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Soft Fault Diagnosis and Evaluation Strategies: An Approach BEYOND the State of the Art to Reduce Emissions Associated with Heating and Cooling in the Residential Sector

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Heat pumps are essential for decarbonization, but their efficiency is often reduced by hidden 'soft faults' that can increase their daily energy consumption up to 26%. This article highlights the state of the art of methods for fault detection and diagnosis, pointing out the advantages of combining Machine Learning techniques with a large amount of synthetic data generated by models, which are calibrated on appropriate and limited experimental datasets. From a perspective of smart services for resilient operation, the presence of concurring soft faults causing deterioration in performance and energy efficiency makes the evaluation of the faults' intensities also important, to evaluate which intervention is economically and/or environmentally convenient. This innovative step is now backed by a strategic EIC-funded project, BEYOND.

Introduction: The Impact of Operational Faults on System Performance

The real-world efficiency of heat pumps, a key decarbonization technology, is often undermined by 'soft faults' like refrigerant leakage or fouling. These issues degrade performance while the system remains functional, often going undetected until they significantly increase energy consumption by up to 26% daily [1] or escalate into a complete system failure. The prevalence of these problems is significant: a study by Pigg et al. [2] found refrigerant charge issues in 69% of inspected AC units, noting that proper maintenance improved energy efficiency by an average of 9.5%.

Addressing these operational inefficiencies through Fault Detection and Diagnosis (FDD) has therefore become a critical area of research. Robust FDD techniques are essential to mitigate performance degradation, lower maintenance and energy costs, and reduce carbon emissions, ensuring that the full energy-saving potential of heat pumps is realized throughout their lifetime [3].

Methodologies for Fault Detection and Diagnosis (FDD)

Modern Fault Detection and Diagnosis (FDD) methodologies, increasingly powered by Machine Learning, are traditionally classified into three categories: quantitative model-based, qualitative model-based, and data-driven approaches [4], [5].

Quantitative, physics-based models are rarely employed due to their complexity and extensive validation requirements. Qualitative, rule-based techniques (e.g., "if subcooling is low, a fault is present") are more common, but their reliability is limited by system-specific thresholds that struggle with complex systems. Consequently, data-driven methods, which analyze historical data without relying on underlying physics, have become the primary focus for both research and industry. These approaches can be broadly classified as knowledge-based, purely data-driven, or hybrid gray-box models (as illustrated in Figure 1).
Despite this academic focus on advanced diagnostics, a clear gap remains between research and commercial application. A patent review by Pelella et al. [6] reveals that industrial innovation still focuses on simple, rule-based methods for single-fault diagnosis. Crucially, existing patents and commercial products lack the ability to precisely evaluate the *severity* of a fault, especially when multiple faults occur simultaneously. This gap highlights a significant opportunity for advanced FDD systems capable of moving beyond simple diagnosis to quantitative fault evaluation, which is essential for optimizing maintenance and system performance.

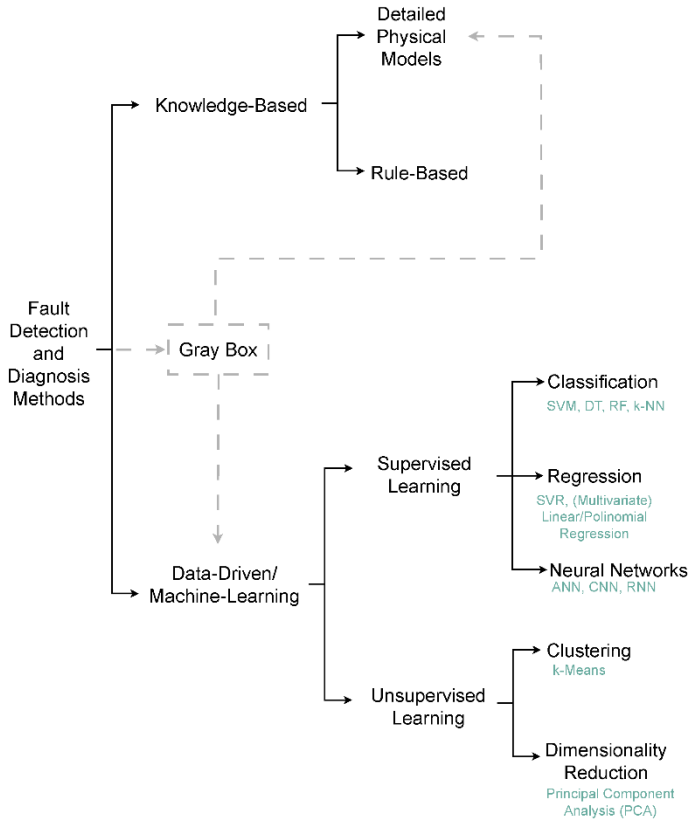

Figure 1. Classification of FDD methodologies based on recent advances.

Discussion on the advantages and limitations of Machine Learning approaches for FDD

While smart devices make field data increasingly available, it cannot be directly used for robust Fault Detection and Diagnosis (FDD). Unsupervised learning, for instance, struggles to reliably distinguish specific fault signatures from normal operational variations, as the type and intensity of any underlying faults are usually unknown and unlabeled. For this reason, supervised learning is preferred for complex FDD tasks, which require large, physics-informed datasets. A common strategy is to use limited, high-quality lab data to calibrate physics-based models that then generate extensive synthetic data for training. This approach is powerful, but its final accuracy depends on several interconnected factors: a) the ML method's generalization capabilities, b) the accuracy of the measurements, c) the chosen step of fault intensity, and d) the model's fidelity for data synthesis.

Recent literature explores these challenges. While studies by Kim et al. [7] and Ebrahimifakhar et al. [8] both demonstrated the high accuracy of SVM models, their work was either not experimentally validated or required an unfeasible number of sensors for residential systems. A recent study by Pelella et al. [9] developed a large synthetic dataset

and, using a limited set of measured inputs, demonstrated that the accuracy of the measurements is strictly connected to the step in the intensity of the fault, which can be determined univocally. This is an important effect that is often not accounted for when assessing the accuracy of ML methods, strongly limiting the generality of the conclusions achieved by the studies. The work by Mauro et al. [10] created a large dataset correlating the effects on the cycle with three concurrent soft-fault intensities (FDD+Evaluation - FDD+E). Then, they imposed some long-time faults' combination (based on assumptions over statistical data from the field), simulated the corresponding condition to have virtual measurements from the simulated cycle. Then, with this set of measurements, they predicted back the faults with different methods: multi-dimensional interpolation and ML tools (Neural Networks -ANN and KNN). The accuracy of all the ML tools is good, but each of them has some indeterminacy zones, which are intrinsically related to the overlapping of effects due to different intensities of soft faults.

A recent study by Llopis-Mengual et al. [11] added to the estimation of the accuracy of the ML method, also the accuracy from the experimental data. They created a synthetic dataset from simulations under different soft-fault conditions and used this data to train a robust machine learning algorithm, a Support Vector Machine (SVM), to distinguish between different faulty states. Figure 2 shows a simple example of how this algorithm works when classifying two different fault states based on the measurement of two variables. The SVM algorithm, trained exclusively with the simulated data, was then tested using real experimental measurements from the same physical unit operating under controlled fault conditions in a laboratory.

The results were highly promising, with the algorithm successfully identifying the correct fault status (including multiple simultaneous faults) with a balanced accuracy of 82%. Nevertheless, some zones of indeterminacy of the faults remain, which cause false predictions that can not be addressed only by the use of ML.

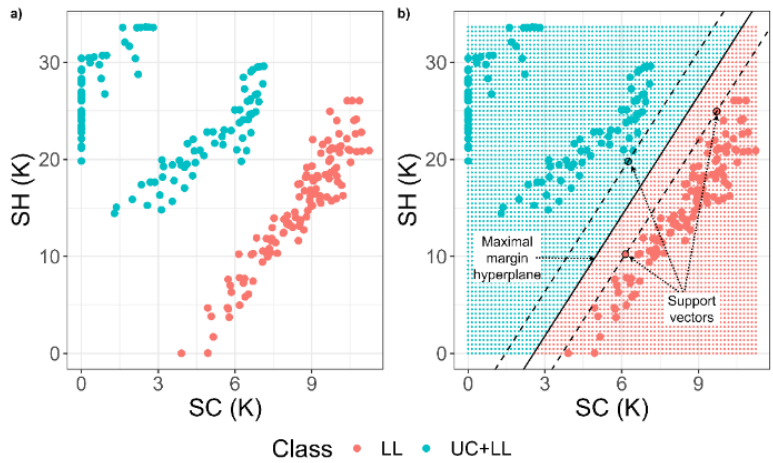

Figure 2. Figure elaborated in [7] under license CC BY-NC-ND. It shows an example of the application of a support vector classifier to distinguish tests with Liquid Line restrictions (LL) or combined LL+UC (undercharge) faults as a function of subcooling (SC) and superheat (SH).

Strategic Research Initiatives: The BEYOND Project

To enable smart maintenance services for heat pumps, it is crucial to evaluate the intensity of concurrent soft faults to assess the economic and environmental convenience of an intervention. Since current methods struggle with quantitative evaluation and solving indeterminacy conditions, the BEYOND project [12] was funded in 2024 by the European Innovation Council's (EIC) Pathfinder program to address this gap under the "Clean and efficient cooling" challenge. The challenge aims to advance novel solutions that increase operational reliability and strengthen the EU's technological leadership. More specifically, the BEYOND project's goal is to develop a novel and cost-effective method for the detection, diagnosis, and quantitative evaluation of simultaneous soft faults in residential heat pumps. The strategy involves running a massive test campaign on air-to-water and air-to-air heat pumps. A dedicated model will be calibrated and validated on these experiments to build a large dataset, which will be used to design and test a completely new algorithm, not limited to standard ML or regression techniques.

Conclusions

Soft faults often reduce the real-world efficiency of heat pumps, a key technology for decarbonization. The use of maps of faults can be used with several techniques to try to solve FDD or even the FDDE. The use of synthetic data from models is a good approach to limit the need for experiments, and ML tools can help to solve the challenge of FDDE, combining speed and accuracy. But the accuracy of the prediction is not only related to the training phase, but also to the accuracy of measurements and of the models. Also, most

importantly, the crucial aspect is that increasing the degree of freedom of the system and the concurrence of soft-faults, the number of indeterminate zones (which cannot be univocally related to the fault intensities) increases. The project BEYOND will face these challenges.

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References

[1] B. Llopis-Mengual, D. P. Yuill, and E. Navarro-Peris, “Time series analysis of field data for soft faults detection and degradation assessment in residential air conditioning systems,” *Appl Therm Eng*, vol. 269, p. 126104, Jun. 2025, doi: 10.1016/j.applthermaleng.2025.126104.

[2] S. Pigg, D. Cautley, and K. Koski, "Improving Installation and Maintenance Practices for Minnesota Residential Furnaces, Air Conditioners and Heat Pumps," 2016.

[3] A. P. Rogers, F. Guo, and B. P. Rasmussen, "A review of fault detection and diagnosis methods for residential air conditioning systems," *Build Environ*, vol. 161, p. 106236, Aug. 2019, doi: 10.1016/j.buildenv.2019.106236.

[4] S. Katipamula and M. R. Brambley, "Review article: Methods for fault detection, diagnostics, and prognostics for building systems—A review, part I," *HVAC and R Research*, vol. 11, no. 1, pp. 3–25, 2005, doi: 10.1080/10789669.2005.10391123.

[5] W. Kim and S. Katipamula, "A review of fault detection and diagnostics methods for building systems," *Sci Technol Built Environ*, vol. 24, no. 1, pp. 3–21, Jan. 2018, doi: 10.1080/23744731.2017.1318008.

[6] F. Pelella, A. F. Passarelli, B. Llopis-Mengual, L. Viscito, E. Navarro-Peris, and A. W. Mauro, "State-of-the-Art Methodologies for Self-Fault Detection, Diagnosis and Evaluation (FDDE) in Residential Heat Pumps," *Energies (Basel)*, vol. 18, no. 13, p. 3286, 2025, doi: 10.3390/en18133286.

[7] D. Kim, S. Kang, J. Yoo, D. K. Kim, and B. Youn, "A study on the quantitative single and dual fault diagnosis of residential split type air conditioners in static operation using support vector machine method," *International Journal of Refrigeration*, vol. 131, no. July, pp. 206–217, 2021, doi: 10.1016/j.ijrefrig.2021.07.002.

[8] A. Ebrahimifakhar, A. Kabirikopaei, and D. Yuill, "Data-driven fault detection and diagnosis for packaged rooftop units using statistical machine learning classification methods," *Energy Build*, vol. 225, p. 110318, Oct. 2020, doi: 10.1016/j.enbuild.2020.110318.

[9] F Pelella, L Viscito, AW Mauro, "Soft faults in residential heat pumps: Possibility of evaluation via on-field measurements and related degradation of performance", *Energy Conversion and Management*, vol. 260, doi.org/10.1016/j.enconman.2022.115646.

[10] A. W. Mauro, F. Pelella, and L. Viscito, "Soft faults evaluation for electric heat pumps: Mechanistic models versus machine learning tools," in *26th International Congress of Refrigeration (IIR)*, 2023, pp. 1576–1587. doi: 10.18462/iir.icr.2023.0753.

[11] B. Llopis-Mengual, D. P. Yuill, and E. Navarro-Peris, "Fault detection and diagnosis algorithm for multiple simultaneous faults in residential air-conditioning systems: Development, validation study and critical analysis," *Appl Therm Eng*, vol. 269, p. 125975, Jun. 2025, doi: 10.1016/j.applthermaleng.2025.125975.

[12] Universita Degli Studi Di Napoli Federico II and Universitat Politecnica De Valencia, "BEYOND - method for smart and affordaBle Evaluation of simultaneous faults in heating and cooling sYstems based ON compresseD vapor technology." [Online]. Available: https://www.beyondproject.eu/#project-overview