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Fuzzy–Bayesian network for refrigeration compressor performance prediction and test time reduction

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ABSTRACT

A typical characteristic of refrigeration compressor performance tests is their long duration. A reduction in the time periods related to this activity can be achieved using unsteady-state data analysis. This paper presents an original approach to predicting compressor performance using Bayesian networks and a hybrid Fuzzy–Bayesian network. All analysis was performed using real test data.

1. Introduction

Performance tests are an experimental activity which aims to measure four fundamental characteristics of a compressor related to its performance: refrigerating capacity; power consumption; isentropic efficiency and coefficient of performance (COP). This kind of test is mainly used for three purposes: research and development (R&D), determination of catalog parameters, and quality control (ASHRAE, 2005; ISO, 1989).

A typical characteristic of these tests is the long time required to achieve stable conditions, under which the measurement can be performed. In general, performance tests last 2½ h.

Most performance tests run by a typical compressor manufacturer are carried out for R&D purposes, to develop new technologies and improvement the current compressors (Borges, 2008). Additionally, improvements in the compressor performance must be statistically proven using a sufficient number of test results.

To achieve shorter test times several studies have been carried out related to: optimization of test benches; use of measurement systems with lower uncertainties; and application of automation and control techniques to improve the performance tests. Nevertheless, the reduction achieved with these actions was insufficient, since unsteady periods of long duration are typical in refrigeration systems (Flesch & Normey-Rico, 2010; Poleto, 2006; Scussel, 2006).

An alternative and original approach to reducing the time required for refrigeration compressor performance tests is proposed in this paper.

The technique proposed is based on unsteady-state data analysis using Fuzzy–Bayesian networks to predict compressor performance. This paper presents a Fuzzy–Bayesian network structure which can be used to achieve a significant time reduction of one third of the complete test time, on average, in the refrigerating capacity evaluation.

The article is divided into the following sections: Section 2 describes the performance test; Section 3 briefly presents the Bayesian networks and Fuzzy–Bayesian networks; Section 4 presents the proposed networks; and Section 5 presents the conclusions.

2. Performance tests for refrigeration compressors

The performance tests are run on special benches, which operate as a refrigeration circuit with many controlled variables. In addition, it is possible to measure a series of variables that are not generally monitored in refrigeration systems.

Refrigerating capacity is measured in watts and is calculated as the product of the mass flow rate of refrigerant through the compressor and the difference between the specific enthalpy of the refrigerant at two points in the refrigeration circuit (ISO, 1989). According to the enthalpy determination points that are chosen, it is possible to obtain different interpretations for the refrigerating capacity (Çengel & Boles, 2007). The most common is the heat removal from the cooled environment. The simplest method for determining the mass flow rate in a refrigeration circuit is to measure it directly using mass flow meters that are available on the market. Equipment that satisfies the measurement uncertainties required by international standards can easily be found. However, the measurement of refrigerating capacity needs to be carried out using two different and independent methods (ISO, 1989).

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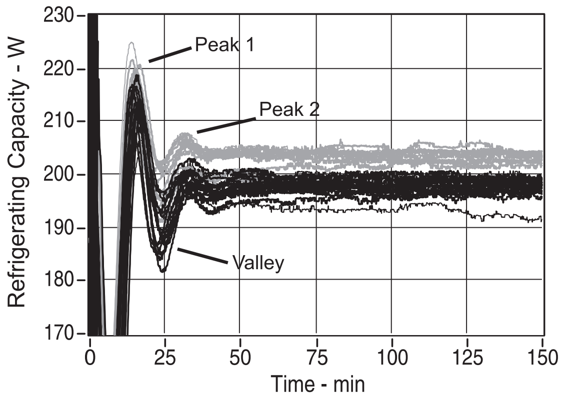

Fig. 1. Refrigerating capacity data.

Typically, in order to ensure the independence of the methods, one method based on the direct measurement of the mass flow rate and another based on the heat balance inside a calorimeter are used.

The refrigerating capacity obtained using the calorimeter method is analyzed in this article. Fig. 1 presents a set of typical examples of refrigerating capacity data obtained during performance tests. These tests were run on compressors of the same model produced by the same manufacturer. It can be noted that two distinct behaviors are presented: steady and unsteady.

Although the behavior after 50 min appears to be steady, in fact, it is not. The steady region is characterized by the refrigerating capacity remaining within ±1% of the final value. This final value is obtained through the mean of the measurements taken during the last hour of the test.

It can be observed that the test data presented in Fig. 1 consider two different classes of refrigerating capacity during the steady region: Class 1, where the final values remain above 200 W; and Class 2, where the final values remain below 200 W. During the unsteady period, three typical behaviors can be observed: two peaks (Peak 1 and Peak 2) and one valley.

These data are used in Section 4 to develop the networks used to classify and predict the refrigeration capacity. The next section briefly presents the concepts used to develop the network.

3. Modeling tools

3.1. Bayesian networks

Probability theory is a well-established and powerful tool for the treatment of uncertainties related to random origins. The randomness relates to nondeterministic phenomena which, under the same test conditions, may not allow a certain prognosis regarding a specific output (Ayyub & Klir, 2006).

Bayesian or probabilistic networks resulted from the combination of the Bayesian theory of probabilities and cause-effect graphical representation of systems, experiments and situations to be modeled (Pan & McMichael, 1998).

A Bayesian network is a graphical structure that provides the user with a representation of and reasoning regarding an uncertain domain. In these networks the nodes represent a set of random variables related to the modeled domain. A set of direct arcs that connects pairs of nodes represents the dependency between different variables. The intensity of these dependencies is quantified by conditional probability distributions associated with each node (Korb & Nicholson, 2004).

The prior conditional probabilities used are typically obtained from experimental data. Therefore, Bayesian networks must be evaluated and the classification errors estimated for confidence levels well-suited to the application (Korb & Nicholson, 2004).

3.2. Fuzzy–Bayesian networks

The fuzzy treatment of information originated with the work of Zadeh (1965) who described the essentials of a natural way to deal with problems where uncertainty is related to the absence of dichotomic thresholds for data classification, despite the presence of random variables.

Pan and Liu (2000) described in the following terms the difference between random and fuzzy approaches to deal with uncertainty: "…probability is a measure of the undecidability in the outcome of clearly and randomly occurring events, while fuzziness is concerned with the ambiguity or undecidability inherent in the description of the event itself". This comparison supports the application of a hybrid approach to model the data related to the stated application domain. Additionally, other authors brought together Fuzzy and Bayesian approaches to deal with uncertainty, for instance, Baldwin and Di Tomaso (2002) and Yang and Cheung (1995).

The hybrid Fuzzy–Bayesian approach is represented in Eq. (1) (Tibiriçá, 2005).

$$P(H_i|\tilde{e}_j) = \frac{P(\tilde{e}_j|H_i) \cdot P(H_i)}{P(\tilde{e}_j)} \tag{1}$$

where:
H_i - hypothesis to be tested;
$\tilde{e}_j$ - fuzzy evidences.

For each evidence $\tilde{e}_j$ a pair of membership functions is defined that describes the ambiguity or undecidability inherent in the evidence description. The unitary summation of hypothesis probabilities related to a set of evidences is represented by Eq. (2).

$$\sum_{j=1}^{k} P(H_i|\tilde{e}_j) = 1 \quad i = 1, \ldots, n \tag{2}$$

where:
k - number of evidences;
n - number of hypotheses.

Each evidence $\tilde{e}_j$ has the normalization constant $\tilde{\Delta}_j$ presented in Eq. (3).

$$\tilde{\Delta}_j = P(\tilde{e}_j|H_i) = \sum_{i=1}^{n} [P(e_j|H_i) \cdot \mu_{ijm} + (1 - P(e_j|H_i)) \cdot \mu_{ijp}] \cdot P(H_i) \tag{3}$$

where:
μ_{ijm} - highest membership grade for each evidence;
μ_{ijp} - lowest membership grade for each evidence;
$P(e_j|H_i)$ - prior conditional probabilities obtained from pure Bayesian approach.

The joint conditional probability is obtained for each set of k evidences using Eq. (4).

$$P(H_i|\tilde{e}_1, \tilde{e}_2, \ldots \tilde{e}_k) = \frac{1}{\tilde{\Delta}_k} \cdot \sum_{i=1}^{n} [P(e_k|H_i) \cdot \mu_{ijm} + (1 - P(e_k|H_i)) \cdot \mu_{ijp}] \cdot P(H_i|\tilde{e}_1, \tilde{e}_2, \ldots \tilde{e}_{k-1}). \tag{4}$$

One can note that Eq. (4) results in weighted grades between prior conditional probabilities and membership grades. In the case of maximum membership grades $\mu_{ijm} = 1$, and consequently $\mu_{ijp} = 0$, the pure Bayesian network arises.

The modeling tools presented in this section are used to implement the networks as outlined in the next section.