Proceedings of the 18th UK Heat Transfer Conference
9-11 September 2024, Birmingham
UKHTC2024-077

# ASSESSMENT OF THE USE OF ARTIFICIAL NEURAL NETWORKS TO DETECT AND DIAGNOSE SOME SOFT FAULTS IN HEAT PUMPS

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## 1. ABSTRACT

This paper aims to explore the use of artificial neural networks for soft fault detection and diagnosis in a water-to-water heat pump. Unfaulty and faulty operational data are collected from a dedicated experimental campaign. The artificial neural networks are first trained o unfaulty conditions to allow them to predict some of the operational parameters that are usually measured in a heat pump during normal operation. Then, their potentiality in detecting and identifying faults is assessed by comparing the parameters measured under faulty conditions with those predicted by the trained artificial neural networks.

## 2. INTRODUCTION

The decarbonization of the heating sector is one crucial imperative to achieve carbon neutrality and meet the targets of the European Green Deal. To this goal, a huge deployment of heat pumps as a substitute for fossil fuel boilers is expected. Being more complex and efficient than boilers, heat pumps lead to significant savings in energy and environmental emissions but are more prone to failure. Therefore, Fault Detection and Diagnosis (FDD) techniques are mandatory to guarantee their correct operation over the full lifetime [1-2]. Generally speaking, faults may be classified as soft faults or hard faults [3]. When a soft fault occurs, the performances of the system or its lifetime worsen, but it may continue to operate. Vice versa, hard faults are catastrophic events that lead to system failure and might be the long-term results of undetected soft faults [4], making the latter the most important one to be detected and diagnosed. The present study wants to contribute to this topic by discussing the potentiality of the use of Artificial Neural Networks (ANNs) as a tool to detect and diagnose some soft faults in water-to-water heat pumps. The analysis is based on the results of an experimental campaign carried out on a heat pump prototype in a laboratory environment both in unfaulty and faulty conditions.

## 3. METHOD

To assess the potentiality of ANNs for FDD, a three-step approach is used. In the first step, several tests are carried out in the laboratory experimental setup both under unfaulty and faulty conditions. The experimental test rig consists of a brine-to-water heat pump equipped with many sensors used to measure pressures and temperatures in several locations as well as the flow rates of refrigerant and secondary fluids and the compressor power. The heat pump is tested by setting the water temperature at the condenser outlet to 45 °C whereas the temperature of the water-ethylene glycol mixture at the evaporator inlet is varied from 0 °C to 20 °C. The soft faults considered in this study are the reduction in the water flow rate at the evaporator (fault "EF", water flow rate from 70% to 100%), the reduction in the opening of the EXV (fault "EXV", opening from 70% to 100%) and the refrigerant overcharge (fault "OC", charge around 104%). It is worth specifying that only non-simultaneous faulty conditions are considered. In the second step, ANNs are trained considering the unfaulty conditions only to obtain a tool able to reliably predict the operational parameters of the heat pump. Among the parameters that are measured in the experimental setup, the temperatures of the secondary fluids flowing through the evaporator and condenser are chosen as input variables (independent variables or predictors) whereas the pressures and temperatures of the refrigerant are chosen as output variables (dependent variables or observations). Indeed, faults have a direct, strong influence on the heat pump "internal

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parameters”, i.e. refrigerant pressures and temperatures, rather than on the “external parameters”, i.e. secondary fluid temperatures since they may occur whatever the source or sink temperatures are, but the refrigerant-side operating parameters have to immediately adapt. To improve the accuracy of the ANNs a regularization technique such as the artificial expansion of the available database is used to increase the number of available data the ANNs are trained on. In the last step, the developed ANNs are applied to the data registered under faulty conditions. In these conditions, discrepancies between the actual operating parameters and those predicted by the ANNs arise, making it possible to detect faults and discriminate among them.

## 4. RESULTS

The analysis of the ability of the ANNs as an FDD tool is carried out considering the refrigerant pressures and temperatures at the compressor inlet and outlet as observations. This choice arises from the consideration that the sensors used to measure these parameters are commonly installed in many heat pumps to check the correct operation of the compressor, being this component the more prone to failure.

Fig. 1 (a) shows the comparison between the refrigerant pressure at the compressor inlet measured by the pressure sensor (actual value, x-axis) and the same parameter calculated by the ANN (predicted value, y-axis). Besides its numerical coordinates, each point is represented together with its uncertainty which is equal to the experimental uncertainty on the x-axis and the model uncertainty on the y-axis. Ther former is computed starting from the accuracy of the instrumentation and is equal to ± 2.1 kPa for the pressure at the compressor inlet, ± 12 kPa for the pressure at the compressor outlet and ± 0.1 K for the temperature. Conversely, the latter is computed using the uncertainty propagation law on the ANNs and considering the experimental uncertainty on the input parameters. This figure reveals that, for each of the three considered faults, this parameter seems a good indicator for fault detection since its values are different from those achieved in unfaulty operations. Indeed, lower pressures at the compressor inlet are found both under EF or EXV scenarios, whereas higher refrigerant pressures are found as a result of refrigerant overcharge. This allows also to distinguish between OC and the remaining faults, permitting the fault diagnosis. Similarly, Fig. 1(b) shows the same comparison but considering the refrigerant pressure at the compressor outlet. This parameter is pretty constant as all the experimental tests are carried out setting the water temperature at the condenser outlet to a constant value since this operating mode is largely adopted in many heat pumps. As a result, the refrigerant pressure at the compressor outlet, i.e. the condensing pressure, is slightly variable and it does not exhibit large variations among the three considered faults. Consequently, this parameter is a good candidate neither for fault detection nor diagnosis.

A similar analysis is applied to the refrigerant temperatures at the compressor inlet and outlet as shown in Fig. 2 (a) and (b) respectively. As expected, the former parameter is quite sensitive to the EXV opening fault, resulting in a good indicator for this kind of fault, whereas it is not appropriate for the other two faults since its values are very close to those predicted by the ANN. On the other side, the refrigerant temperature at the compressor discharge is revealed to be quite sensitive to both the EF and the EXV faults, whereas the OC fault leads to values very close to the predicted ones. Consequently, this parameter is a good indicator for fault detection but a poor indicator for fault diagnosis as it does not allow to distinguish between EF or EXV fault.

All-in-all, it may be concluded that the detection of one of the considered faults may be done considering even just one single parameter (e.g. pressure at compressor inlet), but for the fault diagnosis, it is mandatory to cross-check many of them.

## 5. CONCLUSIONS

In this study, an analysis of the use of ANNs for soft fault detection and diagnosis is proposed. Tests under both unfaulty and faulty conditions are carried out on a heat pump test rig. The former are used to train ANNs whereas the latter are used to check the ability of the ANNs in detecting and diagnosing faults. Secondary fluid temperatures are used as predictors whereas refrigerant pressures and temperatures at the compressor inlet and outlet are considered as observations. All-in-all, it is found that these parameters are suitable to detect and diagnose the three soft faults considered in this study, i.e. the reduction of the water flow at the evaporator, the reduction in the opening of the EXV and the refrigerant overcharge.

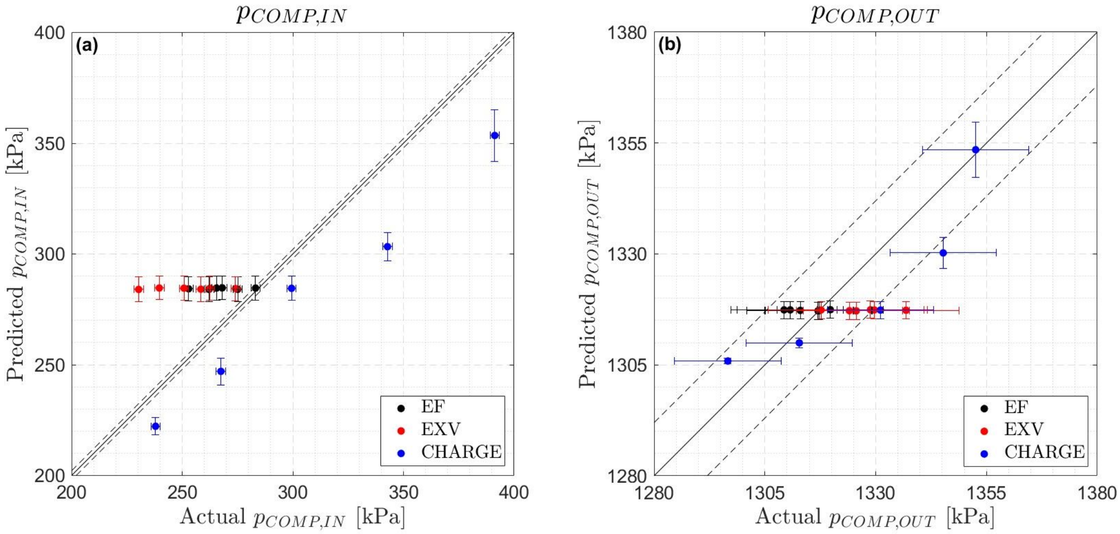


**Fig. 1** Comparison between the measured (x-axis) and predicted (y-axis) values of the pressure at the compressor suction (left) and of the pressure at the compressor discharge (right).

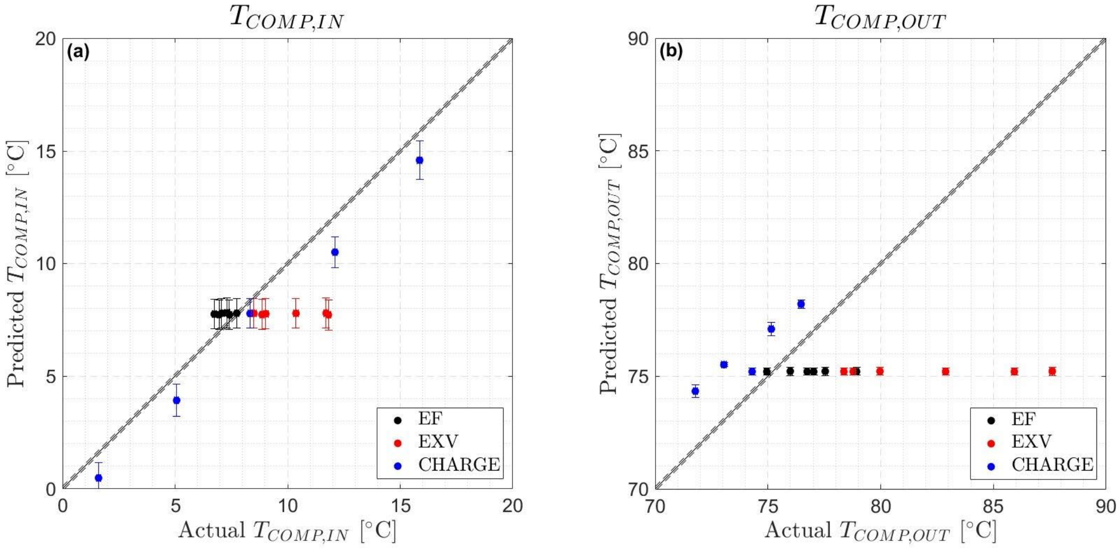


**Fig. 2** Comparison between the measured (x-axis) and predicted (y-axis) values of the temperature at the compressor suction (left) and of the temperature at the compressor discharge (right).

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