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Reservoir computing for detection of steady state in performance tests of compressors

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ABSTRACT

Fabrication of devices in industrial plants often includes undergoing quality assurance tests or tests that seek to determine some attributes or capacities of the device. For instance, in testing refrigeration compressors, we want to find the true refrigeration capacity of the compressor being tested. Such test (also called an episode) may take up to four hours, being an actual hindrance to applying it to the total number of compressors produced. This work seeks to reduce the time spent on such industrial trials by employing Recurrent Neural Networks (RNNs) as dynamical models for detecting when a test is entering the so-called steady-state region. Specifically, we use Reservoir Computing (RC) networks which simplify the learning of RNNs by speeding up training time and showing convergence to a global optimum. Also, this work proposes a self-organized subspace projection method for RC networks which uses information from the beginning of the episode to define a cluster to which the episode belongs to. This assigned cluster defines a particular binary input that shifts the operating point of the reservoir to a subspace of trajectories for the duration of the episode. This new method is shown to turn the RC model robust in performance with respect to varying combination of reservoir parameters, such as spectral radius and leak rate, when compared to a standard RC network.

1. Introduction

A performance test of a refrigeration compressor, for instance, to find out the cooling capacity of the device, has an important role in the research and development of methods to achieve increasingly high levels of energy efficiency in the context of refrigeration thermal machines. The global market indeed requires the continuous enhancement of these compressors, which can be confirmed by the fact that the current leader in compressor production has halved the energy consumption requirements over the last two decades [1]. Thus, the compressor performance test is an essential procedure in the advancement of these technologies. Besides, it also ensures that efficiency settings accorded through contracts are respected: the refrigeration (cooling) capacity is one of the main parameters obtained during a performance test, and is also very important for client companies that buy compressors to build thermal machines.

There are different methods to obtain the refrigeration capacity of a compressor. The ISO 917 standard [2] requires that the measurement of the refrigeration capacity should be done under steady-state conditions: the measured quantities should be within a predefined margin for a minimum interval of one hour [2]. In practice, however, the complete test duration is two and a half hours on average, and can take up to four and a half hours in some cases. In addition, the production volume is very high in a single plant (in the order of tens of thousands), making these types of standardized tests impracticable to be implemented for the whole set of compressors produced, but only to a small sample of it [1].

In this context, it is very desirable to employ techniques that can detect when the refrigeration capacity signal, obtained through measurements during the performance test in the compressor, enters the steady state region. This has the potential to reduce the time needed to run these performance tests, which in turn increase the productivity of the plant and/or the number of compressor samples to be performance-tested.

The objective of this work is to design a dynamic classification model that can be used to detect this steady state entrance. Other important available measurement signals are used as input to the model (as in [3]) in addition to the cooling capacity: the

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compressor shell temperature and the compressor suction pressure. Considering only the current input measurements is not enough to create such model. That is why previous approaches [3] have used black-box models such as feedforward neural networks with extra (specially handcrafted) input features made of moving averages and derivatives of the original signals, totaling 16 input dimensions to the model. In contrast to this, this work employs Recurrent Neural Networks (RNNs) [4–7] to naturally cope with the dynamical intricacies of the task without the need to create special input features.

RNNs can provide a type of state-dependent computation much like cortical functioning in the brain [8], where the trajectory of a high-dimensional dynamical system reflects both the current input as well as previously received input stimuli. Reservoir Computing (RC) [9] is a term recently coined to designate this paradigm of computation based on transients of a fixed dynamical system (such as an RNN). Echo State Networks (ESNs) [10] and networks based on backpropagation-decorrelation learning [11] were the first RC models proposed using analog neurons, while Liquid State Machines (LSMs) [5] basically consist of dynamical reservoirs made of spiking neurons. In RC, the network (see Fig. 2) is composed of a recurrent high-dimensional pool of neurons, with randomly generated and fixed synaptic weights, called reservoir, and a linear adaptive readout output layer which projects the reservoir states to the actual system's output. As only the output layer needs to be trained, usually via linear regression methods, the training is simplified and global convergence guaranteed. On the other hand, traditional methods to train RNNs, such as BPTT (backpropagation through time [12]), have slow training and no global convergence guarantee.

The reservoir can be viewed as a dynamic nonlinear kernel that projects the input to a high-dimensional dynamic space, where linear regression or classification is usually enough for various tasks. Many applications relying on the powerful temporal processing capabilities of RC exist: navigation and localization of mobile robots in partially observable environments [13], periodic signal generation with nanophotonic reservoir computing [14], hierarchical control of robotic arms [15], speech recognition [16], modeling of soft-sensors for offshore oil production platforms [17], etc.

This work also proposes a new RC architecture which uses a priori knowledge to constrain the dynamical reservoir space to a predefined subspace. This subspace is defined by binary inputs to the RC model as in [13] for the task of robot navigation. In our proposal, the a priori knowledge will be given by the application of an unsupervised learning mechanism such as k-means clustering on an initial period (first 13 min) of the performance test. We will see that the resulting model is more robust with respect to the parameters of the RC network (spectral radius and leak rate - see Section 4), producing good generalization performance with less dependence on these parameters when compared to the standard RC network.

This paper is organized as follows: Section 2 explains the performance test process in refrigeration compressors. Next, related works in the literature are compared against the current approach (and its novel aspects) in Section 3. Section 4 presents the reservoir computing model and the proposed self-organized subspace projection method. The results are shown and analysed in Section 5. Section 6 concludes this work and gives future research directions.

2. Performance tests in refrigeration compressors

The performance of a refrigeration compressor is measured on a specific rig that simulates a refrigeration system with several measured and controlled variables. The cooling (or refrigeration) capacity is an indirect measurement defined by the product of the

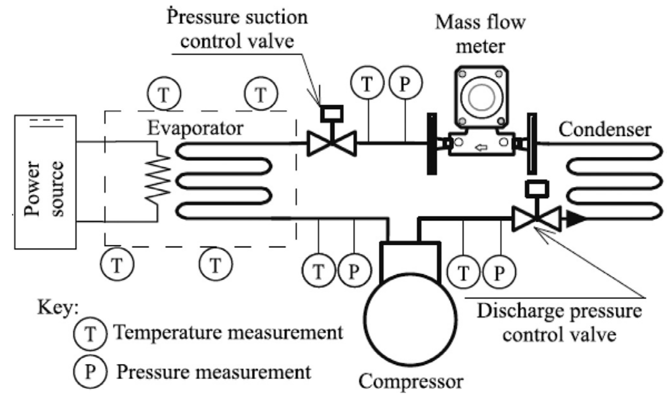

Fig. 1. Simplified schematic of the test rig.

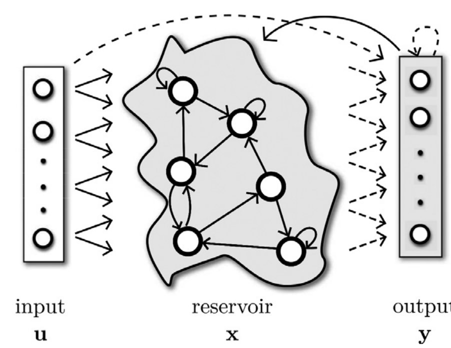

Fig. 2. Reservoir Computing (RC) network. The reservoir is a non-linear dynamical system usually composed of recurrent sigmoid units. Solid lines represent fixed, randomly generated connections, while dashed lines represent trainable or adaptive weights.

mass flow rate of the refrigerant fluid in the compressor and the enthalpy difference between two specific points in the refrigeration circuit [2]. The enthalpy values, in turn, are constants defined by the operating condition of the compressor and the refrigerant fluid. The measurement of the mass flow rate can be done by nine different methods [2]. One of them is obtained by measuring the mass flow rate directly through a commercial mass flow meter that reaches the minimum measurement uncertainty defined by international standards. Another commonly used method for mass flow measurement (which is independent of the former method) is based on heat balance using a calorimeter [2].

A simplified schematic of a test rig to measure a compressor performance (initially described by [18]) is shown in Fig. 1. Basically a rig contains a compressor under test, suction and discharge pressure controller (that can be done through valves), condenser, mass flow meter and a calorimeter (represented by the area inside the dashed rectangle) and pressure and temperature transducers installed at different parts of the circuit to monitor test conditions.

Due to the complexity of the system to reach the steady state condition, the performance test takes 2.5 h on average. The most critical variables that affect the final result of the performance test are the compressor shell temperature, the suction pressure and the discharge pressure. Both the suction pressure and the discharge pressure reach the steady state when their measurements are kept inside the interval defined by ±1% of the set point (that is a value chosen depending on the compressor operation condition). Due to the high sensibility of the compressor to those variables, if their values reach outside the above interval, the steady state inference is restarted to avoid unreliable results.

As each compressor has a different steady state value for the shell temperature, there is no set point to be defined. The shell