process, even for topologies of networks which are the same and trained with subsets extracted from the same database, the results can differ significantly. A strategy to minimize these deviations is to use such an ANN committee that the simple average of the ANN outputs is favourable as it gets closer to the expected value [14−17]. The idea behind a committee machine is the minimization of the random effects induced in the ANN due to the learning process [8, 18]. It is possible to make a direct analogy with the metrology where, in order to determine the value for a measurand with the presence of random effects in the measurement process, the average of several measurements represents a better result than a single individual measurement [19]. Therefore, the random errors of each one of the ANNs are partially compensated when the individual outputs are combined into a committee of ANNs [20].

In this paper, different ANNs were trained with sets of data extracted randomly from the same database – x as input quantities and y as output quantities. The networks that presented a proper behaviour were chosen to constitute a committee and their outputs (y_1, y_2…y_k) were combined using the simple arithmetic mean in order to obtain the inferred value (y) for the refrigeration capacity, as in the model shown in Fig. 2.

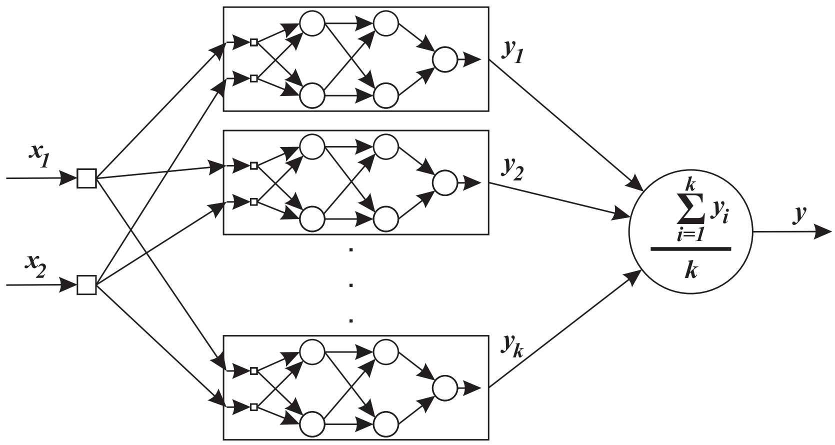

Fig. 2. A committee of ANNs with the output based on the simple arithmetic mean.

4. A proposal for the test on the production line

A proposal for a test procedure able to provide the value for the refrigeration capacity in an extremely reduced duration is based on the classical definition of an air compressor. The compressor is turned on increasing the air pressure within a vessel of a known volume, as shown in Fig. 3. The pressure is measured and its increasing rate is directly related to the refrigeration capacity of the compressor. The main compressor parameter which is responsible for the determination of the refrigeration capacity is the mass flow. Thus, according to (1), assuming that the temperatures and pressures of the suction and discharge are constant, it can be assumed that the greater the capacity of the compressor to generate the mass flow, the greater is its refrigeration capacity. On the other hand, for the pressure increase test, if the volume, pressure and temperature at the start and the end of the test are known, it is possible to determine the displacement of the air mass during the test period.

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Therefore, this mass flow will be directly correlated with the refrigeration capacity of the compressor.

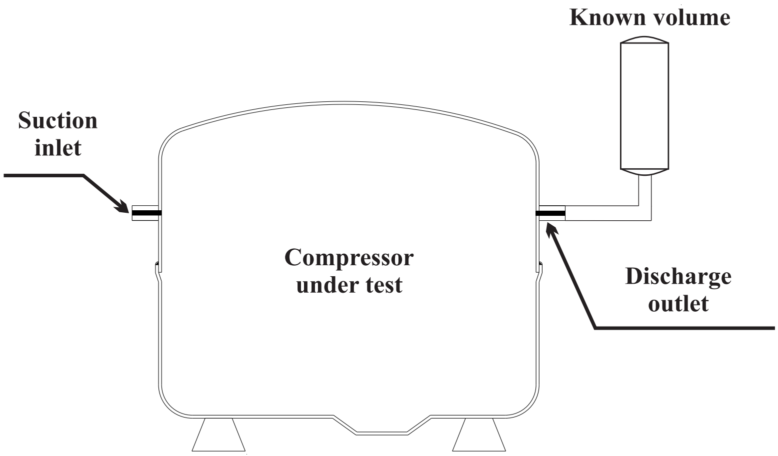

Fig. 3. The test method carried out on the production line.

4.1. A correlation between the refrigeration capacity and the pressure increase rate

In order to verify a correlation between the quantities of interest, 61 compressors with different refrigeration capacity values were tested and respective results for the refrigeration capacity and the pressure increase rate were obtained. The measurements of the refrigeration capacity of 61 compressors took about 270 hours for all compressors and were run on traditional test rigs using the refrigerant fluid that the compressors were designed for; the measurements of the pressure increase rate for all 61 compressors took about 6 minutes and were run on a production line test rig using the dry air. The statistical analysis of the results revealed the Pearson correlation coefficient equal to 0.839 between the refrigeration capacity and the pressure increase rate, with a 95% confidence interval between 0.741 and 0.903. The correlation coefficient indicates a strong linear correlation between these quantities; this situation contributes to the establishment of a neural model able to infer values for the refrigeration capacity based on the pressure increase rate.

4.2. A neural model for the inference

The 61 compressors described above were used to establish a neural model able to infer the values for the refrigeration capacity based on the results obtained in the pressure increase tests. 49 compressors were chosen for the training set, whereas the remaining 12 compressors were allocated to the test set. In the ANN learning process the results for the pressure increase test represented the input and the results for the refrigeration capacity represented the output of the ANN.

The configuration of the selected network was a multilayer feed-forward one, as follows: the input layer containing 8 neurons with data originating from the pressure increase test and also from the compressor design parameters (the pressure increase rate, power consumption, shell temperature, power line voltage and frequency; additionally some relations between these quantities were stated as inputs), the first, second and third hidden layers containing 10 neurons each, and the output layer containing 1 neuron indicating the refrigeration capacity. Several different configurations were evaluated and better results were reached using the architecture described above. The average absolute percentage error for the test set achieved by each ANN was chosen as a criterion for selecting the committee members; the chosen

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ANNs should have the error lower than 10%. Despite this threshold value seems rather high, it was not possible to reach lower values for a sufficiently large amount of ANNs, considering different architectures and generalization issues.

Several ANNs were trained using data extracted randomly from the training set in order to allow a diversity of ANNs [21−24]. 45 ANNs with the same configuration were trained allowing the analysis of committees with different quantities of ANNs.

5. Experimental results

The differences between the test results and the inferences presented by a committee comprised of 45 ANNs were within the range of the measurement uncertainty for the refrigeration capacity, as shown in Fig. 4 for 12 compressors of the test set. Fig. 4 also shows the ±3% measurement uncertainty limits for the refrigeration capacity. Considering that the uncertainty represents a doubt regarding the refrigeration capacity values, it can be concluded that the inferred values are acceptable. Also supporting the validation of the method is the fact that the ISO 917 standard [3] indicates as acceptable a 4% deviation between the values obtained as the result of two distinct methods.

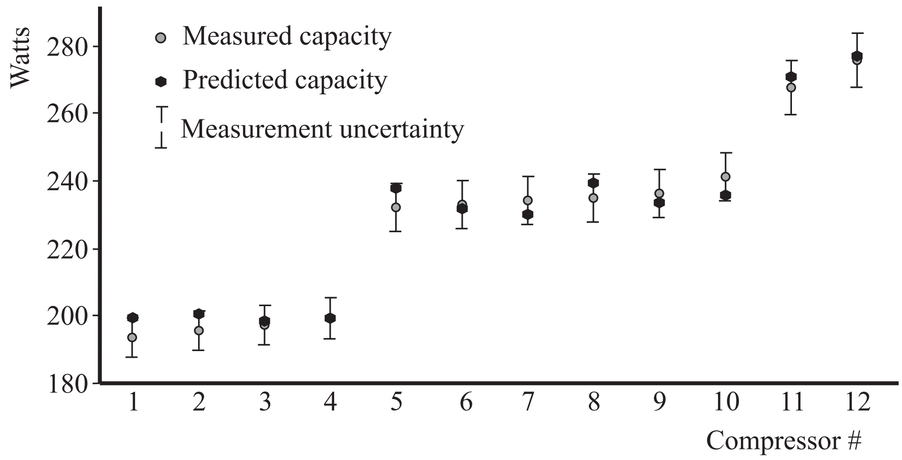

Fig. 4. The comparison of the measured and inferred values.

The use of committee machines was demonstrated to be a suitable solution for the minimization of errors originating from the learning process. Fig. 5 shows the average absolute percentage error for the test set (12 compressors). One can see that the error reduces as networks are inserted into the committee, and a stable behaviour is established for about 30 networks.

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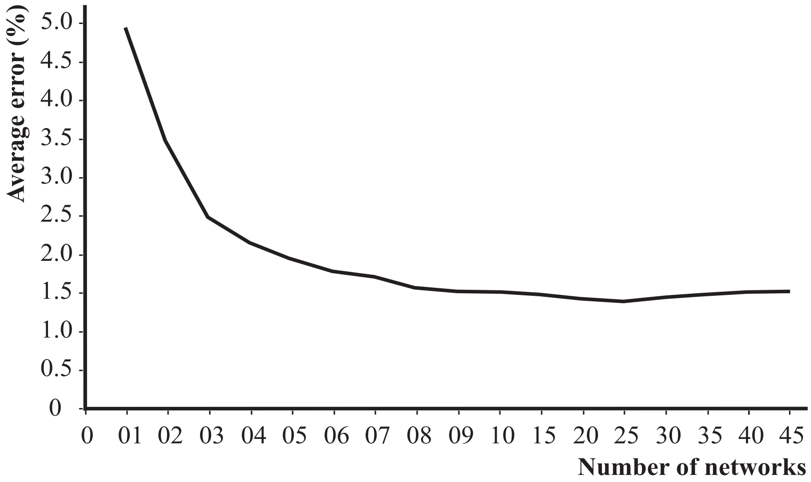

Fig. 5. The average absolute percentage error vs. the quantity of networks in the committee.

As in the case of any model used for the inference, the linear correlation between the values obtained and the values expected should be as high as possible and ideally the Pearson coefficient should be equal to 1, indicating that the model provides the zero error in its inferences [25−27]. The correlation coefficient for the responses provided by the committee was 0.989, indicating that the results presented by the committee are acceptable.

Since the proposal was shown to be suitable for the test set, a further analysis was carried out. The inferences obtained for a lot of 2383 compressors of a specific model were compared to the refrigeration capacity obtained for a quality control sample of 5 compressors tested using the traditional standardized methods. The analysis was performed by comparing the averages and the standard deviations. The average refrigeration capacity value of the quality control sample was 235.68 W with the standard deviation of 2.13 W. For the 2383 compressors tested using the proposed inference method the average result when applying a committee of 10 ANNs was 236.16 W with the standard deviation of 4.21 W. The comparison reveals a small percentage error in relation to the average results. However, the standard deviation was slightly higher for the inference results. The average for a committee of 30 ANNs was 236.53 W with the standard deviation of 2.31 W. The latter analysis shows that the difference in the errors for 10 and 30 ANNs was very low. However, the standard deviation was considerably reduced when the number of ANNs in the committee was increased. Fig. 6 shows more clearly the variation in the average absolute percentage error as the number of ANNs in the committee is increased. It can be observed that the percentage error appears to stabilize with 10 ANNs in the committee. However, as shown in Fig. 7, the standard deviation continued to decrease until reaching 30 ANNs in the committee.

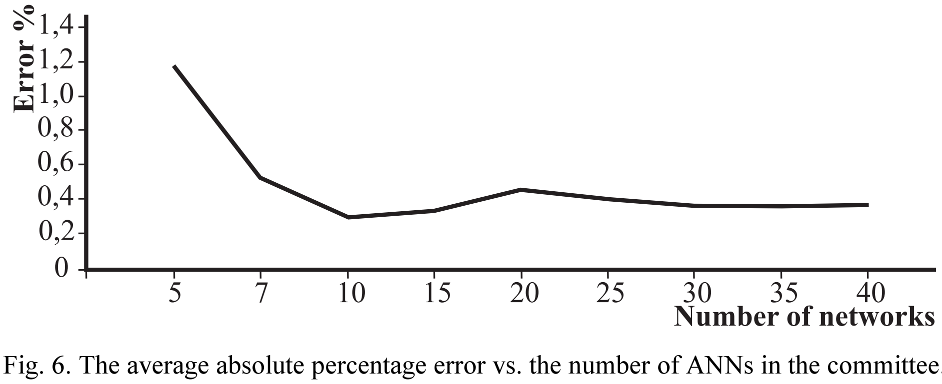

Fig. 6. The average absolute percentage error vs. the number of ANNs in the committee.

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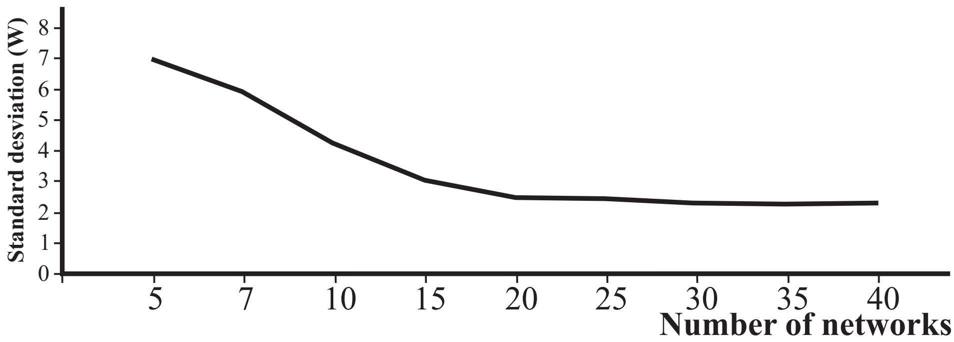

Fig. 7. The standard deviation vs. the number of ANNs in the committee.

Another important analysis to be performed is related to the test duration. The evaluation of the quality control sample comprised of 5 compressors took about 1350 minutes using the standardized test methods, while the total test duration for whole lot of 2383 compressors using the proposed inference method was equal to 278 minutes. It can be noted that - regarding the test duration - the proposed approach can be used on the production lines.

Other analyses carried out on 4 specific compressor models also provided acceptable results related to the average percentage error. The results were compared to the quality control sample (5 compressors for each model) and are presented in Table 1.

Table 1. Production lots results.

Compressor Model	Lot Size	Refrigeration capacity (W) Quality Control	Standard deviation (W) Quality Control	Refrigeration capacity (W) Inference	Standard deviation (W) Inference	Error %
A	5377	197.41	1.80	197.56	0.60	0.08
B	243	197.64	1.3	197.65	0.43	0.01
C	1230	198.98	3.42	199.26	0.74	0.15
D	1031	202.10	2.60	198.46	0.63	-1.71

6. Conclusions

This paper focused on presenting a viable method for obtaining the refrigeration capacity of compressors used in thermal machines, which can be used on the production line. Due to the high production volume of the manufacturers, the proposed method must be sufficiently fast in order to be coupled with the process. To achieve this, a time reduction of 99.95% in relation to traditional methods needs to be reached. In the proposed method artificial neural models are established to infer the refrigeration capacity. The paper demonstrated the viability of the proposed method through experimental results which verified that the errors were relatively low. The test duration was 7 seconds per compressor. The proposed method does not require using refrigeration systems, which dispenses using the refrigerant fluid and the compressor oil. It was also verified that the use of committees of ANNs was a suitable tool to minimize the random errors obtained during the ANN learning process.

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