Utilizing Data Analysis for Optimized Determination of the Current Operational State of Heating Systems

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Abstract: In response to the pressing global challenge of climate change, the emphasis on sustainable energy technologies has escalated, spotlighting the critical role of heat pump systems as eco-friendly alternatives for heating and cooling. These systems stand at the forefront of efforts to reduce greenhouse gas emissions and improve energy efficiency. The advent of Internet of Things (IoT) technology has unlocked the potential for comprehensive data collection on the operational intricacies of heat pump systems in real-world settings, offering precious insights into their performance and guiding technological advancements. This paper introduces an analytical approach to optimize air-to-water heat pump systems using time series data from Bosch Home Comfort Group's systems. Utilizing Fayyad's data-driven analysis model and the Random Forest algorithm, the study tackles system behavior complexities. Characterized by interpretability crucial for application, it achieves a 97.6% fault detection accuracy. The method encounters difficulties in accurately predicting compressor control faults due to limited data quality and a lack of comprehensive system information. The findings highlight IoT's potential to enhance system efficiency and availability, but also point to the limitations of relying solely on data-driven models for fault prediction in field systems.

1 INTRODUCTION

In 2021, German households consumed about 670 terawatt-hours of energy, mainly for space heating, as per the Federal Environment Agency (Icha and Lauf, 2022). Heat pumps are crucial in this regard, known for their efficiency and ability to reduce utility costs and emissions by leveraging renewable energy (Chiang, 2001). However, realizing their full potential requires understanding their entire lifecycle, from production to user operation. Key stages of this lifecycle encompass product development, manufacturing, storage, transport, installation, operation, and maintenance. These stages primarily generate significant data during the development and operational phases (Wiedemann and Schnell, 2006).

The Internet of Things (IoT) has upgraded data collection, allowing for the extensive networking of devices and sensors with the data stored in the cloud (Zhang et al., 2010). Analyzing these data aims to optimize heating systems. The potential incorporation of suppliers and service providers into this analysis enhances system lifecycle understanding, supporting early fault detection and refining system requirements for future models (Wiedemann and Schnell, 2006).

Fault detection methods in systems are crucial for

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improving efficiency, availability, and customer satisfaction (Chiang, 2001). These methods include model-based, data-based, and hybrid approaches (Zhang and Jiang, 2008). Model-based methods simulate and diagnose the system behavior with mathematical precision, but demand thorough understanding and are complex (Venkatasubramanian et al., 2003). Data-based strategies, leveraging machine learning on historical data, suit complex systems, but need high data quality and substantial resources (Chen, 1999). Hybrid approaches combine the strengths of models and data to efficiently detect faults, providing a balanced solution for fault diagnosis in challenging systems (Yang and Rizzoni, 2016). Data-driven methodologies employ structured models for Knowledge Discovery in Databases (KDD), including the Fayyad KDD framework (Fayyad et al., 1996).

As depicted in Figure 1, this model contains crucial steps for knowledge extraction from databases, starting with the selection of relevant data, followed by its cleaning and formatting in the preprocessing phase. Then, the data are transformed into a format appropriate for mining, after which mining is conducted to discover patterns (Fayyad et al., 1996). These patterns are interpreted to determine their relevance, and finally the extracted insights are presented. This comprehensive process is essential for understanding and enhancing system performance (Garcia et al., 2015).

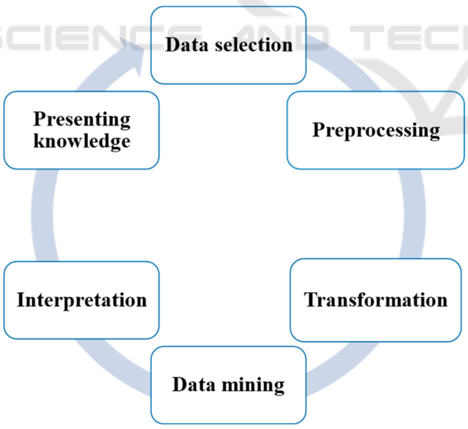

Figure 1: KDD process according to Fayyad.

2 RELATED WORK

2.1 Data-Based Approaches in Heating, Ventilation, and Air Conditioning Systems

With growing demand for efficient and reliable heating, ventilation, and air conditioning (HVAC) systems, the development and application of machine learning algorithms for fault detection and diagnosis (FDD) have become increasingly crucial (Li and O'Neill, 2018). Pioneering work by Gharsellaoui et al. (2020) leverages the Multiclass Support Vector Machine (SVM) algorithm to categorize data within smart buildings effectively. Concurrently, the approach of Ebrahimifakhar et al. (2020) introduces a statistical ML-based classification model using SVM to detect faults in rooftop units by analyzing and classifying data. Similarly, Bode et al. (2020) have developed an innovative FDD model that combines a big data framework with SVMs, aimed at identifying faulty operations in HVAC terminal units through the aggregation and evaluation of data from various sources. Complementing these efforts, Ren et al. (2020) have proposed a comprehensive FDD procedure that merges SVM with principal component analysis (PCA), designed to predict system behavior under new load conditions by extracting pivotal features from the dataset. This ensemble of models underscores the potential and reliability of machine learning in enhancing fault detection and diagnostic capabilities in HVAC systems. An extensive overview of FDD models within the realm of building technology, as detailed in the literature, highlights the eclectic range of approaches and techniques that form the foundation of this field (Li and O'Neill, 2018).

2.2 Key Challenges in Currently Applied Approaches

Heating systems are complex and impacted by diverse operating conditions. The need for interpretable models that can handle this complexity and be applied to different systems is critical. However, challenges arise with data-driven FDD methods developed based on black-box models such as artificial neural networks (ANN) and SVM, mainly due to their lack of interpretability (Yan et al., 2016). This limitation makes it difficult to understand the process of fault identification within these models. Moreover, the effectiveness of data-driven methods largely depends on the quality of the training data (Yang and Rizzoni, 2016). Insufficient data samples and errors in the training data can lead to incorrect classifications. Often the available training data do not cover the entire spectrum of system operation, which limits the model validity to certain conditions. Especially, very critical situations appear only rarely in reality, leading to a deficit of related sensor data. Without interpretability, evaluating model reliability and applicability becomes a challenge (Yan et al., 2016).

2.3 Methodological Contributions

This paper outlines an application-oriented methodology for heat systems employing the Random Forest algorithm for extracting knowledge from data. Central to this approach is its use of decision trees, distinguishing Random Forest by revealing causes of faults through key parameter identification and enhancing model transparency with decision tree visualizations, a clarity lacking in black-box models. Moreover, as an ensemble method, Random Forest reduces overfitting risks by aggregating multiple trees' predictions, ensuring applicability across varied operational conditions (Cutler et al., 2012). This adaptability is essential for analyzing and anticipating system faults, evaluating system performance through error rate analysis, and guiding potential enhancements. Emphasizing its computability, accuracy, and interpretability, this methodology underscores the direct applicability of Random Forest approaches over more complex techniques found in explainable artificial intelligence (XAI), such as Shapley values, ensuring the methodology's efficacy and practical relevance (Başağaoğlu et al., 2022). Thus, this approach provides a fault detection and prediction solution for heating systems in the field, making it particularly valuable for engineers and practitioners in the domain of heating systems.

3 DATA-DRIVEN METHODOLOGICAL FRAMEWORK

This paper presents a structured approach to analyze and explore air-to-water heat pump systems, with a focus 1 faults. Concurrently, the regression segment estimates the remaining time until a fault occurs. These models undergo testing to validate their accuracy in assessing the system status and forecasting faults.

The Model Interpretation stage offers a deep dive into the model's decision-making, elucidating how it identifies the system status and predicts faults. Expert knowledge validates the model's underlying logic.

4 APPLICATION OF METHODOLOGY: INTRODUCTION TO THE USE CASE STUDY

The methodology applied in this paper focuses on an air-to-water heat pump system with a fault in the compressor control. Such control faults arise from issues within the heat pump's control unit and can impact compressor performance. This may lead to inefficient operation of the heat pump, adversely affecting its heating and cooling capacity. Potential causes of these faults include high ambient temperatures around the compressor leading to sensor failures, poor wiring, or incorrect control settings. This analysis was conducted at the Bosch Home Comfort Group. The Heat Pump Development Department was responsible for providing the parameter data and fault information.

The primary objective of this study is to analyze the impact of the fault on the system and to identify the occurrence of the fault using system data. Additionally, the research explores the potential for predicting future fault occurrences. The system data, which describe the system's state, were collected through the bus system. The data analysis is based on time series data with a sampling frequency of 0.83 Hz, covering the period from February 1, 2021, to May 1, 2022. The findings contribute to enhance understanding of the field system's behavior. Based on these insights, strategies to optimize the efficiency and stability of the heat pump system can be developed, ensuring smooth operation in the future.

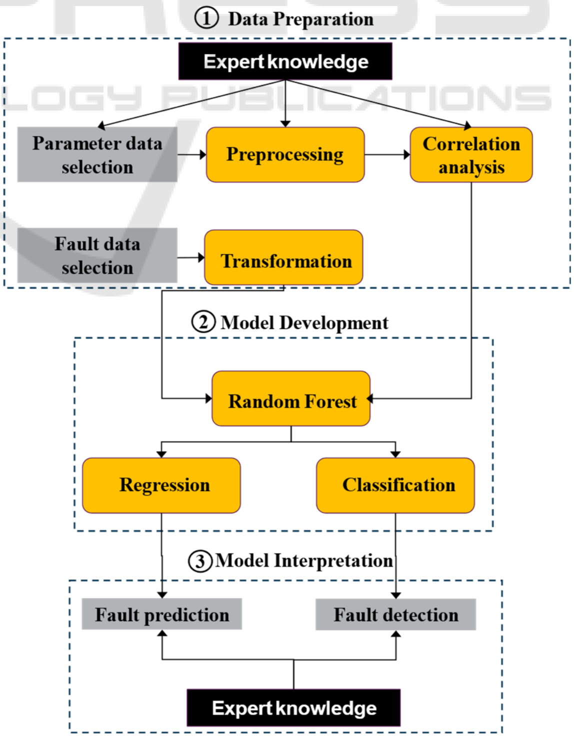

Figure 2: Stages of the methodology.

5 DATA PREPARATION

This stage is designed to achieve a structured and complete dataset. This section outlines how each step of the stage is executed for the investigated use case.

5.1 Data Selection

The data selection for analysis focuses on identifying critical parameters within the heat pump's bus system, which characterize the general state and specifically the control faults in the compressor. This selection is performed in close collaboration with experts in the heat pump development team at Bosch Home Comfort Group to ensure that the chosen data possess the necessary relevance and quality for the study. Verifying the availability and integrity of the data in the bus system is an essential part of this process. Finally, the resulting parameters considered central to the analysis are detailed as follows:

- **Power Setpoint:** Targeted electrical power consumption level for the heat pump, setting the desired performance level for optimal efficiency and meeting heating or cooling demands.
- **Actual Power:** Current electrical power consumption of the heat pump, used to assess energy efficiency and operational status.
- **Actual Compressor Speed:** Current speed at which the compressor is operating, indicating performance level and efficiency of the heat pump.
- **Air Temperature at the Evaporator:** Temperature of air entering the evaporator, helping to evaluate heat exchange efficiency and system load.
- **Temperature of the Compressor:** Current temperature of the compressor, used to monitor compressor health and prevent overheating.
- **Temperature of the Hot Gas:** Temperature of the gas after compression, before condensation, indicating the efficiency of the compression cycle.
- **Evaporator Return Temperature:** Temperature of the fluid returning to the evaporator, assisting in assessing heat absorption efficiency.
- **Outdoor Temperature:** Outdoor ambient temperature, used to adjust operations for optimal efficiency and performance.
- **Condenser Inlet Temperature:** Temperature of the fluid entering the condenser, providing insights into the condensing process efficiency.

5.2 Data Preprocessing

As long as the values of these parameters remain constant, the bus system does not report any values. However, when any value changes, the bus system communicates this change. In the dataset, this leads to empty cells between these two values, which need to be filled to complete the dataset. This is done using the zero-order hold principle, meaning empty cells between two known values are filled with the last known value until a new value is registered.

To detect outliers, data have been visualized using box plots. This decision was driven by the need for a straightforward and visually intuitive method, allowing experts to easily identify and assess unusual values as potential outliers. Box plots were chosen over other methods, because they clearly delineate the range of typical data, making deviations apparent. In the context of missing operational condition details, solely data-driven outlier detection proved to be unreliable (Xu et al., 2020). Instead, combining box plots with expert insights and system specifications enabled a more informed decision on whether values were outliers or relevant variations, ensuring a nuanced and accurate outlier elimination process.

5.3 Correlation Analysis

As mentioned in the previous section, the necessity of this step in the data preparation stage is caused by low data quality. Correlation analysis investigates the relationship between operational parameters to determine how accurately the data represent these physical interactions (Wilcox, 2001). This accurate representation is essential to deliver valid inputs to the model during the training phase. Therefore, the model is enabled to understand the system's status through the available training data and to produce reliable predictions about the system status**.** To achieve this, three sub-steps are involved: a) assessing data normality to select an appropriate correlation method, b) applying the chosen correlation to the dataset, and c) validating the correlation results against the parameters' physical relationships through expert knowledge.

The Shapiro-Wilk test (Ghasemi and Zahediasl, 2012) initially assessed for normal distribution revealed a non-normal distribution that necessitated the use of Spearman's correlation method (Wilcox,

2001) for the analysis. Experts reviewed the correlation coefficients to verify their physical relevance, ensuring that data faithfully represent the system's physical dynamics. This step illuminates crucial relationships between variables and affirms the data's pertinence to the studied physical phenomena.

5.4 Transformation

Fault information is encoded into binary values, with 0 indicating no fault and 1 indicating a fault occurrence, to serve as the target variable for training the Random Forest model. This conversion sets up a classification problem, allowing the model to learn fault detection from parameter data and target variables.

6 MODEL DEVELOPMENT

The Random Forest model is developed to analyze the relationship between various operational parameters and fault occurrences in the air-to-water heat pump system. It comprises two parts: (1) classification model that determines the system's status and (2) regression model predicting the time until a fault occurs. These models were implemented using the scikit-learn library in Python and developed within a Jupyter Notebook.

6.1 System Status Detection

Random Forest Classifier (RFC) employs decision trees on random data subsets, leveraging ensemble learning for accurate classifications while mitigating overfitting and assessing feature importance (Biau and Scornet, 2016). The steps of the model implementation are illustrated in Figure 3. To address the challenge of rare critical situations outlined in Section 2.2, particularly the infrequent occurrence of faults in the compressor control, a down sampling strategy has been implemented.

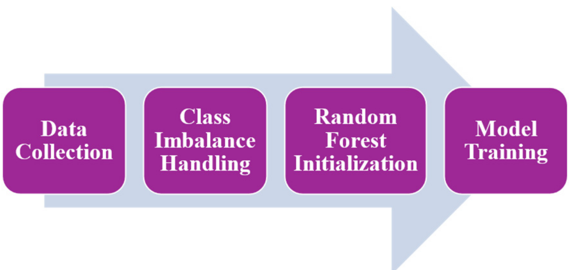

Figure 3: RFC implementation steps.

This method balances the dataset by reducing the number of non-faulty instances to equal the number of faulty instances, ensuring uniform representation. A RFC with three trees (n_estimators=3) and a random_state of 42 is chosen, targeting a balance of model complexity and computational efficiency. The decision to use three trees was based on performance evaluations against a validation set, where adding more trees resulted in only minimal improvements in accuracy, suggesting that further increases would not yield significant benefits. This choice reflects an optimization between simplicity and the ability to capture operational variability, with a random_state of 42 ensuring result reproducibility. Default parameter settings are maintained as detailed in (scikit-learn, 2024).

6.1.1 Evaluation of the Detection Model

The model was validated using test data to assess its reliability in predicting on unknown data, using a confusion matrix for evaluating accuracy and precision. Results are illustrated in Figure 4.

This analysis revealed 191 true positives, indicating non-faulty operation status were correctly identified, and 181 true negatives, which means fault status were accurately detected as such. Additionally, the model encountered four false negatives, representing overlooked fault status, and five false positives, where faults were incorrectly identified in non-faulty operation status. Achieving a high accuracy of 97.6% and a precision of 97.4%, the model demonstrates efficient fault detection and classification. Maintaining a low rate of false positives is crucial; they not only lead to unnecessary fault correction costs, but also could divert resources from actual issues, potentially leaving real faults undiagnosed. This emphasis on minimizing false positives is vital for operational efficiency and cost management. The results highlight the model's effective performance in accurately identifying the operation status, balancing accurate fault detection with the imperative to minimize false alarms.

6.1.2 Model Interpretation

The RFC algorithm addresses the challenge of lack of interpretability in data-driven FDD methods based on black-box models as mentioned in Section 2.2. It identifies key parameters through parameter importance calculation – facilitating an understanding of the classification processes – and enhancing transparency while validating the model’s outputs (Breiman, 2001). Through Python's scikit-learn library, feature importance is determined using

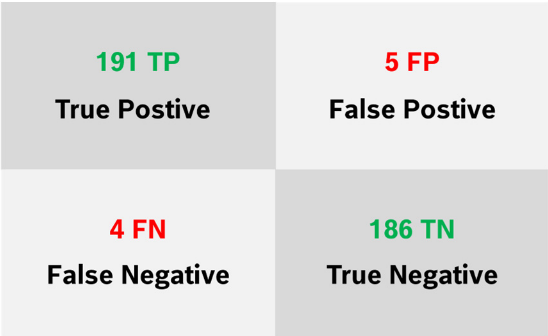

Figure 4: Confusion matrix of the test data.

the Mean Decrease in Gini (MDG) method, which assesses how a feature reduces impurity across the model's trees. MDG values range from 0 (no impact) to 1 (perfect prediction capability), where higher values indicate a stronger effect on model decisions (Biau and Scornet, 2016). This calculation considers the decrease in node impurity, weighted by the probability of reaching that node, averaged over all trees (Breiman, 2001). The key findings of the parameter importance are illustrated in Figure 5.

It indicates that specific parameters, such as condenser inlet and outlet temperatures, hot gas temperature, external temperature, compressor speed, and power setpoint are paramount in fault detection, demonstrating nearly equal importance. Conversely, parameters like evaporator air temperature, compressor temperature, evaporator return temperature, and current performance have a lower impact.

These insights emphasize the importance of temperature-related measurements in detecting the fault. Through the interpretability of the model, these insights into model parameters can be traced back to the faulty state of the system. The relevance of the parameters to the faulty state are confirmed by the experiential knowledge of experts.

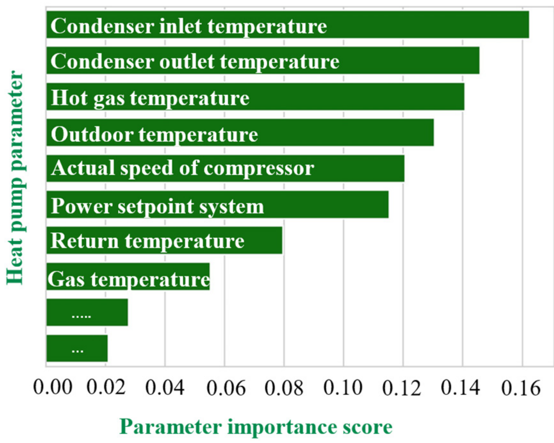

Figure 5: Visualization of the importance of parameters.

This validation not only enhances the development steps of the component to prevent the occurrence of such faults but also expands the knowledge of relevant factors that can lead to faults. In the future, this approach can also be applied to other types of faults to gain valuable insights.

6.2 System Status Prediction

This model aims to predict the remaining time until the next fault occurs, utilizing an ensemble of decision trees to make accurate predictions on continuous values by averaging the outputs of all trees in the forest. Similar to the classifier model, the Random Forest Regressor (RFR) applies ensemble learning, but focuses on estimating continuous outcomes. The implementation of the RFR mirrors that of the classifier model, as depicted in Figure 6.

Figure 6: RFR implementation steps.

The process starts with data collection representing various operational conditions, followed by creating the target variable time until the next fault, which is hereafter referred to as "Time to Failure". This is achieved by reverse iterating through the data to calculate the time until the next fault for each data point, producing a list of minutes until the next fault. For this model, a RFR with ten trees (n_estimators=10) and a random_state of 42 was selected, balancing model complexity with computational efficiency. The choice of more trees for the RFR compared to the RFC reflects the increased complexity needed in regression models to capture data variability and nuances accurately (Corrales et al., 2018). With this optimized tree ensemble, the RFR can more accurately identify and predict underlying trends, enabling precise predictions for the time to failure. The default parameters are retained as described in (scikit-learn, 2024).

6.2.1 Evaluation of the Prediction Model

The model accuracy was validated using test data to assess its reliability in predicting on unknown data using the Mean Absolute Error (MAE). The test

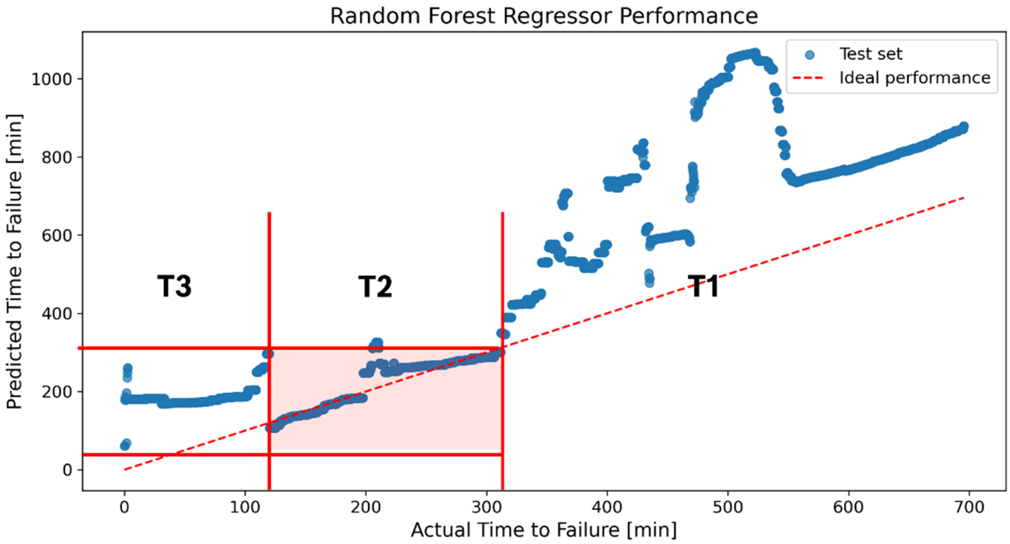

Figure 7: Accuracy of the model with test data.

dataset contains a fault scenario. The results were visualized in Figure 7, where the X-axis represents the actual values and the Y-axis the predicted values of "Time to Failure". Ideal model performance is achieved when data points closely align along the ideal performance line, aiming for an MAE value of 0, indicating precise alignment between predictions and actual events.

The accuracy evaluation of the model reveals three key insights that provide a nuanced view of the model's performance across different periods before a fault event.

- Phase T1: Actual Time to Failure > 320 minutes
- Phase T2: 320 minutes ≥ Actual Time to Failure ≥ 120 minutes
- Phase T3: 120 minutes > Actual Time to Failure > 0 minutes

Phase T1 describes long-term predictions, starting from 320 minutes before the fault occurrence. In this phase, it was observed that the model appears incapable of detecting reliable indicators of an impending fault, resulting in a large discrepancy between predicted and actual values. This limitation highlights the challenges in predicting faults over an extended period. Phase T2 describes mid-term predictions, between 120 and 320 minutes before the fault occurrence. In contrast to Phase T1, the model demonstrates considerably better performance with a MAE of 18.6 minutes. During this critical period, the model effectively analyzes and interprets operational conditions and potential signs of an impending fault, indicating its capability to utilize relevant information for fault prediction. Phase T3 involves short-term predictions made 0 to 120 minutes before a fault occurs. In this phase, the model's accuracy decreases, primarily due to a significant deviation of data points from the ideal line. This reduction in accuracy can be attributed to insufficient information density in the parameters, leading to unreliable predictions.

However, the application of the model to other faulty scenarios has revealed significant limitations, primarily due to the limited availability of faulty data and limited understanding of the underlying causes.

This problem is closely linked to the challenge of data quality and availability, as discussed in Section 2.2. The lack of comprehensive data sets significantly impairs the model's ability to predict under different operating conditions. In addition, the complexity of the heat pump system combined with a limited data set further reduces the model’s prediction accuracy. This is compounded by uncertain causes of failure such as wiring or software issues, which are discussed in more detail in Section 4. Ultimately, these challenges emphasize the urgent need for improved data quality and a deeper understanding of failure mechanisms.

6.2.2 Model Interpretation

In the RFR model, evaluating parameter significance is the key to decoding its predictive logic. This process identifies the extent to which various features impact the model's ability to predict the timing of a fault. Understanding the critical features enhances the insight into the model's operational dynamics. Differing from the RFC model, the RFR model assesses the feature importance via the Mean Decrease in Impurity (MDI). MDI reflects how each feature's variance reduction, averaged across all trees, contributes to the model's accuracy. This method highlights the influence of specific features on enhancing the model's precision by reducing prediction variance through data segmentation.

This analysis reveals that the outdoor temperature and air temperature at the evaporator exert the strongest influence on prediction accuracy, with a combined importance of 50%. Additionally, the condenser exit temperature and the power setpoint also make significant contributions to the forecast, both with importance of 14%. These four parameters collectively account for 78% of the predictive influence.

These results emphasize two major results: (1) temperature-related measurements and the power setpoint in the context of precise fault prediction are crucial and (2) there is a need for the extension of the knowledge about the selection of relevant parameters for fault monitoring and the definition of the time period in which a fault can be predicted. Despite the limited number of fault cases in the system history, these findings are valuable for future research and help in the selection of time periods and relevant parameters in the model training to reduce model complexity.

7 DISCUSSION OF RESULTS

The research findings, which were discussed with engineering experts from the heat pump department at Bosch Home Comfort Group, focus on four key questions:

- How does interpretability clarify causality between system parameters and faults while supporting model scalability?
- Which benefits does a system status detection model offer?
- How does the parameter significance derived from the classification model affect error detection logic and contribute to the optimization of the regression model for error prediction?
- How could more diverse data improve fault prediction, and what are the challenges?

Regarding the first aspect (interpretability), discussions with the experts in the heat pump department emphasize the importance of interpretability for scaling the model to systems with similar data deficiencies. As explained in Section 6.1.2, the interpretability of the model enables the exact quantification of the meaning of the parameters. This improves the understanding of how each feature affects the predictions of the model. This insight is crucial for accurate adjustments when applying the model to new systems. This ensures the effectiveness of the model in different operating environments. This detailed interpretative analysis also helps to adapt the model and standardize fault detection practices across different environments.

Regarding the second aspect (benefits of a detection model), experts highlight the significant benefits of a system status detection model, especially for systems that do not capture fault data. Such a model enables an understanding of the system's behavior in operation, identification of common faults, and efficient resource planning, directly contributing to the optimization of the system design.

Concerning the third aspect (parameter significance), discussions with experts emphasize the importance of specific parameters, such as condenser inlet and outlet temperatures, hot gas temperature, and outdoor temperature, identified in Section 6.1 as crucial for detecting faults within the compressor control. Expert opinions indicate that future research could significantly enhance prediction accuracy by redesigning the error detection logic to reflect parameter relevance and optimizing the online monitoring of these parameters. Achieving this improvement also involves intensified collaboration with service companies to obtain detailed fault information, including causes of occurrences. This collaboration forms the foundation for a more efficient predictive control system, aimed at reducing downtime and improving overall system performance.

The last aspect discussed with the experts involves analyzing the predictive model's capability to determine the precise time phase when a fault can be anticipated within the system**.** The model – under the constraints of current assumptions and data rarity – identifies early symptoms of errors occurring between 120 and 320 minutes. This preliminary insight is crucial as it suggests that expanding our dataset with a broader range of failure cases could potentially reduce the need for extensive training data and help avoid overfitting. Enhancing the dataset in this manner would improve the model's accuracy and its applicability to similar systems.

8 SUMMARY AND FUTURE WORK

This paper explores the potential of time series analysis of sensor data from heating systems in operation for detecting and predicting errors, a critical area complicated by the significant distance between users and manufacturers. A procedure based on Fayyad's model was implemented and applied to an air-to-water heat pump system to identify and forecast specific control faults in the compressor.

A RFC model was developed to recognize system status and assess the impact of parameter weights on fault detection. This model successfully determined the status of the systems, achieving a detection accuracy of 97.6% and a precision of 97.4%. A key challenge was the limited dataset, which complicated the expert validation and underscored the necessity for a larger data foundation. The analysis underscored the significance of certain parameters, particularly temperature readings, in fault detection. Experts validated these findings, emphasizing the need for ongoing adjustment of weight factors.

The limited availability of fault data and the lack of system information restricts the effectiveness of the RFR model. This limitation stems from the system's lifecycle; after sale, third-party service and maintenance companies oversee installation and upkeep, while manufacturers conduct field monitoring for a brief period. As a result, failure data collection is primarily limited to this monitoring phase, thus affecting the model's ability to predict accurately.

Future research directions, inspired by this work, will explore the potential of Random Forest models to analyze more extensive datasets with increased error instances and assess other machine learning algorithms for error detection and prediction in heat pump systems. An optimized dataset, including detailed parameter and fault information, is crucial for developing models that accurately reflect system reliability and behavior. Additionally, future studies should explore the reliability of specific system components and their impact on overall system reliability. Future investigations should incorporate not only existing data but also laboratory results, simulations, and physical models. The integration of physics-based models will be explored to establish causal relationships between system parameters and fault occurrences, thereby enhancing the model's ability to predict and diagnose faults with higher accuracy. This approach is expected to improve the overall effectiveness of the system, contributing to a deeper understanding of system dynamics, and advancing control strategies for heating systems.

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