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# Fault Detection and Diagnosis by Machine Learning Methods in Air-to-Water Heat Pumps: Evaluation of Evaporator Fouling

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**Abstract:**

Heat pumps have emerged as key technology to pave the way for a sustainable heat supply in buildings. However, the ongoing shortage of trained experts counteracts the current heat pump trend. Increasing the capacity of experts, services like Fault Detection and Diagnosis (FDD) can support the identification of malfunctions and integration of methods for predictive maintenance. The primary objective of FDD is to detect faults, diagnose their causes, and possibly enable correction to prevent efficiency losses as well as system damage or downtime. This involves a comparison between a fault-free reference case and the real system. In research, machine-learning methods like Artificial Neural Networks (ANN) show the capability to learn the behavior of fault-free systems. In practice, however, the implementation of ANN is limited due to missing data in operation for training. Therefore, it is common to utilize physically simulated data for pre-training.

One way to achieve high efficiency in heat pumps is to maximize heat transfer in the evaporator. Fouling within this component therefore leads to significant performance degradation and reduced system lifespan. As a result, this work introduces and evaluates an extendable FDD method for evaporator fouling in air-to-water heat pumps. To detect evaporator fouling during operation using an ANN, a transient model of a refrigerant cycle provides the training data. Based on literature, the fouling effect is emulated afterwards, serving the data for the reference system considering faulty operation. Applying the present concept, we reveal a reduction in *COP* due to evaporator fouling of approximately 3 % over a whole year, while our fault detection methodology detects 55.65 % of the faults within the given heat pump model. Overall, this study provides insights into the performance of FDD methods for evaporator fouling in air-to-water heat pumps, which can help to improve the efficiency and reliability within the system lifespan. The results of this study demonstrate that the concept of FDD offers the potential to be applied in practice, and proposes recommendations for future perspectives about ANN within FDD in heat pump systems.

**Keywords:**

Operational Optimization, Digital Twins, Data-Driven Modeling and Simulation, Artificial Neural Networks

## 1. Introduction

As part of the agreements of the Paris Climate Convention, a sharp decrease in greenhouse gas emissions is enforced [31]. This also affects the building sector. One of the objectives of the German government is to achieve a nearly climate-neutral building stock by 2045 and thus a sustainable energy supply for the building sector [32].

Most renewable energy is available as electric energy, which can only be converted into commonly used forms such as methane with significant energy losses. Thus, sector coupling by electrification seems to be essential for decarbonization in the building sector. Heat pumps represent a key technology in this field and offer a good possibility to replace fossil fuel-based heat production with electric power [33]. Due to a limited availability as well as high demand for renewable energies, a reduction of primary energy consumption through increased efficiency is also necessary for the success of the energy transition. [35]


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The heat pump efficiency is thereby strongly dependent on a fault-free operation of the system. The rising challenges such as the ongoing lack of technicians, the gas crisis or the increasing demand due to the decision of the *Heat Pump Summit 2022* in Germany carries the risk that the vast number of new installations and maintenance of heat pumps cannot be handled. The consequences are, that specialized companies will be overwhelmed, system efficiency decreases and comfort is reduced. [4] [36]

A promising approach to face these challenges is the integration of Fault Detection and Diagnosis (FDD) methods. The development in technology and sensor devices provides a basis for embedding continuous system monitoring and thus implementing such algorithms [6]. FDD is about detection and identification of the reduced functionality or performance within a component at an early stage, as well as localization and determination of the causes [10]. In technical systems, the goal of Fault Detection and diagnosis (FDD) is to guarantee the quality, safety, and efficiency of operation. One way to achieve this is the automated detection of faults in operation, so the fault can subsequently be resolved rapidly [1]. Thus the integration has the potential to minimize system installation/control errors, detect performance degradation during operation, avoid unnecessary visual inspections and component replacement as well as reduce maintenance costs and downtime [37]. Madani et al. [37] furthermore states that already small modifications in heat pump systems can reduce size and costs caused by the fault. Their suggested framework *Smart Fault Detection and Diagnosis* (SFDD) system is capable of Detection and Diagnosis of possible faults in installation and operation phases in order to reduce maintenance costs and system down time.

FDD is a well-established research field with broad utilization. These fields include, for example, the aviation, automotive, chemical, and power plant industries. In contrast, FDD is still in an early stage for the building sector. This can also be seen in the lack of consistent terminology. [2] [28]

Isermann [29] differentiates the following notions in the context of FDD:

- **Fault Detection** - Determination of faults in a system and the time of their detection.
- **Fault Isolation** - Determination of the type, location and time of detection of a fault via evaluation of its symptoms; follows after Fault Detection.
- **Fault Identification** - Determination of the impact and evolution of a fault over time.
- **Fault Diagnosis** - Determination of the type, impact, location, and time of detection of a fault via evaluation of its symptoms; follows after Fault Detection and includes Fault Detection, Fault Isolation, and Fault Identification.

A considerable amount of FDD methods have been developed for building energy systems in the last decades, such as for air handling units, chillers, or HVAC system levels [9]. Only a small part of FDD methods relates to heat pump systems. Bellanco et al. [11] have summarized several common faults and their effects on system performance from literature for different types of heat pumps; some of them are stated in Table 1. Particles or impurities such as rust can lead to clogging or deposits in the filter, affecting the refrigerant mass flow. Consequently, the superheat increases and the cooling capacity decreases in cooling mode [13]. However, this effect is negligible for moderate fault level, when using units with thermostatic expansion valves [13]. This also applies to refrigerant undercharge, which represents a fault of the design phase [40]. The effect on system performance like *COP* due to refrigerant overcharge, though, seems to be more significant [41]. [14] and [30] refer that refrigerant leakage, which occurs especially due to broken valves on the suction and discharge line of the compressor, can negatively affect the *COP* of vapor compression systems in particular [11]. According to Kocyigit et al. of [12], fouling of the outdoor unit (e.g. by fallen leaves) has a major influence on the *COP* in cooling mode for air-to-air systems. Primarily caused by an increased thermal resistance at the fin heat exchangers due to fouling as well as a decrease of the external air flow rate, whereby the former shows a more significant impact on the *COP*. While the emulation of common faults for experimental validation such as refrigerant leakage [15] or liquid line restriction [39] are complex studies in some cases, fouling is frequently conducted in the literature by simply blocking the area of the heat exchanger with paper or cardboard [15] [16] [39]. Therefore the present work focuses on evaporator fouling.

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**Table 1**. Common faults in heat pump systems [11].

| Faults type | System | Effect | Reference |
|---|---|---|---|
| Outdoor unit fouling (FO) | Air-to-Air (cooling mode) | *COP* decreases 9 %<br>Capacity decreases 14 % | [12] |
| Indoor unit fouling (FI) | Air-to-Air (heating mode) | *COP* remains | [39] |
| Valve leakage (VL) | Air-to-Air (heating mode) | *COP* decreases 4.4 % | [39] |
| Ref. overcharge (RO) | Air-to-Water (heating mode) | *COP* decreases 3.4 % | [38] |
| Ref. undercharge (RU) | Air-to-Water (heating mode) | *COP* decreases 1.2 % | [38] |
| Liquid line restriction (LL) | Air-to-Air (heating mode) | *COP* and Capacity remains | [12] |

Typically, FDD methods are integrated as follows: The calculations of a simulation model representing the fault-free state of the device are compared to the behavior of the system in which a fault has been injected [17]. There are two modeling techniques in order to represent the fault-free behavior. First-principle models are (partly) based on physical knowledge of underlying physical phenomena to describe the system. Unfortunately equations describing real systems are complex and usually difficult to solve. For this reason, data-driven models are attracting more and more attention [17], using experimental or simulative data to learn the relationship between the inputs and outputs of the system to build both linear and nonlinear models. Apart from established methods like Support Vector Machine (SVM) [18] or Partial Least Squares (PLS) [19], Artificial Neural Networks (ANN) [7] [8] revealed comparatively better results [sources]. [6]

Few references dealt with the study of air-to-water heat pump systems in heating mode, although this is one of the most common heat pump systems in the building sector with further increasing interest in the future [3]. To bridge this research gap, this paper proposes the development of FDD for air-source heat pumps. For implementation, we include an ANN-model that simulates the fault-free operation of the plant and calculates the *COP* (Section 2). The actual fault is then injected in a further (physical) simulation for simplicity reasons and compared with the *COP* of the fault-free calculation. Based on the deviation between the two simulation models, a methodology for Fault Detection in case of evaporator fouling is developed (Section 3), and the results are presented (Section 4). Finally, the main conclusions are given in Section 5.

## 2. Methodology

The methodology used within this paper for FDD can be isolated based on Figure 1 (red section). Here, Melgaard et al. [20] aggregated from [23] a generic framework for engineering systems. In a first step, the real system or device is monitored metrologically to detect any abnormal conditions. The data is subsequently analyzed and evaluated in the process of Fault Detection (FD), Fault Isolation (FDD), and Fault Identification (FDD). In case a fault is detected, a notification is provided (FD). The FDD also provides information about the location, time and length of the fault occurrence as well as the fault's level. In a final step, the fault is evaluated in terms of the level and significance of its impact on system performance (e.g. costs, energy consumption and other performance indicators). The Fault Evaluation allows to make a decision about the further procedure and handling of the fault inside the fault tolerant control. [23] Within the scope of this work, as first step, fault detection (FD) without further evaluation is carried out (red section), which serves as a basis for future developments.

### 2.1 Modeling

An essential part of FDD is typically a model, which in case of data-driven based methods can represent either a classifier or a regressor. Classification methods described for example in [9] provide a simple approach to detect and diagnose faults. However, a major disadvantage of this technique is the necessity of large labeled datasets (subdivided into faulty and fault-free modes) for the training procedure. This means the fault behavior must be emulated experimentally, which may cause high costs and efforts. Regression-based methods as used in [24] compare a simulated variable (obtained e.g. from a trained ANN) with the measured variable of the real system in order to detect and/or diagnose a fault by comparing both. Therefore, the model learns in a preceding training process the fault-free behavior of the system with measured features, which are ideally not affected by the fault itself. Thus, only fault-free operation must be modeled, which is why this approach is addressed within this work (section 3).

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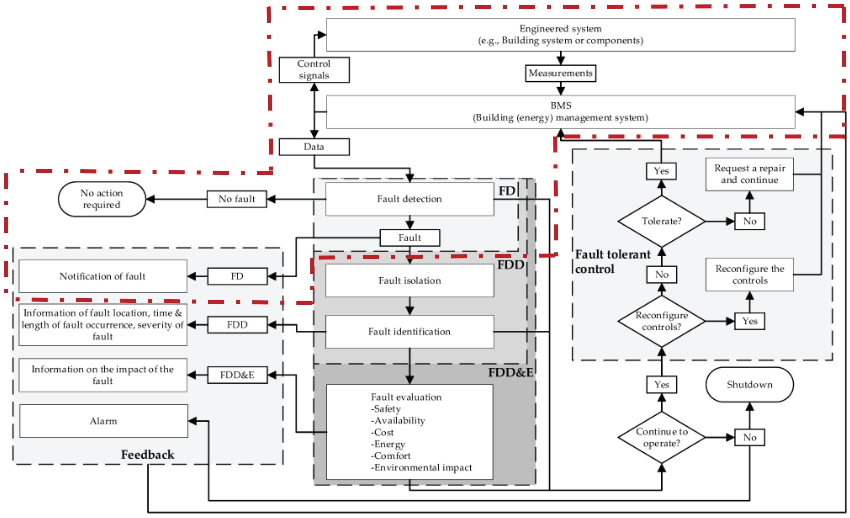


**Figure 1:** Generic FDD framework for building energy systems according to [20]. The marked red section describes the scope within this work.

### 2.2 Notification of faulty operation

A further important aspect is the implementation of a subsequent method, which detects the fault as reliably as possible depending on the described comparison between the real system and the ANN. Keliris et al. [21] introduced a simple threshold-based approach using the residual of the real and simulated system (Figure 2). Essential and subject of current research is the selection of a proper threshold for the residual from which a fault is detected. This strongly depends on the model, the real system and the use case. Within this work, the threshold is subsequently adjusted according to the fault level (section 4).

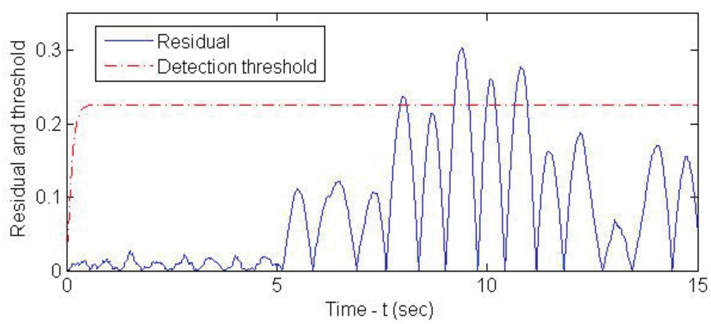


**Figure 2:** Example of a threshold-based method for a Fault Detection and Diagnosis using the residual [21].

### 2.3 Evaluation of FDD method

To evaluate the proposed FDD method, the literature suggests a classification into the following parameters, as shown in Table 2. The False Alarm Rate (FA) may be the most serious for FDD, since it could be trigger service being done on a properly working system. Although the algorithm or protocol does not trigger any unintended operations by services in the case of Missed Detection Rate (MD), the failed fault detection can lead to further subsequent faults and performance degradation in the long term. [22]

Yuill et al. [22] also take into account the fault intensity when evaluating the algorithm or protocol. The key parameters within this paper are the FA and MD parameters. However, this is because the intensity of the fault is not considered and the FDD focuses solely on the fault of the evaporator fouling. A Missed Diagnosis can thus be excluded as well as No Response.

**Table 2:** Evaluation parameter of FDD methods [22].

| Parameter | Declaration |
|---|---|
| False Alarm Rate (FA) | Algorithm returns fault notification during fault-free operation. |
| False Negative Rate or Missed Detection Rate (MD) | Algorithm fails to detect faulty operation. |
| No Response (NR) | No response from algorithm. |
| Missed Diagnosis Rate (MDI) | Algorithm diagnosed wrong fault. |

## 3. Modeling of Artificial Neural Network and reference system

The literature shows great potential for the using ANN, especially for fault detection in complex HVAC systems, improving the results compared to other data-driven methods [25]. The ANN in the context of this work is intended to represent the fault-free state of the system, the dataset used for training and the reference case as well as the hyperstructure of the model is explained below. The investigation period covers one year with an hourly resolution.

### 3.1 Simulated reference system

In order to consider the effect of the air flow rate on the evaporator capacity, this paper uses the TiL-Suite [34] to model the heat pump. This allows a detailed and transient simulation of the refrigerant cycle. The heat exchanger in the evaporator is designed as fin tubes in crossflow mode and is based on the finite volume approach. We use a simple refrigeration cycle and the medium is propane. The *COP* is then obtained from an energy balance of the evaporator, condenser and compressor. This model is applied in section 3.2 in order to train a fault-free ANN.

To simulate evaporator fouling, the external air flow rate in the evaporator needs to be decreased. In this paper, a gradual reduction of the fan speed is implemented using tangens hyperbolicus (Eq. 1), motivated by [26]. $n_{\mathrm{fan}}$ is the fan speed with its maximum value of 15 Hz, $t$ the time and $t_{\mathrm{half}}$ the time at half a year in hours. The assumption in this context is that fault-free operation correlates to a fan speed of 15 Hz (Figure 9).

$$n_{\mathrm{fan}}(t) = 15Hz - 7.5Hz \cdot tanh(\frac{\pi}{2} \cdot \frac{t}{t_{\mathrm{half}}}) \quad (1)$$

### 3.2 ANN model for fault-free operation

The selected hyperstructure of the ANN is shown in Figure 3 and will be used within this work to represent the fault-free mode of the reference heat pump. The structure is a result of a predefined hyperparameter optimization beforehand and consists of two hidden layers and a total of 176 neurons to calculate the *COP* (“signal”). The input variables (“features”) represent compressor speed $n_{\mathrm{comp}}$, discharge temperature $T_{\mathrm{dis}}$ from the compressor and refrigerant mass flow $\dot{m}_{\mathrm{ref}}$. The feature selection is a result of an optimization using ADDMo [27], a tool developed by the Institute for Energy Efficient Buildings and Indoor Climate at RWTH Aachen University. This tool automatically calculates the correlation of different features to the signal based on the Pearson correlation coefficient.


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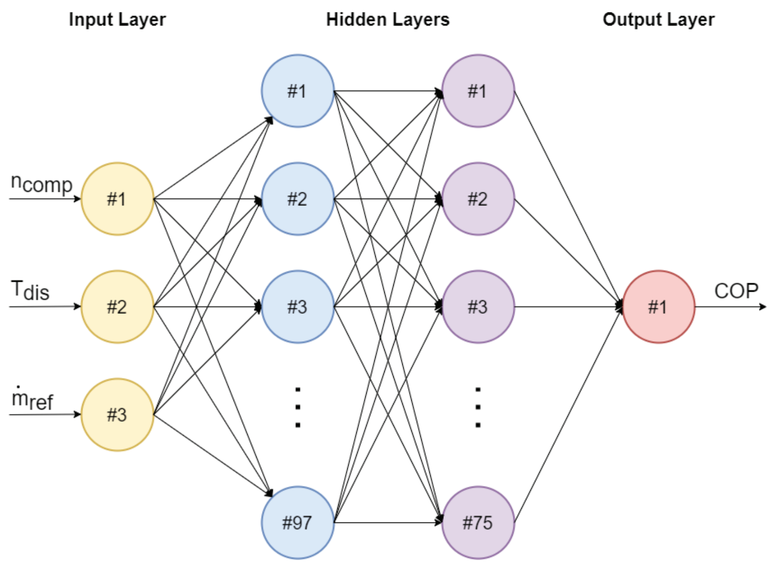


**Figure 3:** ANN hyperstructure used within this work for calculation of *COP* in fault-free operation. The model's features are the compressor speed, the discharge temperature of the compressor, and the refrigerant mass flow rate.

## 4. Results

In this section, the fault detection results obtained from the described methodology (section 2) using simulated data (section 3.1) and the ANN model for training and testing (section 3.2) are presented and discussed afterwards.

### 4.1 Validation of *COP* model

In order to train an ANN for fault-free operation, the relevant simulation data for one year is presented below for validation. For simplification, we assume an operation of the heat pump over the whole year. The data are subsequently shuffled to obtain a heterogeneous and randomly spread data set for the training of the ANN. The result is shown in Figure 4; the *COP* ranges between about 3.5 and 6.

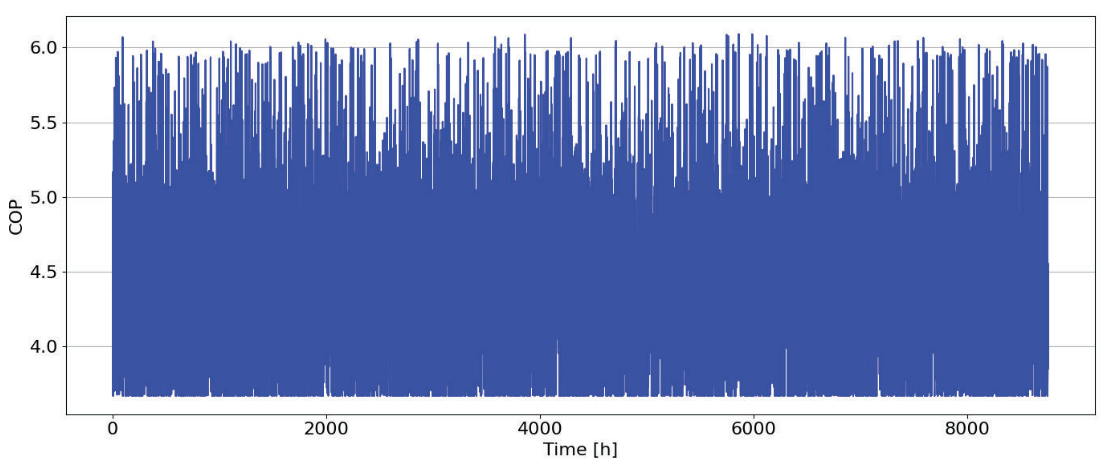


**Figure 4:** Shuffled dataset of *COP* within the yearly simulation and an hourly resolution.

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Figure 5 provides a part of Figure 4, which is used for training (400 hours) and testing (100 hours). This corresponds to a 75 to 25 % split. The majority of the data points are below a *COP* of 5, similar to Figure 4. In addition, Figure 6 shows the test data set used to validate the ANN based on *COP* comparisons to the reference model. The result is an RMSE of about 0.03 for mapping fault-free operation by the ANN.

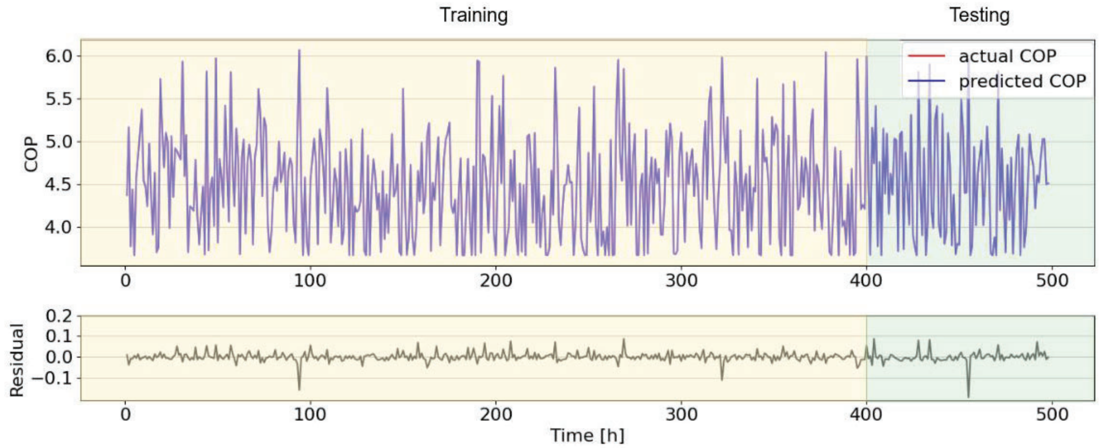


**Figure 5:** Shuffled dataset of Training and Testing period for ANN Validation.

In Figure 7 we compare the predicted *COP* from ANN and the reference system from the simulation with TiL-Suite (section 3.1) in fault-free operation combined with the residual of both. An RMSE of 0.023 is obtained, hence the ANN seems to be able to model the *COP* quite well. The residual is significantly higher in the summer period compared to winter. This might be due to the composition of the training data set (Figure 5), where the amount of data coming from the winter period is higher, even after shuffling the data. This can be observed as well in the histogram of Figure 8.

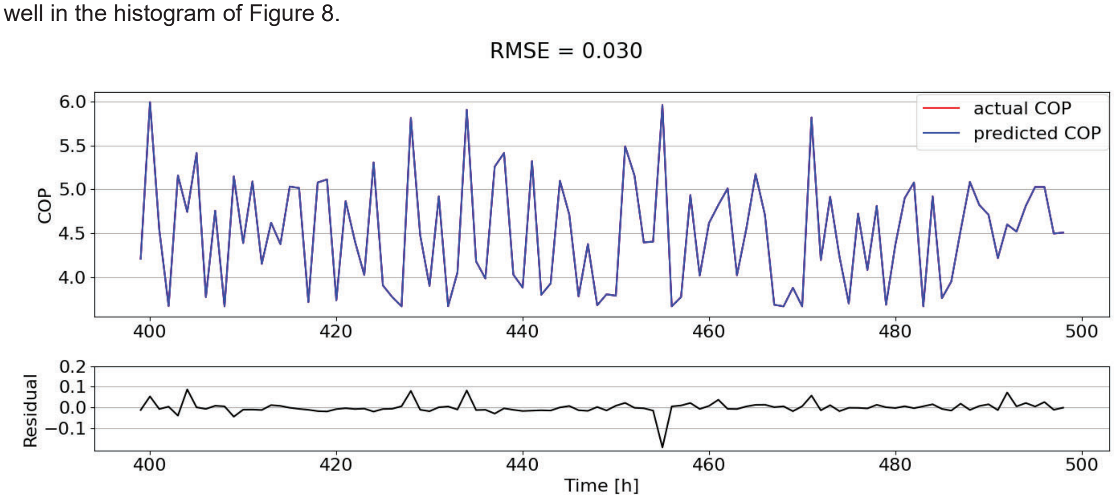


**Figure 6:** Testing period for ANN Validation from Figure 5.

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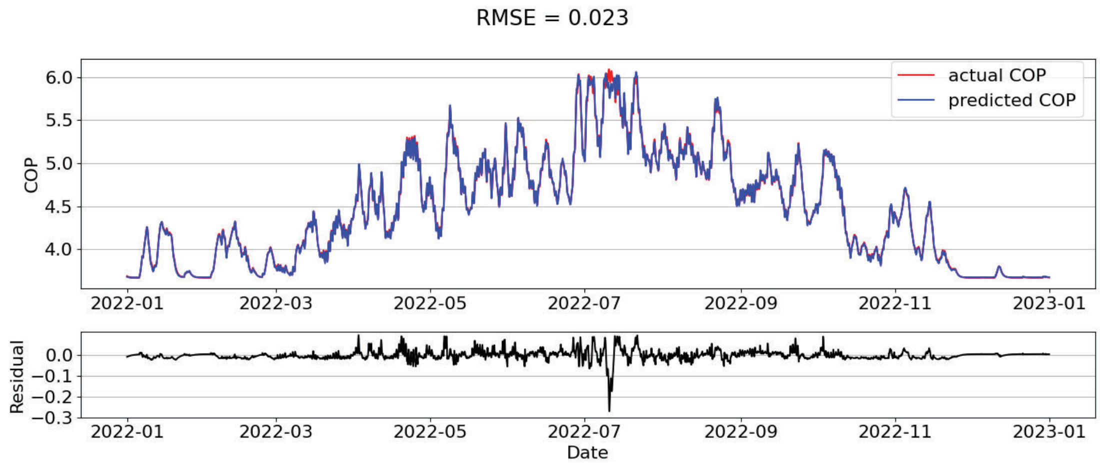


**Figure 7:** Above: Predicted *COP* with ANN (blue) and *COP* of reference system (red) within the study period. Below: Residual of predicted and actual *COP*.

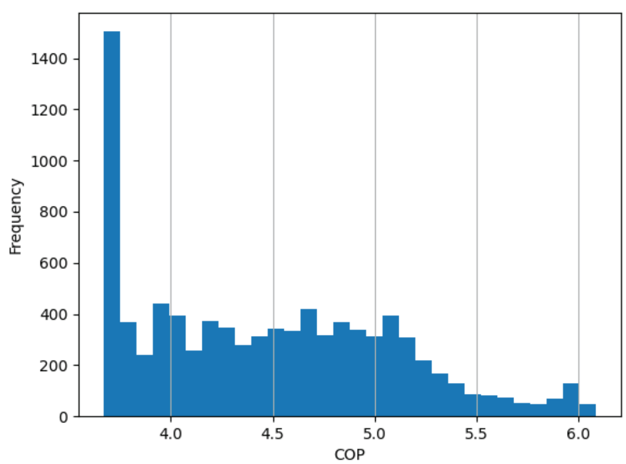


**Figure 8:** Histogram of occurred *COP*s in the Simulation.

### 4.2 Model tests for Fault detection

In Figure 9, we again show the *COP* of prediction from ANN and the reference system (with injected fault) from the simulation with TiL-Suite (section 3.1) combined with the residual of both. The green plot demonstrates the fault intensity, which increases according to equation 1 from 0 to 100 %. The maximum fault indication is limited to a reduction of the fan speed by 50 %. The residual increases significantly from April and hence a fault intensity of around 70 % (fan speed accordingly corresponds to 10.5 Hz) on average. It can be observed that the residual increases from April and thus an error intensity of around 70 % (fan speed thus corresponds to 10.5 Hz) on average. The *COP* does not seem to be affected significantly at lower fault intensities. This seems to be partly due to the problem described in section 4.1 above, where the ANN is generally poorer at representing the *COP* in the summer periods, but an increased residual compared to Figure 7 can be detected clearly as well.

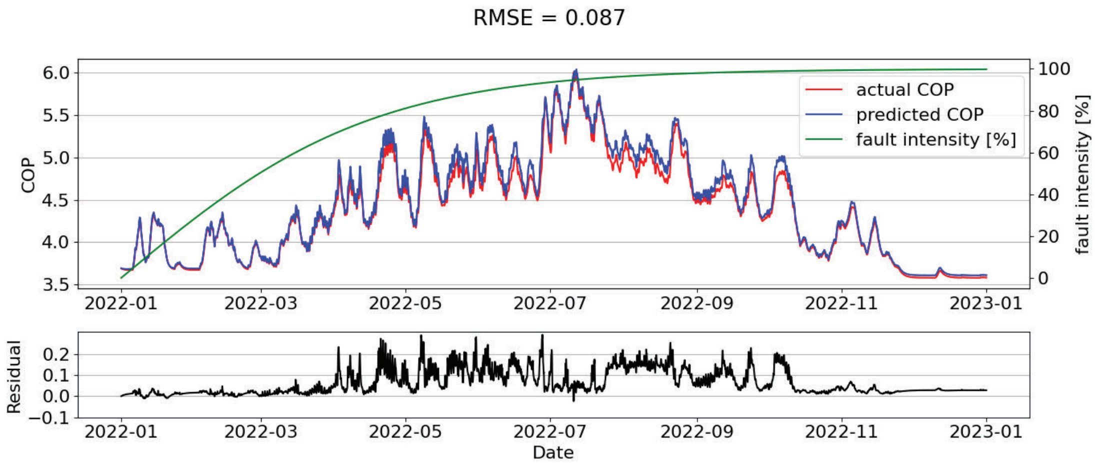


**Figure 9:** Above: Predicted *COP* with ANN (blue) and *COP* of reference system (red) within the study period including the fault injection. The fault intensity is shown in green. Below: Residual of predicted and actual *COP*.

Based on the results shown in Figure 7 and Figure 9, the threshold value, which serves the basis for fault notification, is defined to be a residual of 0.05. Exceeding this value leads to a notification and in this case to a MD of 44.35 % and FA of 1.35 % (Evaluation is carried out starting from a fault intensity of 70 %).

### 4.3 Limitations of the work

Within the scope of this work, all results were obtained from simulation data in order to emulate the effect of evaporator fouling. The associated model has not yet been completely validated, but has been compared with similar results from the literature. Hence, a validation based on real experiments, focusing the effect of evaporator fouling, is necessary in the future. For evaluation the threshold value (Section 4.2) has a significant impact on both the MD and the FA. The divergence in model accuracy between the winter and summer periods of the ANN leads to a significant increase in MD starting from early October. A further decreasing of the threshold may help here, but leads to an increase of FA, thus a pareto-optimization is necessary. Thus, this work has demonstrated the importance of training data selection for data-driven model performance. For future work, we expect better accuracy of the fault detection results by using a confidence interval instead of a threshold approach. Moreover, a valid benchmark for the evaluation of FDD methods by e.g. MD and FA is missing in the literature so far and needs to be elaborated.


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## 5. Conclusion

This paper provides a first proof of concept for FDD using Artificial Neural Networks (ANN) to detect any abnormal behavior like evaporator fouling in air-to-water heat pumps early on. The early detection of faults like evaporator fouling is essential in maintaining the efficiency and performance of air-to-water heat pumps. Fouling causes a decrease in heat transfer, which reduces the system efficiency and increases energy consumption. Fault detection enables the scheduling of maintenance before significant performance degradation or system downtime occurs. For this purpose, an ANN is trained to predict the *COP* representing the fault-free operation of an annual simulation. The training data is obtained based on a transient simulation of a refrigerant cycle from the TiL-Suite, which also represents the reference system for fault injection. By gradually reducing the fan speed in the model, the heat transfer within the evaporator is decreased, thus emulating the fouling effect. Subsequently, using the residual of the ANN and the reference model, the deviation of *COP* correlates to the fault and a notification is provided based on a predefined threshold value. This way we are able to detect 55.65 % of all occurring faults and a false alarm is raised only in 1.35 % of the cases.

In future work, instead of using simulation data, we intend to apply experimental data to monitor and detect the effect of fouling and other faults more accurately. Furthermore, we will extend the fault notification method by including a confidence interval and further examine the selection and effect of training data to the ANN. Another crucial aspect in this paper is that a reduction of *COP* is no indication for a specific type of fault. Thus, a key for further development towards fault diagnosis in the future will be the identification of decoupled features which indicate specific fault characteristics or at least isolate potential fault types.

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## References


- **Journals**:

[1] Shi Z., O'Brien W., Development and implementation of automated fault detection and diagnostics for building systems: A review. Automation in Construction 2019; 104:215–229. DOI: 10.1016/j.autcon.2019.04.002. URL https://linkinghub.elsevier.com/retrieve/pii/S0926580518312354

[2] Melgaard S. P., Andersen K. H., Marszal-Pomianowska A., Rasmus L. J., Heiselberg P. K., Fault Detection and Diagnosis Encyclopedia for Building Systems: A Systematic Review. Energies 2022, 15(12):4366, January 2022. DOI: 10.3390/en15124366. URL https://www.mdpi.com/1996-1073/15/12/4366

[3] Rosenow, J., Gibb, D., Nowak, T., & Lowes, R., Heating up the global heat pump market. Nature Energy 2022, 7(10), 901-904.

[4] Li Y., O'Neill Z., A critical review of fault modeling of HVAC systems in buildings. Building Simulation 2018, 11(5):953–975. DOI:10.1007/s12273-018-0458-4. URL https://doi.org/10.1007/s12273-018-0458-4

[5] Madani H., The Common and Costly Faults in Heat Pump Systems. Energy Procedia 2014, 61:1803–1806. DOI: 10.1016/j.egypro.2014.12.217. URL https://linkinghub.elsevier.com/retrieve/pii/S1876610214032469

[6] Song Y., Rolando D., Avellaneda J. M., Zucker G., Madani H., Data-driven soft sensors targeting heat pump systems. Energy Conversion and Management 2023, 279 (2023): 116769. DOI: 10.1016/j.enconman.2023.116769. URL https://doi.org/10.1016/j.enconman.2023.116769

[7] Varlamis I., Sardianos C., Chronis C., Dimitrakopoulos G., Himeur Y., Alsalemi A., et al., Smart fusion of sensor data and human feedback for personalized energy-saving recommendations. Appl Energy 2022, 305:117775.

[8] Fan Y., Tao B., Zheng Y., Jang S-S., A data-driven soft sensor based on multilayer perceptron neural network with a double LASSO approach. IEEE Trans Instrum Meas 2019, 69(7):3972–9.

[9] Zhao, Y., Li Tingting, Thang X., Zhang C., Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future. Renewable and Sustainable Energy Reviews 2019, 109: p. 85-101.

[10] Aguilera, J. J, et al. A review of common faults in large-scale heat pumps. Renewable and Sustainable Energy Reviews 2022, 168: 112826.

[11] Bellanco, I., et al., A review of the fault behavior of heat pumps and measurements, detection and diagnosis methods including virtual sensors. Journal of Building Engineering 2021, 39: 102254.

[12] Kocyigit N., Bulgurcu H., Lin C. X., Fault diagnosis of a vapor compression refrigeration system with hermetic reciprocating compressor based on p-h diagram, Energy Econ, 2014. 45 44–54, https://doi.org/10.1016/j.ijrefrig.2014.05.027

[13] Mehrabi M., Yuill D., Generalized effects of faults on normalized performance variables of air conditioners and heat pumps, Int. J. Refrig. 85, 2018. 409–430, https://doi.org/10.1016/j.ijrefrig.2017.10.017

[14] Breuker M.S., Braun J.E., Common faults and their impacts for rooftop air conditioners, HVAC R Res. 4, 1998. 303–318, https://doi.org/10.1080/10789669.1998.10391406

[15] Li H., Braun J.E., A methodology for diagnosing multiple-simultaneous faults in rooftop air conditioners, HVAC R Res. 13, 2004. 369–395.

[16] Armstrong P.R., Laughman C.R., Leeb S.B., Norford L.K., Detection of rooftop cooling unit faults based on electrical measurements, HVAC R Res. 12, 2006 151–175, https://doi.org/10.1080/10789669.2006.10391172

[17] Rogers, A. P., F. Guo, and B. P. Rasmussen, A review of fault detection and diagnosis methods for residential air conditioning systems, Building and Environment, 2019. 161: 106236.

[18] Herceg S., Andrijić Ž.U., Bolf N., Development of soft sensors for isomerization process based on support vector machine regression and dynamic polynomial models, 2019. Chem. Eng. Res. Des.,149:95–103. https://doi.org/10.1016/j.cherd.2019.06.034

[19] Zheng J., Song Z., Semisupervised learning for probabilistic partial least squares regression model and soft sensor application, 2018. J. Process Control, 64:123–31.

[20] Melgaard S.P., Andersen K.H., Marszal-Pomianowska A, Jensen R.L., Heiselberg P.K., Fault Detection and Diagnosis Encyclopedia for Building Systems: A Systematic Review. Energies, 2022. 15(12):4366. https://doi.org/10.3390/en15124366

[21] Keliris C., Polycarpou M., Parisini T., A Distributed Fault Detection Filtering Approach for a Class of Interconnected Continuous-Time Nonlinear Systems, 2013. IEEE Transactions on Automatic Control. 58. 2032–2047. DOI: 10.1109/TAC.2013.2253231

[22] Yuill D. P., Braun J. E., Evaluating the performance of fault detection and diagnostics protocols applied to air-cooled unitary air-conditioning equipment, 2013. HVAC&R Research. 7. 882-891. DOI: 10.1080/10789669.2013.808135

[23] Katipamula S., Brambley M., Review Article: Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems—A Review, Part I, 2005. HVAC&R Research. 11. 3-25. DOI: 10.1080/10789669.2005.10391123

[24] Mavromatidis G., Acha S., Shah N., Diagnostic tools of energy performance for supermarkets using Artificial Neural Network algorithms, Energy Build, 2013. 62:304–14 URL https://doi.org/10.1016/j.enbuild.2013.03.020

[25] Nelson W., Culp C., Machine Learning Methods for Automated Fault Detection and Diagnostics in Building Systems—A Review. Energies, 2022. 15(15):5534. DOI: 10.3390/en15155534. URL https://www.mdpi.com/1996-1073/15/15/5534

[26] M. S. Abd-Elhady, Malayeri M.R., Asymptotic characteristics of particulate deposit formation in exhaust gas recirculation (EGR) coolers, 2013. Applied Thermal Engineering 60.1-2: 96-104. URL http://dx.doi.org/10.1016/j.applthermaleng.2013.06.038

[27] Rätz M. et al., Automated data-driven modeling of building energy systems via machine learning algorithms, 2019. Energy & Buildings. 202. URL https://doi.org/10.1016/j.enbuild.2019.109384

- **Chapter in a book**:

[28] Gertler J., Fault Detection and Diagnosis. In Baillieul J. and Samad T., editors. Encyclopedia of Systems and Control, Springer, London, 2015. p. 417–422. DOI: 10.1007/978-1-4471-5058-9_223. URL https://doi.org/10.1007/978-1-4471-5058-9_223

[29] Isermann R., Terminology in fault detection and diagnosis. In Rolf Isermann, editor. Combustion Engine Diagnosis: Model-based Condition Monitoring of Gasoline and Diesel Engines and their Components, ATZ/MTZ-Fachbuch, p. 295–297. DOI:10.1007/978-3-662-49467-7_9. URL https://doi.org/10.1007/978-3-662-49467-7_9

[30] Du Z., Domanski P.A., Payne W.V., Effect of common faults on the performance of different types of vapor compression systems, Appl. Therm. Eng., 2016. 98 61–72, https://doi.org/10.1016/j.applthermaleng.2015.11.108

- **Web references:**

 https://doi.org/10.52202/069564-0074

[31] Vereinte Nationen. Übereinkommen von Paris, December 2015. Available at: https://www.bmz.de/de/service/lexikon/klimaabkommen-von-paris-14602 [accessed 10.03.2023]

[32] Presse und Informationsamt der Bundesregierung. Generationenvertrag für das Klima, 2022. Available at: https://www.bundesregierung.de/breg-de/themen/klimaschutz/klimaschutzgesetz-2021-1913672 [accessed 10.03.2023]

[33] Umwelt Bundesamt. Umgebungswärme und Wärmepumpen, 2022. Available at: https://www.umweltbundesamt.de/themen/klima-energie/erneuerbare-energien/umgebungswaerme-waermepumpen [accessed 10.03.2023]

[34] TLK-Thermo GmbH. TIL Suite Softwarepaket zur Simulation thermischer Systeme. Available at: https://www.tlk-thermo.com/index.php/de/til-suite [accessed 10.03.2023]

- **Books and other monographs:**

[35] Quaschning V., Quaschning C., Energierevolution jetzt! Mobilität, Wohnen, grüner Strom und Wasserstoff: Was führt uns aus der Klimakrise - und was nicht? Hanser, München, 2022.

- **Conference Papers**:

[36] Roth, Kurt W., Westphalen D., Llana P., Feng M., The energy impact of faults in US commercial buildings. International Refrigeration and Air Conditioning 2004.

[37] Madani H. et al., Smart Fault Detection and Diagnosis for Heat Pump Systems, Refrigeration Science and Technology 2016, 3703-3710.

[38] Noel D., Riviere P., Marchio D., Non-Intrusive Performance Assessment Method For Heat Pumps : Experimental Validation And Robustness Evaluation Facing Faults, in: 17 Th, Int. Refrig. Air Cond. Conf. 2018.

[39] Ho Yoon S., Vance Payne W., Domanski P.A., Residential heat pump heating performance with single faults imposed. http://docs.lib.purdue.edu/iracc/1107, Int. Refrig. Air Cond. Conf. 2010.

[40] Mehrabi M., Yuill D., Normalized effect of condenser fouling and refrigerant charge on performance of vapor compression air conditioning systems, Int. Compress. Eng. Refrig. Air Cond. High Perform. Build. Conf. 2016.

[41] Noel, D., Teuillieres, Riviere P., Cauret O., Marchio D., Experimental Characterization of Fault Impacts on the Functioning Variables of an Inverter Driven Heat Pump, 2018.