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Is it returning too hot? Time series segmentation and feature clustering of end-user substation faults in district heating systems

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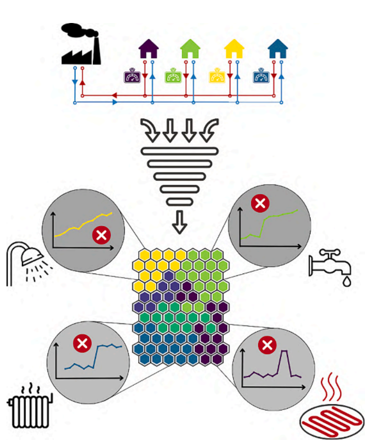
HIGHLIGHTS

- Self-organizing maps and k-means for fault clustering in heating systems.
- 50 cases were analyzed, revealing distinct features related to a fault occurrence.
- Demonstrating time series decomposition for automated anomaly identification.
- Highlighting challenges in data truncation and fault diagnosis accuracy.
- Proving the effectiveness of data segmentation in detecting various fault anomalies.

GRAPHICAL ABSTRACT



ARTICLE INFO

Dataset link: Code/Scripts repository (Reference data)

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ABSTRACT

This study explores the challenges and advancements in collecting ground-truth data to enhance fault diagnosis models for district heating systems. Initiated by the need to address limitations in previous data collections, this research leverages an enriched dataset from a Danish district heating utility to identify faults in household substations. Despite some inaccurate fault categorizations, complex fault patterns, and truncated measurements, the analysis of 50 detailed cases out of 127 fault reports reveals that, while return temperature reliably indicates faults, energy usage patterns do not. By employing self-organizing maps combined with k-means clustering, fault symptoms and patterns were categorized adequately, demonstrating the utility of high-dimensional data clustering in fault diagnosis. Additionally, an algorithm using time series decomposition is suggested to identify extreme and subtle anomalies, enhancing fault detection capabilities. The paper concludes that these methodologies significantly improve the accuracy and dependability of fault diagnostics in district heating systems, paving the way for more efficient operational management.

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1. Introduction

In the European Union, district heating (DH) and cooling provide 12 % of the energy to the building stock [1]. Despite this relatively small share, DH is considered vital for decarbonizing the heating sector, and its share is expected to increase in the following years [2]. With this increasing implementation, one of the future goals in the DH sector is the integration of renewable energy sources for heat production instead of traditional fossil fuel-based ones [3]. However, lowering the fluid-supply temperature of the thermal grids is required to incorporate these alternative energy sources and industrial heat waste/surplus [4,5]. This is at the core of the 4th generation of DH systems and represents the next natural step towards decarbonizing the building sector.

The return fluid temperature mainly depends on the end-user side and how effectively it can extract heat from the heat-carrier fluid. This depends on the installation design, control, and the presence of faults in the building heating system [6]. To maintain the return temperature at acceptable levels, the DH utility companies might charge their high-return temperature consumers an additional fee to motivate them to change their behavior or fix the existing system's faults [7,8]. Nevertheless, research has been conducted to investigate whether utilities should change their business model in providing their services and expertise to their clients by offering constant monitoring to detect, diagnose, and solve faults [8,9]. Aligning the business model to establish a closer relationship between utilities and consumers can expand access to building heat substations and secondary heat systems, thus enabling a deeper understanding of the different faults that might occur in the latter. Combining this new set of information on the customers' installations with the smart heat meters (SHM) data that has already been collected on a large scale in several countries (e.g., Denmark, Sweden) can lead to the next step of fault detection and diagnosis (FDD) by consolidating the causality between anomalous symptoms observed in the measurements and the actual cause of these symptoms (ground truth). Having this ground truth is vital to developing automated FDD algorithms that utility companies can deploy at a large scale, thus improving their business model and the sustainability of the DH system by keeping their customers' installations at optimal performance [10,11]. In more detail, the benefits of a DH system to integrate automated FDD processes are the following:

- Optimization of energy usage and system efficiency: FDD can help optimize energy usage by ensuring that all components of the DH system are functioning correctly. This optimization improves overall system efficiency, reduces energy waste, and lowers operational costs [12].
- Early detection of faults and anomalies: FDD algorithms can detect potential faults or anomalies early on, allowing DH operators to take corrective actions before these issues escalate into more significant problems. Early detection helps prevent major system failures and prolongs the lifespan of DH components [13].
- Minimization of downtime and service interruptions: Early detection and diagnosis of faults enable prompt intervention and maintenance activities, minimizing downtime and service interruptions. This ensures that the end-users have a more reliable heating supply, enhancing customer satisfaction [13].
- Effective prioritization of maintenance activities: By identifying recurring issues, DH operators can prioritize maintenance activities more effectively. This targeted approach to maintenance ensures that the most critical issues are addressed first, optimizing resource allocation [14].
- Reduction of operating costs: By reducing the need for emergency repairs, FDD helps lower operating costs for district heating providers. Preventive maintenance enabled by FDD reduces the frequency and severity of repairs, contributing to cost savings [15].

1.1. Related work

Two different review scientific articles [16,17] were published to map out the current developments of data-driven FDD methodologies in the DH sector. One of their main conclusions is that to push forward in this field, more high-quality data needs to be collected and to include ground truth about fault occurrence and nature. Despite this lack of a large-scale collection of labeled data of occurring faults complemented with SHM measurements, several studies propose different FDD algorithms to be implemented in the DH grid. This subsection reviews these methods targeting the DH end-users (buildings connected to the grid).

One of the first works conducted in this field is [18], where a statistical assessment was performed for 135 substations in different types of buildings to find the ones with at least one of the three fault symptoms: anomalous heat patterns, low average annual temperature difference, and poor substation control (i.e., poor correlation between heat demand and outdoor temperature – energy signature). Around 75 % of buildings presented at least one of these symptoms, showing the potential and need for systematic fault detection campaigns. Similarly, the authors proposed in [5] a novel threshold-based method for fault detection using the temperature difference signature (relation between the DH temperature difference of supply and return and outdoor temperature). Calikus et al. (2018) employ a similar method to spot hindered building substations via their energy signatures and introduce a ranking method to sort the substations with prominent abnormality symptoms [19]. These methods are all dependent on set thresholds triggering alarms. This means that they cannot account for the dynamic nature of heating systems, where normal operating ranges can vary significantly under different conditions, leading to false alarms or undetected faults [20]. Contrastingly, modern FDD methods leverage machine learning (ML) algorithms to overcome these limitations: they can learn from the historical data to identify specific patterns and anomalies [21].

Within ML, supervised learning trains algorithms on a labeled dataset containing ground truth on the target outputs, meaning that it learns from data that already contains the answers (outputs) associated with given inputs. This approach is particularly powerful for predictive tasks, as the model can infer relationships between features and outcomes, making it capable of making predictions on new, unseen data. In the context of FDD for buildings connected to the DH, Månsson et al. (2018) developed a model of well-performing DH substations using gradient boosting regressor and SHM data to detect deviation patterns indicating possible faulty operation [22]. Similar works can be found in [23–27]. On the other hand, unsupervised learning deals with identifying patterns in a dataset without pre-existing categorization, i.e., the algorithm tries to infer the structure from the dataset itself. In FDD for buildings connected to DH systems, unsupervised learning is beneficial for identifying unusual patterns or anomalies that could indicate faults. For instance, clustering techniques can group similar operational profiles of heating systems and identify outliers. These outliers represent operational anomalies, which could be linked to system failures or distinct systems operations by the occupants. Due to the lack of labeled datasets with ground truth on faults, unsupervised learning is, by far, the dominating method in the field. Calikus et al. (2019) clustered heat profiles using the k-Shape method, and the anomalous profiles were segregated and investigated further [28]. Xue et al. (2017) employ a methodology that uses several clustering algorithms with association rules analysis to find abnormal behaviors in substations from SHM data [29]. Other unsupervised methods for FDD in DH data can also be found in [30–35].

Lastly, there is a growing trend of using deep learning techniques to analyze buildings connected to the grid to diagnose suboptimal substations. Deep learning is a subset of ML that utilizes large artificial neural networks to model complex patterns and relationships in data and can be employed for supervised and unsupervised learning purposes. These models are particularly effective in handling large volumes of data and time series. Choi and Yoon (2021) developed an autoencoder to generate relevant features and detect faults and applied a multilayer perceptron (MLP) for classifying faults in a multi-family residential building in South Korea [36]. Kim et al. (2021) propose a DH substation fouling detection and diagnosis method using k-means clustering, MLP, and virtual sensor-assisted. The k-means method is used for pattern identification to segment data for training and testing, while an MLP model incorporates measurements from virtual sensors and predicts system variables to detect fouling based on threshold violations [37]. Other deep learning methods applied in FDD are proposed in [38–40]. Despite the merits of these methodologies, they typically share a significant limitation: they need to provide a comprehensive view of fault occurrences at both the substation and building (indoors) levels. Studies of system faults involving diverse sensors and fault types tend to cover only a limited number of building cases. Conversely, studies encompassing a broad range of buildings generally offer less detailed information about occupants, fault types, or heating installations. This issue is widely acknowledged in the field as a major challenge [12,41,42]. To address this, a standardized methodology for collecting fault label information was proposed [43]. Furthermore, van Dreven et al. (2021) have developed an experimental setup to gather ground truth data from faulty heating systems. This initiative aimed to generate high-quality data distinguishing between normal and abnormal system behaviors, and identifying the specific faults associated with different operational profiles [44]. Despite this advancement, the overall landscape of ground truth data remains scarce, and this knowledge gap underscores the necessity for more extensive and varied data collection efforts to enhance the reliability and accuracy of FDD processes in DH systems.

1.2. Contributions and novelty of the present study

In response to this need, Aalborg Forsyning, a Danish DH utility company, launched its own initiative to engage with key customers on their heating grid who exhibited low-temperature differences between supply and return. During these engagements, technicians visited these households, diagnosing their primary issues and documenting them with any corrective actions taken in intervention reports. Consequently, access to these reports, coupled with the measurements collected from the buildings' SHM, permits to draw certain correlations between the heating data and the nature of the faults identified. In that context, the work presented in this article advances the field of FDD in the DH sector with the following:

1. Explanation of the characteristics and challenges in collecting fault reports for ground truth in fault diagnosis models, and comprehensive analysis of SHM data from 50 DH household substations with verified faults:

Sections 2.1 and 2.2 shed light on the challenges arising when collecting fault reports to create models that can classify and diagnose system faults. It delves into the complexity of establishing a robust ground truth dataset, underlining difficulties such as variable reporting standards, the subjective nature of human diagnoses, and the impact of incomplete data. Additionally, a thorough investigation is presented on SHM data collected from a cohort of 50 DH substations, where each dwelling substation has documented instances of malfunctions verified by a technician. This meticulous analysis described in Sections 2.3 and 2.4, and presented in Section 3.1, aims to correlate specific data patterns with the confirmed faults, thereby refining the predictive accuracy of maintenance protocols.

2. Proposal for employing a time series decomposition methodology and introduction of a clustering framework for categorizing symptoms and patterns of faults in DH customer systems:

A proposal, described in Section 2.5 and presented in 3.2, advocates for the utilization of a time series decomposition method developed for satellite image recognition [45], to identify and delineate anomalous data within monitored systems. By decomposing the time series measurements into their fundamental components (trend, seasonality, abrupt changes, outliers, and residuals), the methodology makes it possible to segment the data that signify operational faults, thus supporting its applicability in DH fault detection systems. Additionally, the paper proposes a clustering methodology in Section 2.6 to systematically group the diverse symptoms of faults reported by DH customers. This novel approach, based on self-organization maps (SOM) and k-means, lays the groundwork for the initial stages of fault diagnosis, potentially streamlining the identification process and enhancing the accuracy of subsequent maintenance efforts.

3. Discussion of lessons learned and the next steps for automated FDD integration in DH systems:

The paper concludes in Section 3.4 with a discussion of the insights gained from this research, and outlines the next steps necessary for the optimal integration of automated FDD processes in DH systems. It emphasizes the importance of leveraging the clustering framework to improve the accuracy and efficiency of fault detection. It also suggests future enhancements in data collection, analytics, and real-time monitoring to fully realize the potential of FDD in these systems.

1.3. Outline

Following the introduction in Section 1, Section 2 describes the methodology behind the data collection and treatment process, the manual and automated time series segmentation for fault detection, and the applied clustering algorithm for fault diagnosis. The results from the investigation and discussion on the lessons learned are presented in Section 3. The article closes with conclusions in Section 4.

2. Methodology

This section presents in Section 2.1) a description of the case study and how the data was collected from SHM with its associated fault reports filed by technicians; 2.2) the major challenges encountered with these datasets; 2.3) a brief explanation of how the data was preprocessed for analysis; 2.4) an overview of the manual analysis conducted to inspect and visualize various measurements alongside their associated faults; 2.5) a suggestion on how to automate fault detection from these SHM data; and 2.6) a proposal of a method to cluster the studied faults according to their measurement and diagnose them according to their systems.

2.1. Case study description

The SHM systems in this study comprise several key components: two temperature sensors, a flow sensor, and an integrated computer that calculates and transmits the energy data. The flow sensor records the water flow through the primary side, while the temperature sensors measure the temperatures of both the supply and return hot water on the primary side. The meter calculates the energy transfer from the primary side to the secondary side (customer), and this energy is the one billed by the heat provider. The control systems and sensors on the secondary side are generally not owned by the utility company, making these data often unavailable.

This study exploits SHM data from 127 residential buildings connected to the DH network, along with 356 fault assessment reports. All buildings are residential, predominantly single-family homes, located in Aalborg municipality (Denmark). They are equipped with space heating (SH) systems, which may consist of radiators and/or underfloor heating (UFH), and domestic hot water (DHW) production based on heat exchangers or storage tanks. Originally, the measurements are recorded with an hourly resolution. Some buildings have measurements from 2017 until 2023, depending on their SHM installation date. The fault reports in this study encompass the assessment outcome from the utilities technicians after visiting the faulty installations of the targeted consumers. This assessment was made during on-site visits or telephone calls with the occupants. This reporting process started in 2022, and the report's structure was simplified to optimize completion by the technicians. These reports, therefore, consisted of only three important inputs (see Table 1).

This report format was the one investigated in [42]. This previous study has shown that having open-text comments to report a fault might cause ambiguous descriptions depending on the degree of detail written by the technicians. Furthermore, this type of reporting makes it cumbersome to select and group similar faults when coding, as their description text is different from each other. Therefore, a second iteration of the faults reports format was developed and applied afterward by the DH company. This new format of the report includes a combination of multiple drop-down menus featuring pre-set options of possible faults, along with a section for free-text comments to be used if necessary. Originally composed in Danish, these reports have been translated into English and subsequently reviewed throughout this analysis for accuracy. One can see in Table 2 the structure of such a new report.

Despite the extensive scope of the second iteration dataset, it is not without its limitations. The following section outlines the challenges that could potentially complicate the data analysis and interpretation.

2.2. Challenges

Inconsistent standards and quality of the reports: The dataset suffers from a lack of uniform standards and quality control. This is observed even after the implementation of the second iteration reporting format: e.g., some technicians might choose different answers for the same fault. Moreover, some technicians tend to have different levels of detail when providing information in the fault description commentaries: e.g., not mentioning if a specific valve is broken in the fully open or closed position. This inconsistency introduces variability that complicates the analysis of SH and DHW systems across the diverse ranges of residential buildings when combined with the SHM data and the specific patterns these faults generate.

Multiple faults occurring at the same time: In some cases, there might be more than one fault during the intervention visit; however, the technician only described one of them: e.g., a broken SH system component with high settings in the DHW production system. "High settings" refers to the operational parameters of the DHW system, such as temperature or flow rate, being set to higher-than-normal levels. These settings can strain the system and lead to inefficiencies or additional faults. However, during a visit, if these two faults are found, a technician might opt to report only the broken component and not address the high settings in the system. Thus, it becomes difficult to discern the full extent and development of each individual fault's pattern. This complexity can mask the interactions between the different faults and their impact on the overall DH system's performance.

Timing of interventions: The interventions, often occurring soon after the detection of a fault, may prevent the complete evolution of the fault pattern from being captured. As a result, the SHM dataset may not fully reflect the progression and potential impact of these faults over time. In terms of energy efficiency, a quick intervention is positive but not for the aspect of collection, analysis, and categorization of faults.

Most of the faults go unnoticed by residents: Most of the faults in this dataset have likely persisted over long periods without causing noticeable disruptions to the occupants. Therefore, the dataset lacks instances of faults with immediate and evident consequences, such as system leakages or deficiency in DHW production which trigger a more urgent response by the dwellers, therefore being solved before DH company takes any intervention measures.

Table 1
First iteration of the fault assessment structure.

Parameters	Type of input	Definition
Meter ID	Individual single number	A unique identifier of the SHM installed in the building
Assessment date	Date	The date of the technicians' visit, formatted as day/month/year
Fault description	Open text answer	Open-ended comments for the technician to describe the fault

Table 2
Second iteration of the fault assessment structure.

Parameters	Type of input	Definition
Meter ID	Individual single number	A unique identifier of the SHM installed in the building
Assessment date	Date	The date of the technicians' visit, formatted as day/month/year
Contact type	Predefined multiple-choice answer	The method used to contact customers, with the given options: • Telephone/*E*-mail • Physical visit
Hydraulic connection type	Predefined multiple-choice answer	The existing type of DH connection to the heating systems in the building, with the given options: • Direct • Indirect
SH system	Predefined multiple-choice answer	The existing type of SH systems in the building, with the given options: • Radiators • UFH • Combined (both radiators and UFH)
DHW system	Predefined multiple-choice answer	The existing type of DHW system for heat production in the building, with the given options: • Heat exchanger • Storage tank
Faulty component	Predefined multiple-choice answer	The component where the fault was identified by the technician is categorized into specific labels, with the given options: • In SH system: o Pressure differential regulator o Radiator thermostat o UFH shunt o Etc. • In DHW system: o Temperature regulation valve o Incorrect settings in the temperature regulation valve o Incorrect pump settings o Etc.
Fault description	Open text answer	Open-ended comments for the personnel to describe the fault in detail.
Fault identification status	Predefined multiple-choice answer	The status of fault analysis, with the given options: • Proven (fault identified and confirmed by the technician) • Suspicion (unverified assumption of a fault by the technician)
Technician action	Predefined multiple-choice answer	Actions undertaken to rectify the fault, with the given options: • Error is resolved (fault fixed) • The customer must contact a plumber to fix the fault • No action (no measures taken)

2.3. Data pre-processing

Initially, the dataset comprised hourly measurements, which were subsequently aggregated into daily values. This transformation was crucial for two main reasons. Firstly, it helped reduce computational complexity, making the dataset more manageable for analysis. Secondly, it addressed issues arising from potential data truncation by utility companies [46]. Hourly measurements often suffer from truncation (measurements being rounded down to the nearest integer), leading to inaccurate representations of energy, volume flow, and temperature measurements. By aggregating them into daily values, the impact of truncation errors is minimized, and more reliable data can be obtained for analysis. Nevertheless, despite the conversion to daily values, the dataset still contained a few erroneous values, primarily due to truncation. To rectify this, these incorrect data points are replaced with 'NA', denoting missing measurements.

The next step in this process involved expert analysis to segment the time series corresponding to fault occurrences. Given the complexity of the systems under study, multiple operating systems (e.g., radiators combined with DHW production) could potentially contribute to fluctuations in the measurements. Therefore, expert analysis by the authors was necessary to pinpoint the most reliable periods when faults occurred. This segmentation process allows to isolate and focus on the specific intervals relevant to fault analysis, facilitating more targeted and insightful investigations. To maintain the integrity and reliability of the dataset, buildings with incomplete data (marked by missing measurements) were excluded. This exclusion criterion ensured that the dataset used for analysis comprised only complete and accurate information, minimizing the risk of bias or erroneous conclusions. Finally, the dataset was refined by filtering out instances where fault reports lacked verification from on-site technician visits. Only faults confirmed and assessed by technicians were retained for analysis. Additionally, fault reports were considered valid only if the fault was conclusively "proven" in the report as the genuine cause of the faulty measurements. This stringent filtering process ensured that the dataset contained high-quality, verified fault labels, enhancing the credibility and reliability of subsequent analysis. By undertaking all these steps, the original dataset of 127 SHM and 356 fault reports was reduced to 50 cases with SHM data with combined reports.

2.4. Manual detection and analysis of the fault patterns

This section aims to provide insights into the patterns associated with various faults and how these patterns correlate with the operational metrics of the heating system. This is achieved by analyzing individually each SHM time series of the 50 cases. By exploring each case individually, the analysis highlights the specific occurrences and characteristics of fault patterns, offering a comprehensive overview of their temporal distribution, their impact on the different measurement variables, and their overall significance in system performance.

This analysis begins by aggregating the data to count and categorize occurrences by fault label, identifying the frequency of each fault across all monitored buildings. This step helps in understanding which faults are most prevalent within the system (see Table 4). Next, the month in which each fault is predominant is determined. This calculated month is neither the month when the fault starts nor when it is identified by the technicians. The mean value between these two is selected instead: e.g., if the fault starts in January and the intervention date (technician's visit) is in March, this value will be assigned as February. This enables us to identify any potential seasonal trends that could influence system performance (see Fig. 2).

During the manual analysis of the time series of each case, the principal pattern of the measurements recorded during the fault period was a key characteristic. The return temperature, volume flow, and energy were the analyzed variables. By examining these variable recordings, specific patterns could be observed for the different fault occurrences (as seen in Fig. 1).

As illustrated in Fig. 1, various patterns in the measurement variables during the fault period become discernible:

a) The degradation pattern is characterized by a gradual and sustained increase in the variable over time, signifying a progressive decline in system performance. This is the most extended pattern among those identified, indicating a slow beginning of the fault.
b) In contrast, the stroke pattern emerges abruptly, marked by a rapid and intense change. This pattern represents a swift and significant event, suggesting a sudden fault occurrence.
c) The level shift pattern is akin to the stroke in its immediate change; however, it distinguishes itself by stabilizing at the new level post-fault. This implies that after the initial sharp increase, the variable maintains a consistent higher value.
d) A level shift with subsequent degradation is observed when, following the initial abrupt increase, the variable continues to trend upwards. This denotes a compound fault scenario where the system not only experiences a quick shift but also continues to degrade over time.

One should note that the stroke pattern may not always be as it appears. In some instances, what is identified as a stroke could in fact be a level shift misidentified due to the proximity of the intervention date to the fault event (as mentioned in one of the challenges for this type of data in Section 2.2). Hence, these cases may exhibit similarities. Additionally, it is crucial to mention that there are instances where no discernible pattern is observed, which are categorized as "Not observed". This lack of pattern can be as significant as the others, indicating scenarios where the fault's manifestation does not conform to the typical behaviors captured by the other categories. Further analysis explores whether the observed patterns in each measurement's variables are associated with each other (see Fig. 4). Also, the patterns are investigated to identify whether or not they are repeated across different periods (see Fig. 5).

Furthermore, the duration of each fault and the difference between the starting and ending measurements during the segmented period are calculated (see Fig. 6 and Fig. 7). Lastly, another characteristic that was calculated in the different segments is volatility (see Fig. 8). The volatility (Eq. 2) was calculated as the standard deviation of all the time series measurements obtained by Eq. 1 for each measured parameter:

$$y_t = log(x_t) - log(x_{t-1}) \tag{1}$$

$$\text{volatility} = \sqrt{\frac{\sum (y_t - \overline{y_t})^2}{n-1}} \tag{2}$$

where x_t and $x_{t\text{-}1}$ are the measurements of a specific parameter, e.g., return temperature, at a specific day and its prior. While the value y is the logarithmic difference between these two values, and volatility is the standard deviation of the all-calculated y-values. The volatility is obtained in this form to disregard the trend in the time series, and only account for the daily variation. Another consideration in this calculation is the period where it is calculated. If a pattern is identified as a degradation, its volatility is calculated when the degradation starts. If the pattern is a level shift or a level shift with degradation, the volatility is calculated after the larger spike. In all buildings with a stroke pattern, the volatility is not calculated.

2.5. Automated detection of the fault patterns (time series segmentation)

The FDD analysis discussed in Section 2.4 heavily depends on the segmentation and pattern recognition of time series data. Originally, the segmentation and pattern recognition tasks were performed manually by the authors based on expert knowledge, which is not scalable to larger datasets. To manage these extensive datasets effectively and

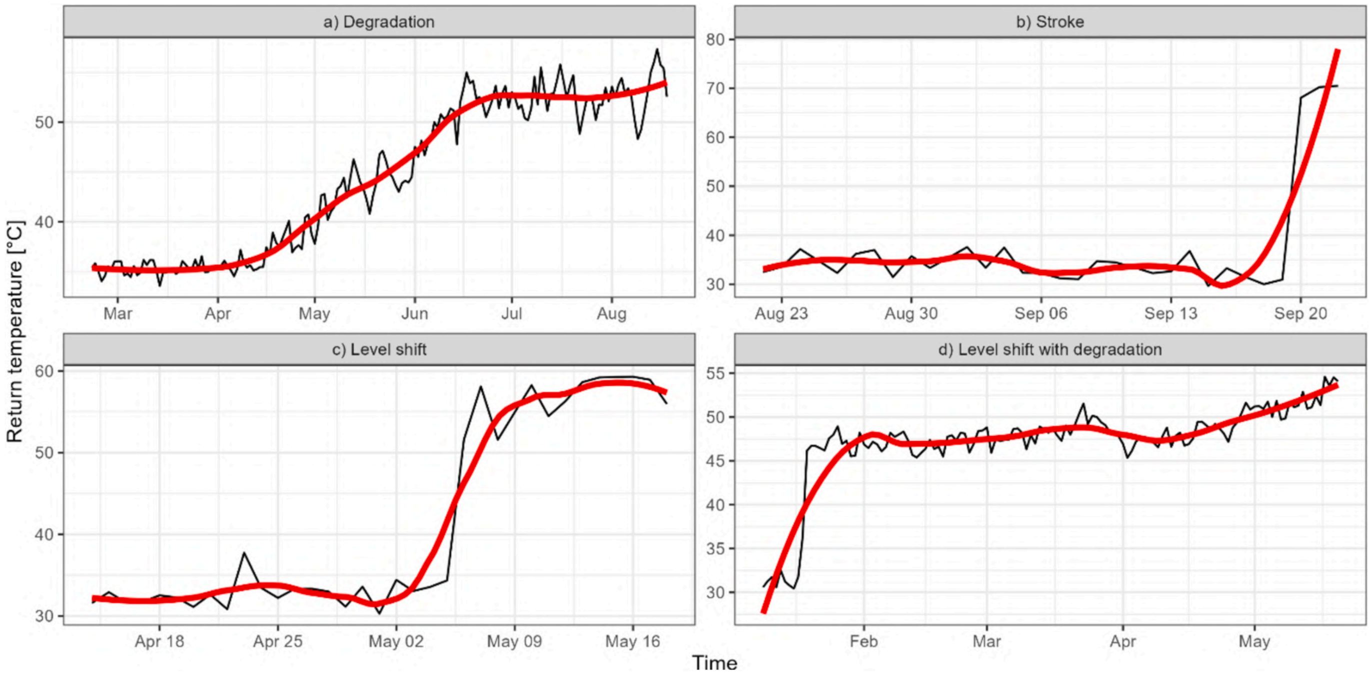

Fig. 1. Representation of the different patterns (free scales).

identify data segments based on their main features, the application of the BEAST method from the "Rbeast" package [45] is suggested for further research and implementation on automated FDD processes. BEAST (Bayesian Estimator of Abrupt change, Seasonality, and Trend) is tailored for time series analysis and decomposition, helping to solve common issues such as trend detection, seasonal adjustment, and identifying change points. Originally developed to analyze land dynamics from satellite data, BEAST decomposes time series into trend, seasonal, and residual components using Bayesian models. This decomposition is crucial for uncovering underlying patterns, such as consistent seasonal effects or long-term trends. The package efficiently handles various types of seasonality, trends, and noise, making it highly adaptable to different time series structures. A key feature of BEAST is its capability to detect abrupt changes, known as level shift patterns, and identify outliers. BEAST employs the Bayesian averaging technique in an ensemble method to robustly estimate model parameters, accommodating uncertainty and variability in time series analysis and detecting the outlier points that deviate significantly from the fitted model.

While this study employed manual segmentation and pattern recognition for the FDD analysis, the proposed application of the BEAST methodology offers a valuable tool for future research. This approach would be particularly beneficial for analyzing larger datasets, as it automates the segmentation and pattern recognition tasks, improving scalability. In this article, the BEAST method is tested on two building cases. This serves as a proof of concept for its effectiveness in identifying trends, outliers, and change points within DH data. The decomposition process in this analysis did not consider seasonal components, focusing only on the trend, outlier detection, and abrupt changes.

2.6. *Self-organizing maps and clustering*

Further on, SOM [47] is used to visualize the features identified in the dataset during the manual analysis in Section 2.4. This method is primarily designed for dimensionality reduction and is thus particularly well-suited for visualizing high-dimensional data. SOM helps to simplify complex, nonlinear statistical structures into simple geometric relationships in a low-dimensional space. In more detail, SOM operates as an unsupervised learning algorithm, which uses competitive learning to map data points into a predefined grid based on their similarity. The algorithm iteratively adjusts the weight vectors assigned to each node on the grid, effectively clustering similar data points together. One key advantage of SOM is that it preserves the topological relationships within the data, meaning that nodes close to each other on the grid represent data points with similar patterns.

In this study, SOM is implemented in R [48], opting for a hexagonal grid configuration for its nodes. This particular layout was chosen for its ability to maintain more uniform distances between nodes, which is essential for the accurate representation of the input data's topological features. Hexagonal grids, in comparison to rectangular grids, offer a more flexible neighborhood structure, improving the accuracy of the mapping in cases of complex, high-dimensional datasets. When determining the size of the grid (number of nodes), it was aligned with the intricacy of the data at hand. A more extensive grid captures a higher level of detail, which simultaneously requires increased computational efforts and more extensive data for effective model training. Therefore, a 4×4 grid was ultimately selected, which proved to be a balanced decision that reduced quantization error and boosted the explained variance, ensuring that almost every node was populated with data points.

The input data consisted of 17 variables retrieved from Section 2.4, which encompasses both one-hot encoded and numeric variables. The one-hot encoded variables represent categorical data, which were converted into binary form, encoding the presence or absence of certain characteristics. One can see in Table 3 each variable used in the SOM. In practical terms, SOM enabled the visualization of the complex patterns identified across multiple variables, providing a structured way to assess relationships within the data that may not have been obvious through traditional analysis methods. The combination of categorical and numeric data types in the SOM inputs allowed for a rich representation of system behaviors, particularly in identifying recurring patterns associated with faults.

Upon the implementation of the SOM on the dataset, k-means clustering [49] is integrated to further segment the data. The k-means algorithm was calibrated to form 5 distinct clusters. This number of clusters was identified as optimal due to its association with the highest silhouette score, an indicator of cluster cohesion and separation. The integration of SOM with k-means clustering provided a two-step

Table 3
SOM input variables.

Input category	Input	Type
Pattern – Return temp.	Stroke Level shift Degradation Level shift with degradation	One-hot encoding
Pattern – Volume flow	Stroke Level shift Degradation Level shift with degradation Not observed	One-hot encoding
Pattern – Energy	Stroke Level shift Degradation Level shift with degradation Not observed	One-hot encoding
Volatility – Return temp.	Calculated with Eqs. 1 and 2	Numeric
Volatility – Volume flow	Calculated with Eqs. 1 and 2	Numeric
Volatility – Energy	Calculated with Eqs. 1 and 2	Numeric
Season (fault period)	Values ranging from 0 to 5, where the lower numbers represent colder months and higher numbers represent warmer months	Numeric

approach: SOM structured and visualized the complex data, while k-means ensured a more precise segmentation, grouping the nodes based on their proximity and pattern similarities. The clustering results underwent a comparison against the ground-truth data derived from fault reports, providing meaningful and validated insight into the underlying structure of the fault characteristics.

3. Results and discussion

This section presents the results of the analysis and discusses the challenges of identifying and diagnosing faults within the DH systems at the consumer level. Through the manual analysis of the return temperature, volume flow, and energy measurements from the SHM, distinct patterns were identified to indicate system's irregularities. These patterns (degradation, level shifts, and unexpected fluctuations) serve as indications of potential faults. This investigation does not merely catalog these occurrences but also examines their durations, frequencies, and volatility within the data. Supplementing the manual inspection, a detection algorithm that employs statistical methods to pinpoint changes in the measurement profiles and quantify these deviations automatically is suggested. The combination of manual and algorithmic approaches provides a comprehensive overview of the system's performance, enhancing our ability to rapidly detect, identify, and mitigate faults.

3.1. Manual detection and analysis of the fault patterns

This section focuses on the initial manual examination of the DH substation operational data to highlight anomalies and trends that may indicate faults. By plotting the number of cases per fault label and mapping them onto the temporal axis, one can discern patterns and irregularities specific to the time of occurrence. Such visual insights not only aid in the identification of immediate issues but also contribute to a deeper understanding of the system's behavior over time. One can see in Table 4 the distribution of fault type labels for the considered 50 cases.

The categorization of faults is closely tied to the system component and the nature of the fault: 'Defective' implies a broken component, 'High settings' are generally ascribed to user preferences, and 'No details' signify insufficient information in the fault reports. All recordings in the dataset are consistent across the faults related to DHW heat exchangers (HEX), DHW storage tanks, radiators, towel dryers, and UFH systems. From Table 4, it is apparent that 'Radiator – High settings' represent the most prevalent issue within this dataset. Faults in 'Radiator' and 'DHW HEX' span across all subcategories, reflecting a diversity in the types of issues encountered. Conversely, 'UFH – High settings' and 'Radiator – Defective' are the least common faults to be detected.

A significant observation is the substantial number of reports marked with 'No details,' which substantially impedes comprehensive analysis and illustrates a broader issue with the reporting process. The prevalence of under-detailed reports underscores the necessity for a more structured and explicit reporting procedure.

Fig. 2 presents a time-based overview of fault occurrences across different buildings, overlaid with a grey shading area that denotes the warmer months from May to September (a period traditionally understood as having a small or no share of SH usage). One can observe that faults related to DHW production are more frequent during the summer season, as highlighted by the grey area. In contrast, issues with SH systems predominantly arise during the colder months, outside of the shaded area. This seasonal pattern suggests a correlation between the demand for specific heating services and the emergence of faults.

Despite the clear seasonal trend, some anomalies deviate from the expected patterns. These exceptions can be attributed to several factors. First, faults are not confined to any season and can occur due to random component failures, independent of the time of year. Additionally, human behavior introduces unpredictability. Instances of radiator usage, and consequently faults during summer months, highlight this. This contradicts the common assumption that radiators remain dormant in warmer weather. Similarly, UFH system usage in summer, driven by personal preferences like wanting warm bathroom floors, can lead to unexpected faults.

Furthermore, seasonal variations in DHW and SH usage further complicate fault detection through system monitoring data. Because the proportion of SH and DHW contributions to the SHM readings changes throughout the year, faults in one system might be masked by the dominant operation of the other. During winter, the higher demand for SH can mask DHW-related faults. Conversely, during summer with minimal or no SH demand, SH component faults might go unnoticed.

During this phase of the analysis, a key characteristic that emerged was a few consistent patterns in the measurements (return temperature, volume flow, and energy) recorded during the fault period. In Fig. 3, one can see the distribution of the different pattern types observed in each measured variable for each type of fault.

When analyzing the return temperature, it is evident that "Stroke", "Degradation", and "Level shift" patterns are prevalent, with "Level shift with degradation" being less common. Faults in radiators primarily show stroke and level shift patterns, whereas DHW production faults often exhibit patterns indicative of degradation (degradation and level shift with degradation). The volume flow variable displays patterns that mirror those found in return temperature measurements but includes a small number of "Not observed" instances across various fault labels. Energy measurements are distinct in that they do not present any cases

Table 4
Number of cases with a specific fault label.

Fault label	Number of cases
DHW HEX – Defective	3
DHW HEX – High settings	2
DHW HEX – No details	4
DHW Tank – High settings	2
DHW Tank – No details	4
Radiator – Defective	1
Radiator – High settings	14
Radiator – No details	6
Towel dryer – High settings	4
UFH – Defective	2
UFH – High settings	1
UFH – No details	7
Total	**50**

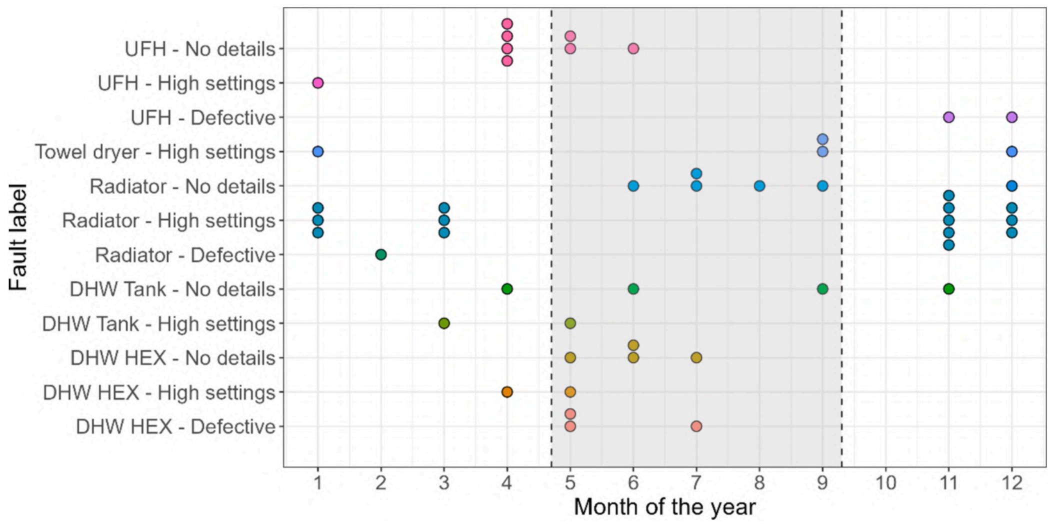

Fig. 2. Representation of the month where each fault occurred per building. The grey shading is the months from May to September that is established as the summer season (no SH usage expected).

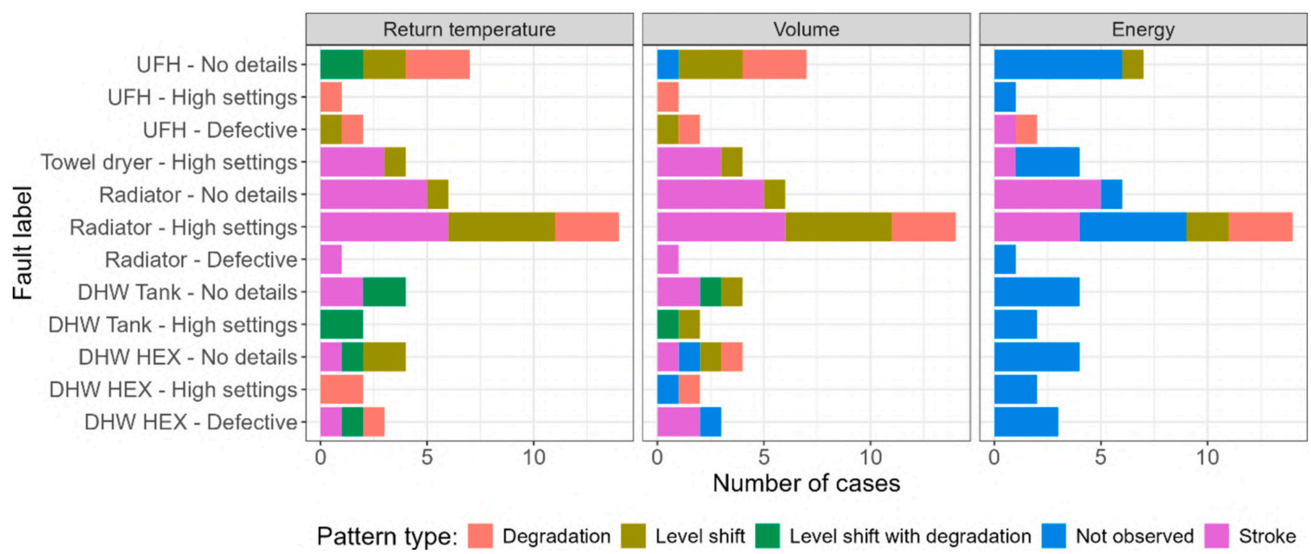

Fig. 3. Horizontal bar chart of the distribution of the pattern types for the different fault labels and measurement variables within the heating system of the different monitored households. The y-axis lists various fault labels – while the x-axis tracks the number of occurrences for each fault label.

of “Level shift with degradation”, and a considerable amount of faults are categorized as “Not observed”. Most of the detectable faults related to energy are associated with SH systems, particularly with radiator faults.

From Fig. 3, one can see that radiator faults typically manifest stroke or level shift patterns (indicating an immediate fault response) across all three variables measured. Faults in towel dryers are similar to those in radiators, but no energy patterns are typically observed, possibly because towel dryers have a much lower energy output compared to radiators. This could also explain why some radiator faults exhibit no discernible pattern in energy consumption, likely because these are smaller units found in less critical areas like basements or bathrooms, where their faults have a negligible impact on energy output. Additionally, degradation and level shift with degradation are patterns more frequently observed in DHW and UFH systems. In these instances, there is typically no clear pattern in energy output, possibly due to the minimal impact of these smaller systems on overall energy usage. This is also compounded by the fact that these readings have daily resolution and in the summer months, when these types of faults occur more, the overall energy demand is reduced.

In Fig. 4, one can see how these patterns are associated with each of the measured variables (return temperature, volume flow, and energy) across different systems in which the fault was encountered and identified by the technicians. This series of Sankey diagrams depicts some sort of fingerprint of typical patterns in the recordings of faulty subsystems like radiators, UFH, towel dryers, DHW tanks, and DHW HEX. The different patterns are categorized as follows: Strokes (S), Level shift (LS), Level shift with degradation (LD + D), Degradation (D), and Not observed (NO). The lines in the Sankey diagrams have thicknesses proportional to the frequency of observed patterns between measurement variables, highlighting where faults occurred in each system. In radiators, faults typically appear as strokes and level shifts, particularly affecting energy demand. Towel dryers show similar patterns to radiators, like strokes and level shifts in return temperature and volume flow, but without impacting energy usage. Unlike radiators, most other systems do not show significant patterns in energy usage, possibly due to their lower energy output. It can be noted that return temperature and volume flow often display consistent patterns across all systems. For

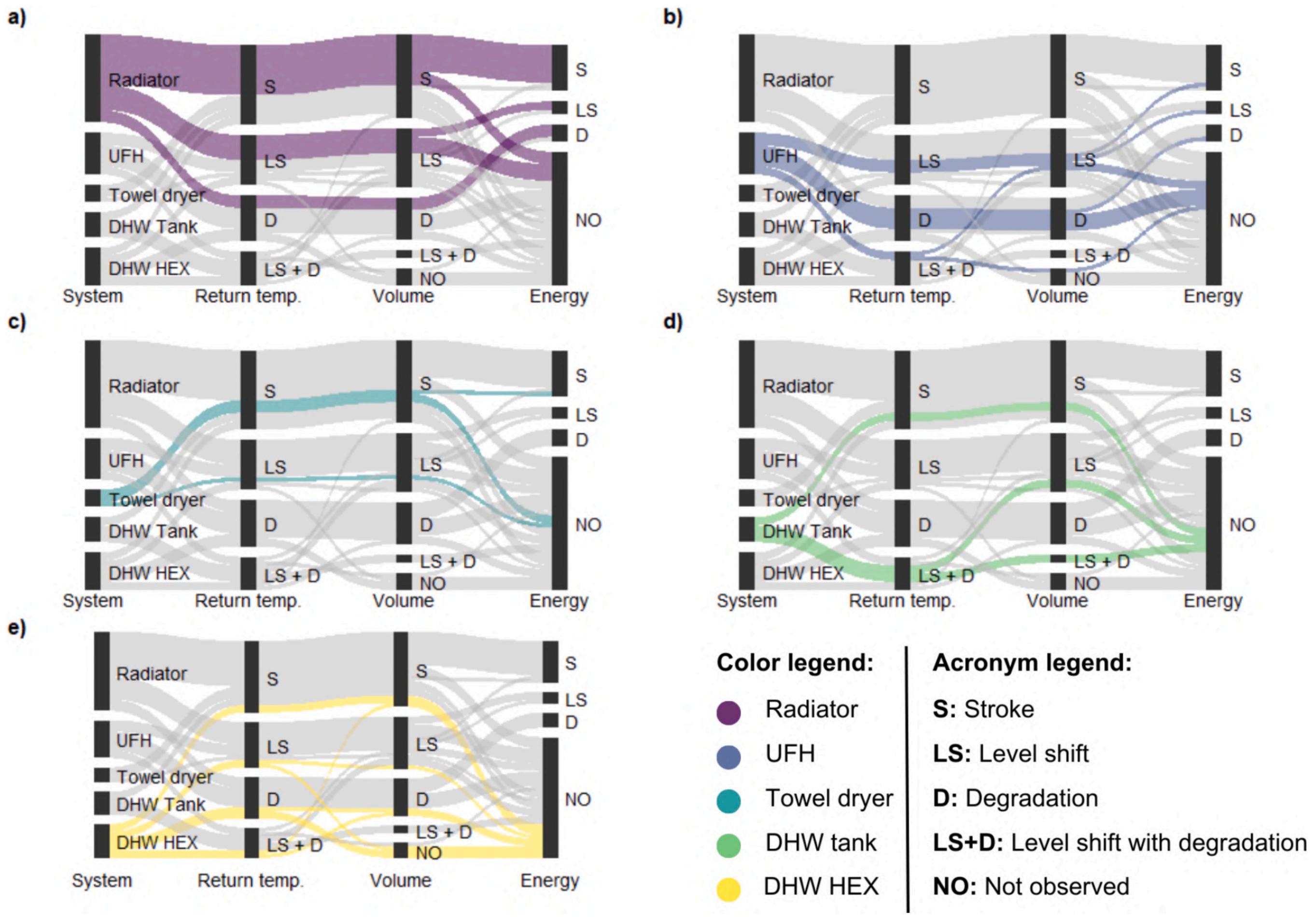

Fig. 4. Sankey diagrams presenting the distribution of the patterns observed in the time series of the different measurement variables for the different systems where the fault occurred.

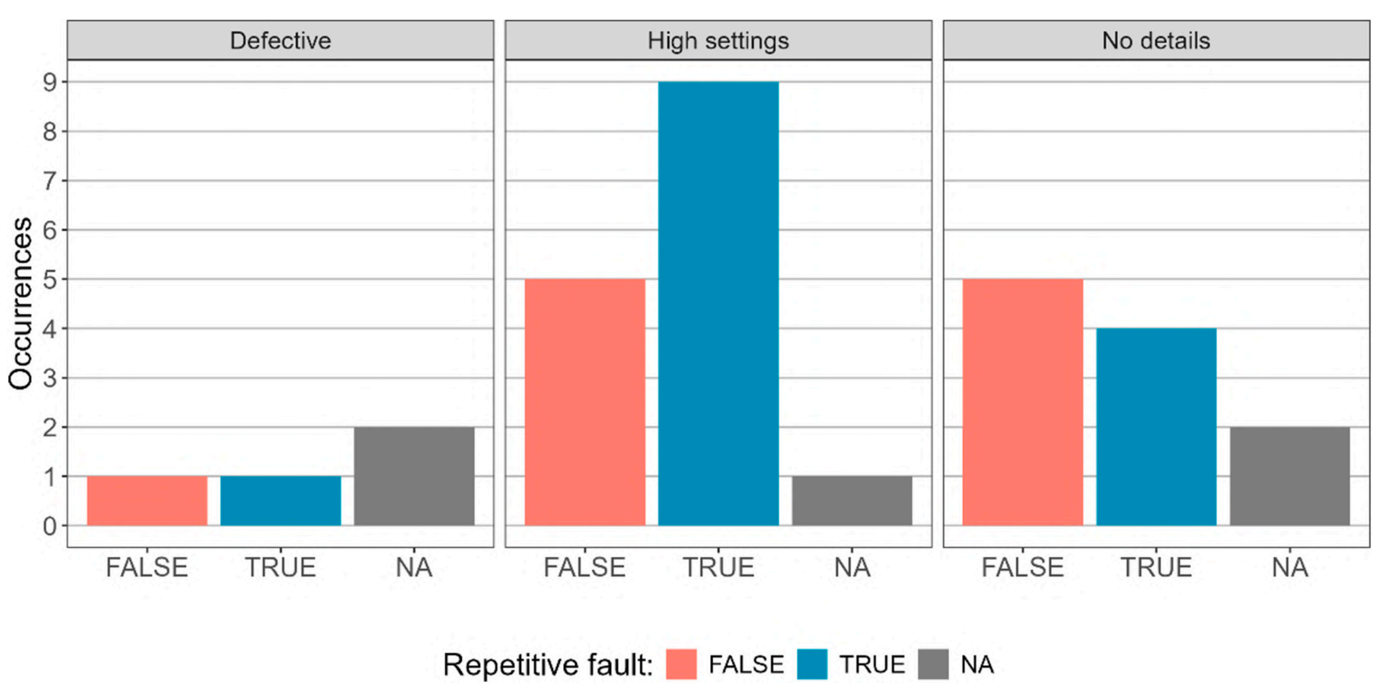

Fig. 5. Visualization of whether or not a fault pattern is observed more than once in the data.

instance, a stroke in return temperature is mirrored by volume flow. In UFH and DHW HEX, degradation is a common pattern, whereas the DHW tank system frequently shows a level shift combined with degradation.

Another feature to highlight is the understanding of whether of not these patterns are repeated throughout the dataset, i.e., if the faulty patterns identified in our analysis have more than one occurrence. In Fig. 5, one can see if there is more than one faulty pattern occurrence in the same building (TRUE) or only the one identified (FALSE). The buildings with too few data points are categorized as NA. This is usually due to the repetition of faults occurring during similar seasons: e.g., if the fault was identified during summer, it is possible that this fault might have occurred in the summer season of the previous year. This analysis was made by distinguishing faults originating from high settings and defective components. Unfortunately, as explained above, there are cases where it is not possible to know the origin of the fault: these were labeled as "No details".

This chart can be used to understand patterns in the performance or issues related to a heating system's components. It particularly focuses on whether certain conditions (like being defective or having high settings) are associated with repetitive patterns throughout the measurements. One can see that there are fewer instances (TRUE, FALSE, and NA) in the "Defective" category, suggesting fewer occurrences of component defects. However, the limited number of cases makes it difficult to conclude if faults caused by defective components are repetitive or not. The "High settings" category contains the majority of cases, primarily marked as TRUE, indicating a high frequency of repetitive faults when a component is set too high. This suggests a possible correlation between high settings and the occurrence of repetitive faults. This aligns with observations that these faults, often unnoticed by building occupants, are detected through data analysis by utilities. The "No details" category shows a similar frequency of TRUE and FALSE labels, indicating an equal distribution of cases with and without repeated faults. This category likely includes faults related to both defective components and high settings.

In theory, it is expected that high settings caused fault should be more repetitive throughout the dataset unless the occupants changed radically their heating settings due to tenants moving out or more impactful energy-saving measures. While the faults caused by a broken component are expected to be much less repetitive because it is the type of failure that occurs once and their impact is much visible to the occupants who will take measures to solve it.

the difference between the measurements during the start and end of the fault was determined. The daily increase or decrease of these values was also assessed by measuring these differences and dividing them by the number of days of the segmented period of the identified faults. In Fig. 6 and Fig. 7, one can find two sets of plots displaying data points for return temperature, volume flow, and energy against their difference in values, and difference per number of days for the given fault labels, respectively.

Fig. 6 presents a multifaceted view of the measurement changes during faulty operation periods. In Fig. 6, the scatter of data points reflects the extent of measurement variations. The return temperature exhibits a notably higher variation than volume flow and energy measurements. Interestingly, energy readings include negative values, which predominantly occur during the transition from colder to warmer seasons, signifying a drop in the energy demand while the fault does not show a significant impact. When examining volume flow, the deviations related to the DHW production system are more pronounced than those for other components, hinting at a significant impact of faults in this system. In Fig. 7, the normalization by the number of days results in a denser clustering of data points along the x-axis, indicating that the variations are less pronounced when accounting for time. However, SH systems like radiators and towel dryers present larger differences due to sharp increases over brief periods. Conversely, the UFH systems and DHW production, which exhibit more gradual degradation patterns over extended periods, display smaller normalized differences.

One last feature considered in this assessment is the volatility. In Fig. 8, one can observe the volatility calculated for each measured parameter. The volatility is proposed as an indicator of the daily variation of the measurements during a degradation period (upward trend) or after an abrupt changepoint (variability after a level shift pattern). All stroke patterns were quantified as zero, due to the lack of data points after this sudden increase.

In Fig. 8, one can see that for return temperature measurements, UFH systems and, to some extent, radiators demonstrate a larger volatility, which reflects the broader range of changes in the system's return temperature. DHW systems, in contrast, exhibit a smaller spread in these values, suggesting less variability in return temperature due to faults. When examining the volume flow and energy measurements, there is an apparent similarity in variability across all systems. Notable exceptions include the towel dryer and a few instances with radiators, where the observed volatility is lower. Additionally, the scale of calculated volatility differs significantly across the parameters. Return temperature presents a much smaller range of volatility when compared to volume flow and energy. This suggests that the impact of faults on the heating

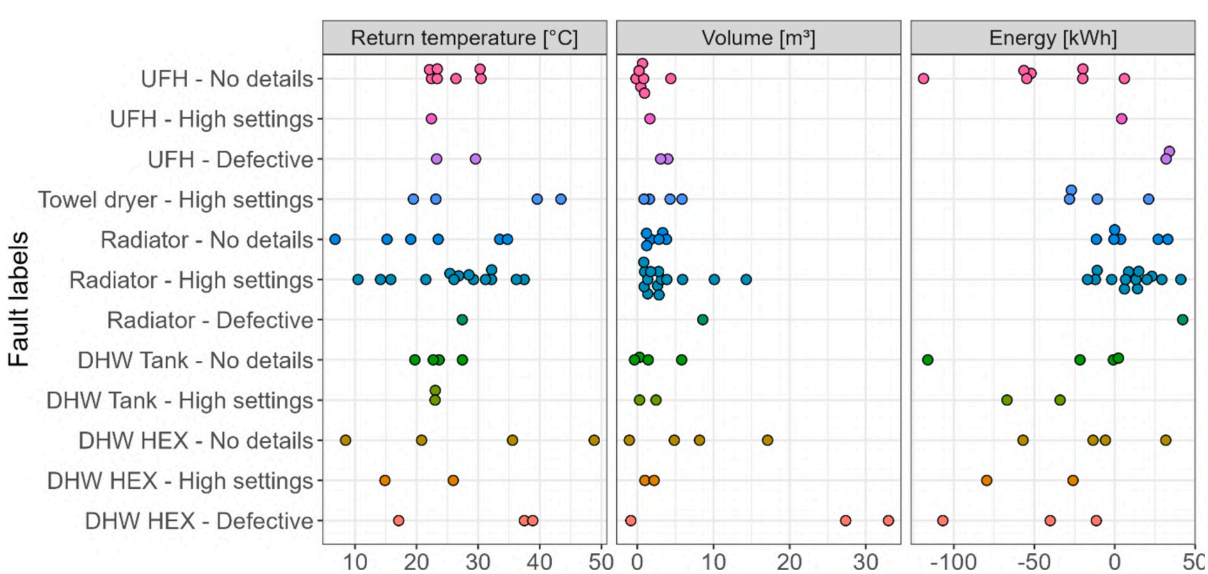

Fig. 6. Difference of the measurements at the start and end period of the identified fault.

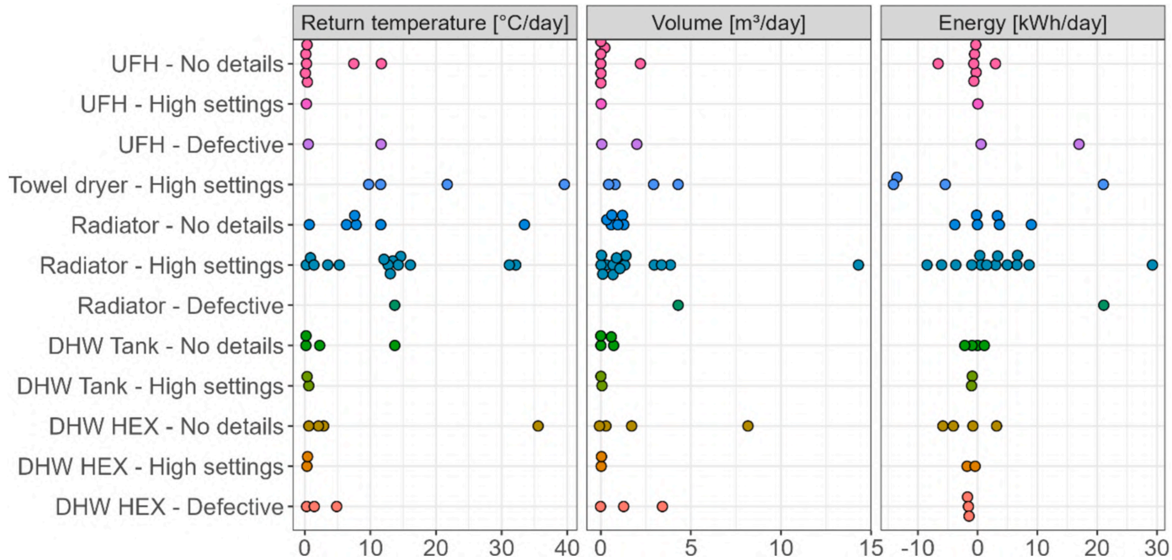

Fig. 7. Difference of the measurements divided by the number of days of the segmented period.

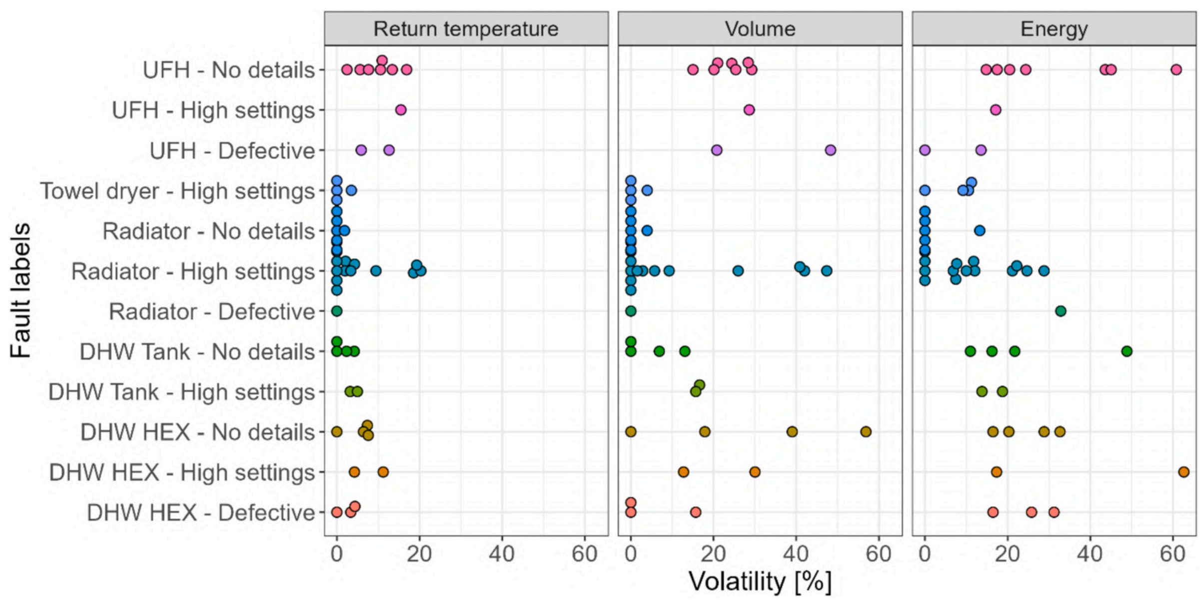

Fig. 8. Volatility per fault label.

system is more noticeably reflected in variations in volume flow and energy usage rather than return temperature.

3.2. *Automated detection of the fault patterns (time series segmentation)*

As observed in Fig. 3, the return temperature in all cases is the measured parameter where a fault always displays an anomalous pattern. Therefore, it is proposed that any FDD analysis for DH substations starts with a return temperature anomaly detection. From this, a time series segmentation must be performed around the return temperature data that display an anomalous pattern. This segmented data is then used for further analysis regarding the other variables: volume flow and energy. This section presents the application of the BEAST method for detecting automatedly anomalous behavior in the time series by analyzing two different cases. The purpose is to exemplify the application of the method for enabling automated FDD.

The measurements in Fig. 9 are from 2021-01-01 until 2023-09-26. The orange region displayed in the plot is the fault segment used in the analysis of this study, while the green region is the period following the technician's visit. The identified pattern is a degradation of the return temperature, while volume flow and energy do not show any singular pattern that might indicate a problem. However, it is observed that after the intervention, there is a large but short drop in the return temperature and water volume flow followed by a small longer-lasting reduction.

This specific fault report shows that this failure was due to a defective component in the heat exchanger of the DHW production. Specifically, the technician reported: "*A lack of cooling with high consumption. The domestic hot water is really warm. It is estimated to be a regulator valve (TPV) for controlling the hot water. The heat exchanger was closed and consumption fell significantly. The customer was advised to contact a plumber*". This confirms the large drop in return temperature and volume flow (by the technician closing fully the defective valve) and is followed by a small reduction of these variables (changing valve settings until the plumber replaces the component). From this building case, one can also observe a high return temperature during the majority of 2022

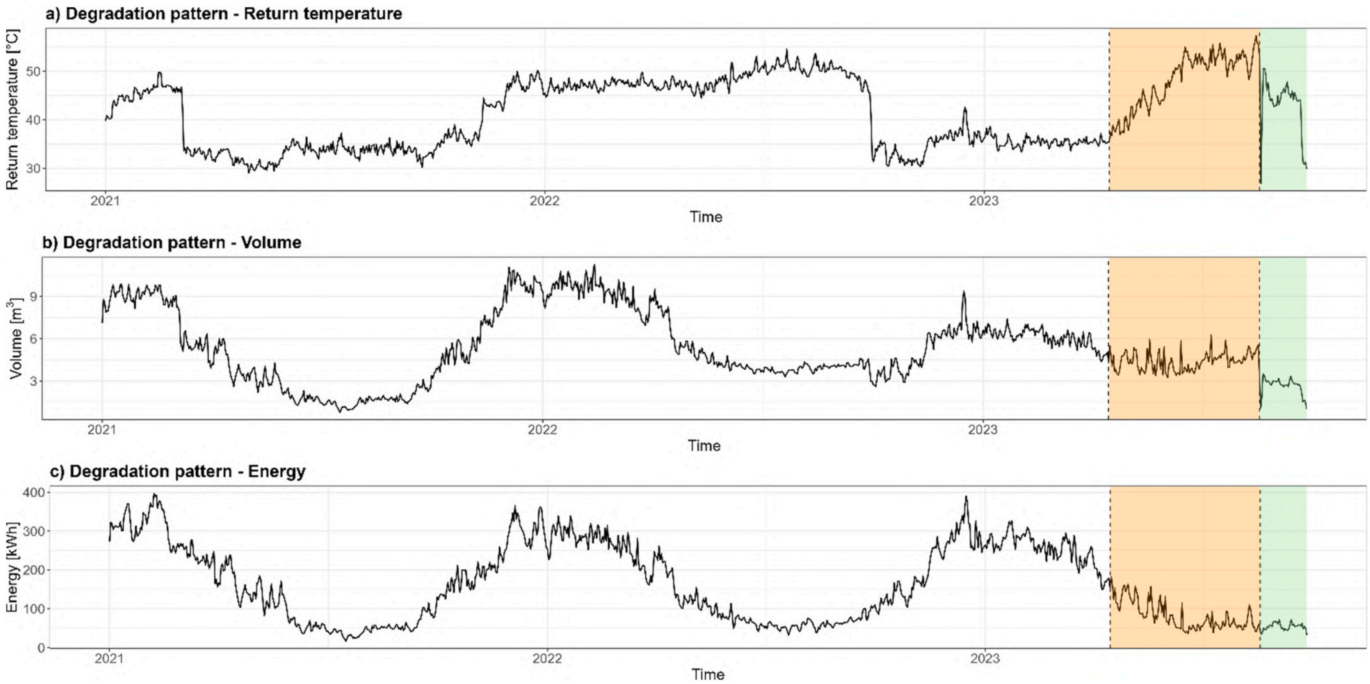

Fig. 9. Segment with degradation pattern. a) Return temperature; b) Volume flow; c) Energy. The orange region identifies the fault segment analyzed in this study. The green region represents the period after the technician's visit. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(winter season included), which most likely implies another failure in the system that was fixed before the technician's visit. In Table 5, one can see the list of obtained outputs from the BEAST methodology.

In Fig. 10, one can observe the BEAST algorithm output of the return temperature time series of the building case mentioned in Fig. 9. Interpreting the plot in the context of return temperature and building heating system efficiency reveals that the applied methodology is accurate at identifying all the major change points within the temperature measurements. This capability extends to recognizing various types of anomalies, which is crucial for thorough monitoring. The analysis does not solely pinpoint abrupt shifts, it also encompasses the detection of gradual trend reversals, capturing instances where the trend shifts from rising to falling or stabilizes. Such nuanced detection is instrumental in identifying degradation patterns that emerge without sudden changes, which is an important aspect of preventive maintenance. Moreover, the outlier detection method employed here is refined enough to distinguish stroke patterns from level shifts or typical fluctuations. This refinement enhances the precision of the diagnostic tools and can be particularly effective in flagging irregular patterns that may indicate inefficiencies or faults within the heating system. Overall, these insights are invaluable for maintaining optimal operation, leading to potential improvements in the efficiency and reliability of building heating systems.

Another building case is presented in Fig. 11 and Fig. 12, however with a level shift pattern in the return temperature. The measurements in this substation are from 2021-01-01 until 2023-09-26 (similar to the one above). The identified pattern is clearly a level shift in the return temperature and volume flow, while the energy profile presents an initial stroke followed by lower values. After the intervention, there is a large reduction in the return temperature and water volume flow followed by stabilization of these measurements, whereas the energy does not display any significant change before and after the intervention, besides the aforementioned stroke. This specific fault report showed that this failure was due to a defective component in the UFH system. However, there were no other documented details regarding the nature of this fault.

In Fig. 12, one can see the results of employing the BEAST method for the return temperature of this case. Interpreting the plot about the return temperature provides valuable insights into the building's heating system efficiency. This showcased that the BEAST method is capable of precise detection and segmentation of anomalies, aligning closely with segments identified by expert assessment during the manual analysis. This includes the level shifts clearly demarcated within the dataset. The utility of the method extends beyond the identification of significant shifts to capturing smaller, abrupt changes, as evidenced around the 200-day mark on the timeline. Further scrutiny of the data post-intervention reveals that both the water volume flow and return temperature experience a decrease, thereafter stabilizing until the end of the observed period. This observation is in agreement with the findings in [50], which assert that well-functioning heating systems typically exhibit a constant and low return temperature throughout the year. This steadiness is an indicator of system efficiency and is a critical factor in the assessment of the heating system's performance. Through such analysis, the method not only confirms previous conclusions about system behavior but also offers a reliable means of monitoring and evaluating system efficiency over time.

Table 5
BEAST output list.

Output variable	Description
Y	The original time series – Return temperature measurements.
Trend	The time series fitted trend component.
Pr(tcp)	The probability of a data point being an abrupt changepoint in the trend component.
SlpSign	Likelihood of the trend slope being upward (indicated by the red area), flat (represented in green), or downward (shown in blue).
Outlier	The detected outliers present in the time series.
Pr(ocp)	The probability of a data point being an outlier in the time series.
Error	The model residuals.

3.3. *Self-organizing maps and clustering*

In the analysis, SOM was combined with the k-means clustering

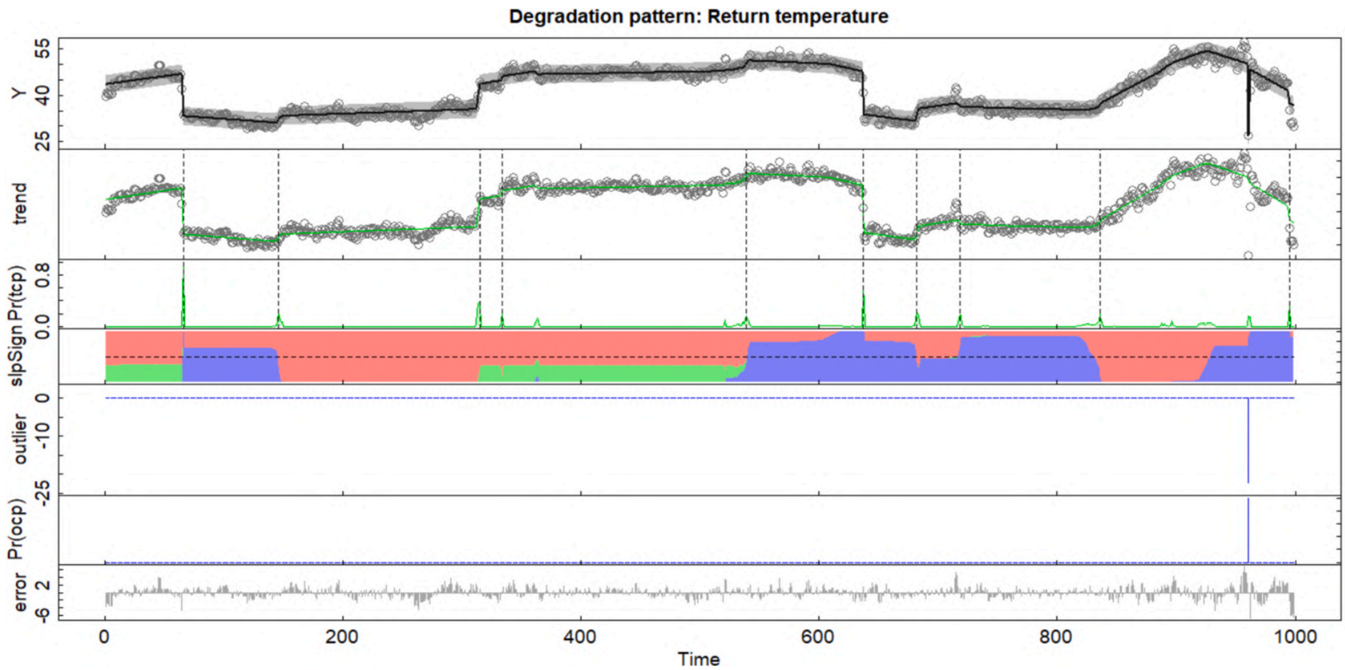

Fig. 10. BEAST method application for degradation pattern detection.

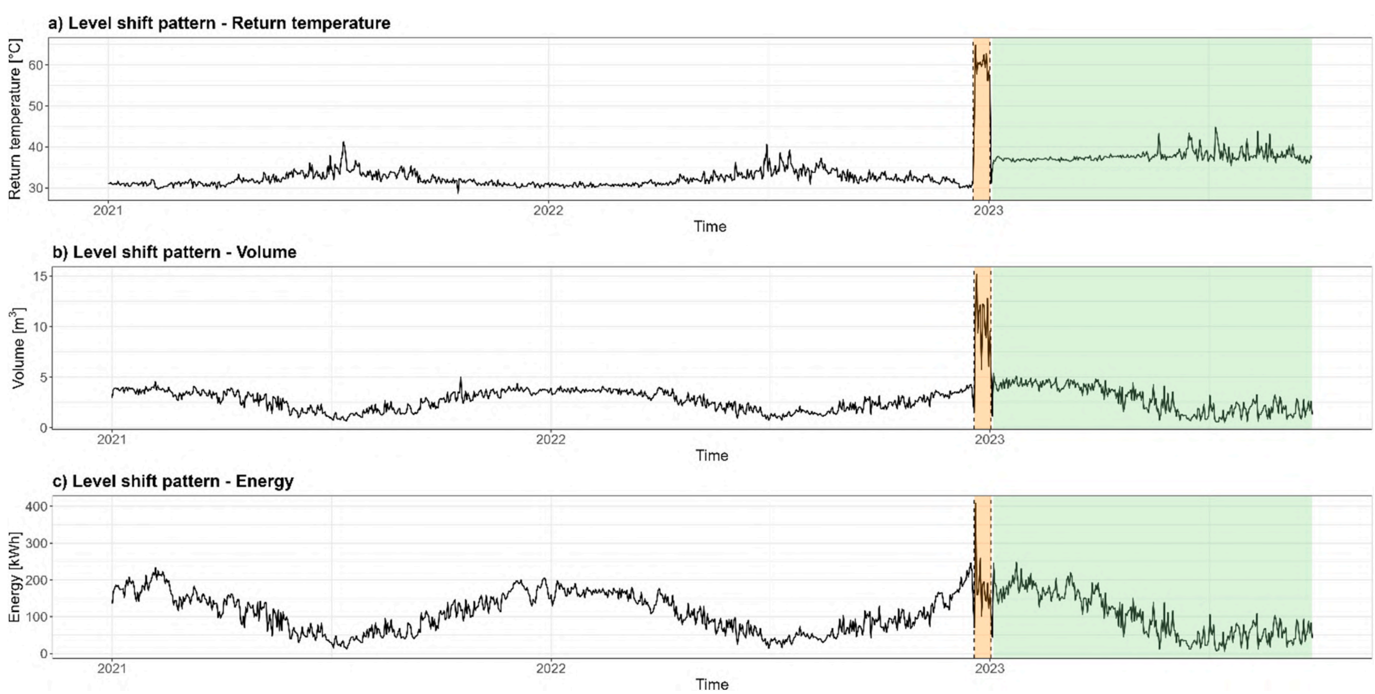

Fig. 11. Segment with level shift pattern. a) Return temperature; b) Volume flow; c) Energy. The orange region identifies the fault segment analyzed in this study. The green region represents the period after the technician's visit. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

algorithm, as this integrated approach facilitates a more nuanced visualization and categorization of the complex patterns within the dataset. The focus was put on assessing pattern types, volatility levels, and fault periods, as these aspects seemed most relevant to identify the type of fault. However, the differences in measurements before and after a fault were not considered, as these are heavily dependent on the specific systems present in individual households (this information was not available). Additionally, the feature of fault repetitiveness due to insufficient data was disregarded for a reliable analysis of this characteristic.

In Fig. 13, one can see the SOM property plots that delineate the distribution of nodes according to the observed patterns in return temperature, volume flow, and energy. The analysis reveals that each plot is distinctively related to a specific measurement parameter and displays diverse patterns such as stroke, level shift, level shift with degradation, and degradation. The individual nodes of the SOM are structured with hexagonal cells, with a colour-coding scheme that reflects the intensity of the measured variables according to the legend and its placement on

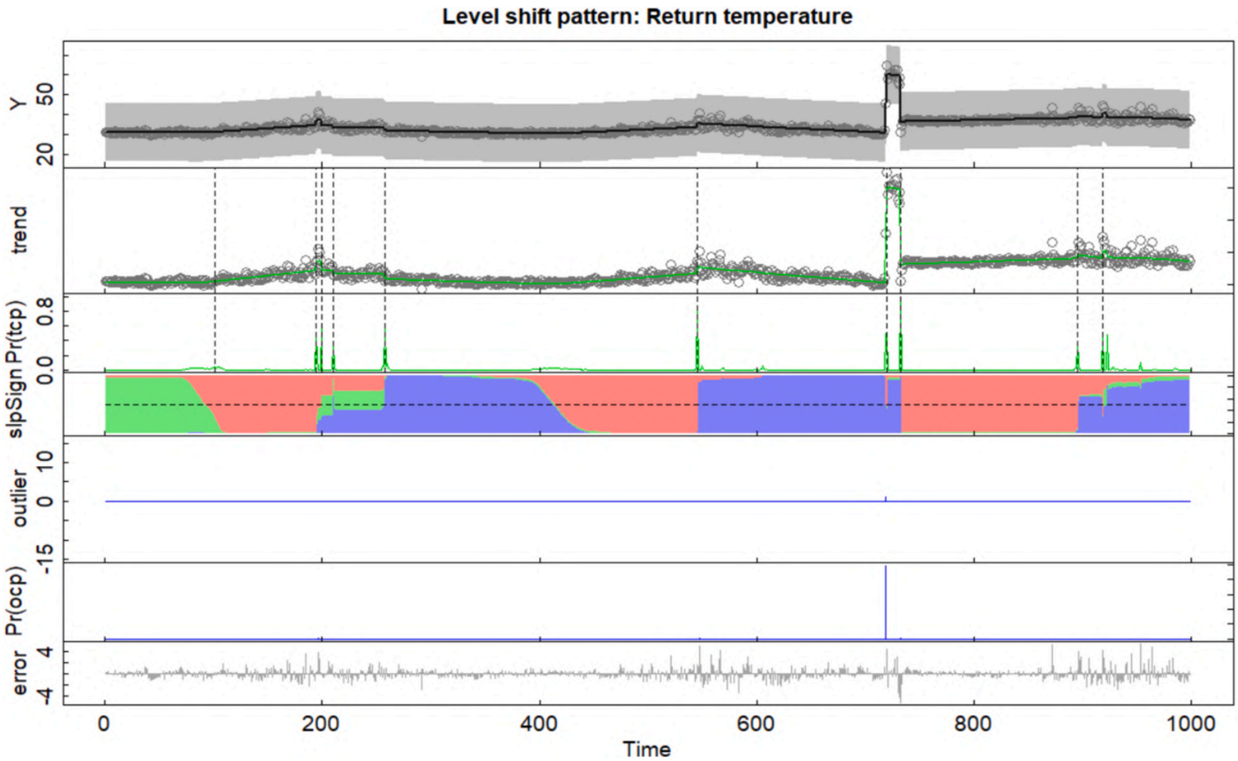

Fig. 12. BEAST method application for level shift pattern detection.

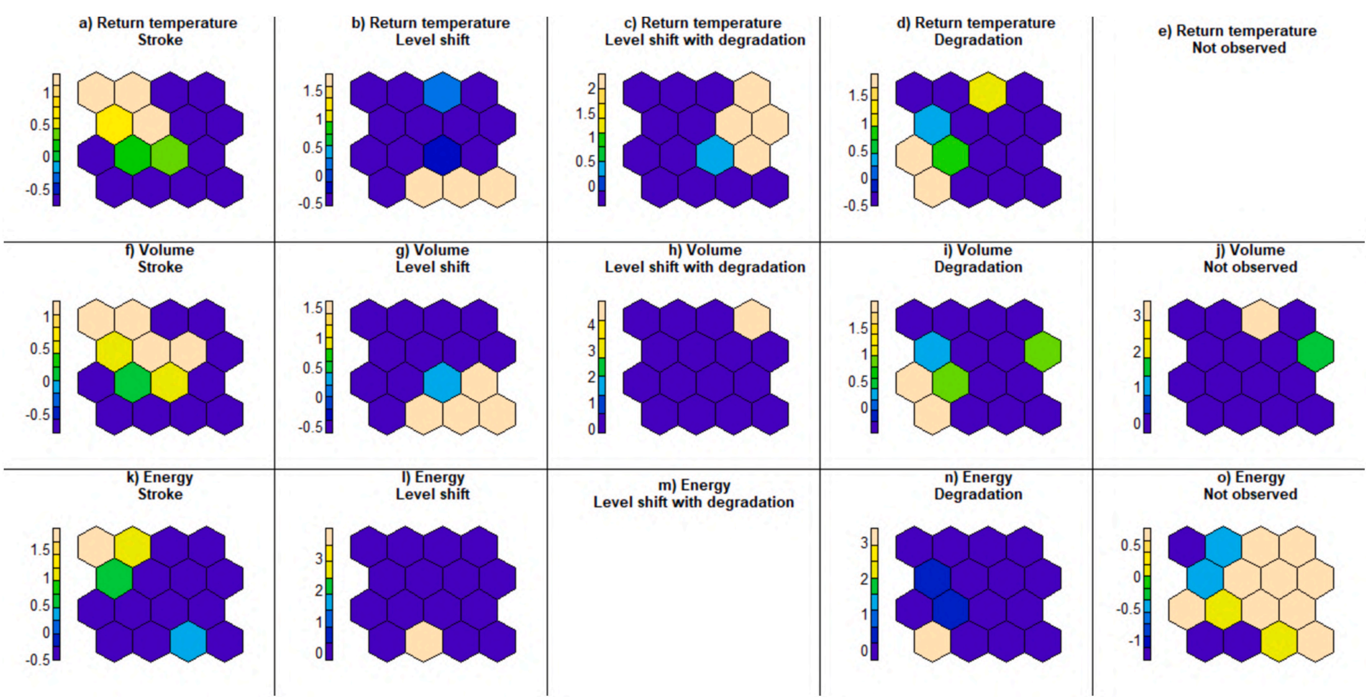

Fig. 13. SOM property plots – Pattern features (one-hot encoded variables).

the grid. Thus, data points with similar patterns are placed in nearby hexagons.

In terms of the observed conditions, the plots exhibit several grid layouts. The stroke condition, for instance, manifests itself with its cases being predominantly located towards the high left edge across all three variables, echoing a pattern of associated strokes identified in all variables as seen in earlier figures. The level shift pattern is primarily observed in the lower right corner. In contrast, the level shift with the degradation pattern takes prominence in the top right area, with the return temperature showing a higher frequency of this pattern compared to volume flow. This particular pattern was not evident within the energy data. Conversely, degradation patterns are more apparent on the bottom left side of the map, with return temperature exhibiting a greater number of cases than the other variables. Lastly, the "Not observed" designation signals the absence of recorded patterns, a scenario most prevalent in the energy data, whereas no instances were noted for return temperature.

Combined with the patterns' features, the SOM was developed using the calculated volatility of each measurement parameter and the season variable derived from the feature "fault month" (in Fig. 2) where the fault occurred. The SOM of each of these features can be seen in Fig. 14.

In Fig. 14, one can conclude that data points indicating higher volatility, specifically those related to faults, tend to cluster differently per parameter of the map. In terms of return temperature and volume flow volatility, these values are similarly placed on the bottom left side of the map, with a few nodes also appearing in the top right corner. The spread of energy volatility across the map is more diffuse, with a notable concentration in the top right corner, corresponding to the "Not observed" pattern of Fig. 13. The seasonal feature presents a less scattered pattern across the map. The colder months, marked in blue indicating lower values, are found in the lower level of the map. Conversely, the faults that occurred during warmer months are attributed to higher values of the scale, which are situated in the top right corner. Comparatively with Fig. 13, the "Level shift" and "Degradation" patterns are associated with nodes representing colder months. On the other hand, the warmer months coincide with the "Level shift with degradation" pattern for return temperature and volume flow, and with the "Not observed" patterns for both volume flow and energy variables.

The k-means clustering is then applied to the developed SOM with 5 clusters to combine the nodes with similar properties. In Fig. 15, one can observe the cluster map where k-means was applied to SOM. The results from the clustering and the layout of each of its variables from Fig. 13 and Fig. 14 are summarized in Table 6.

To understand how the different features can lead to fault diagnostics, the different clusters are associated with ground truth obtained from the technician reports when inspecting faulty systems (see Fig. 16).

In the study, five distinct clusters were identified based on fault occurrences in various heating systems, differentiated by seasonal timing, observed patterns, and volatility levels. In Fig. 16, each main system was compared within the attributed cluster in order to observe if the different input variables could be used to diagnose the type of system where the fault occurred.

Cluster 1 – composed of 19 cases, primarily SH system faults, with a noticeable prevalence of radiator and towel dryer issues. These faults predominantly occur during months with mid-range external temperatures. A consistent pattern observed across this cluster is the stroke pattern, with a few instances where the pattern was not observed in energy measurements. Volatility across all measured parameters is generally low, with occasional medium volatility noted in energy.

Cluster 2 – composed of 11 cases, also features faults in SH systems, notably radiators and UFH systems, with a significant number of radiator cases. The timing of these faults corresponds with colder to mid-external temperatures. The level shift is the consistent pattern in this cluster, with some energy patterns being "Not observed". Volatility varies medium-low for return temperature, high-low for volume flow, and low for energy.

Cluster 3 – composed of 9 cases, once again shows faults primarily in SH systems, including radiators and UFH systems, with a significant number in the latter and occurring during the cold months. The degradation pattern is common here, with some cases of "Not observed" patterns in energy measurements. Volatility is noted as high to medium across all parameters.

Cluster 4 – is composed of 6 cases and is characterized by faults in the DHW system, particularly in storage tanks. These faults tend to happen in months with warmer to mid-external temperatures. This cluster exhibits predominantly the level shift with degradation pattern for return temperature and no observable pattern for energy, suggesting diverse fault characteristics. The levels of volatility are recorded, as medium and low for all three parameters.

Cluster 5 – composed of 5 cases, mostly comprises DHW system faults in the heat exchanger and occurs during warmer months. The return temperature often shows a level shift with degradation and degradation alone patterns, while no patterns are observed for volume flow and energy measurements. Each parameter exhibits varied volatility: low-medium for return temperature and medium-high for volume flow and energy.

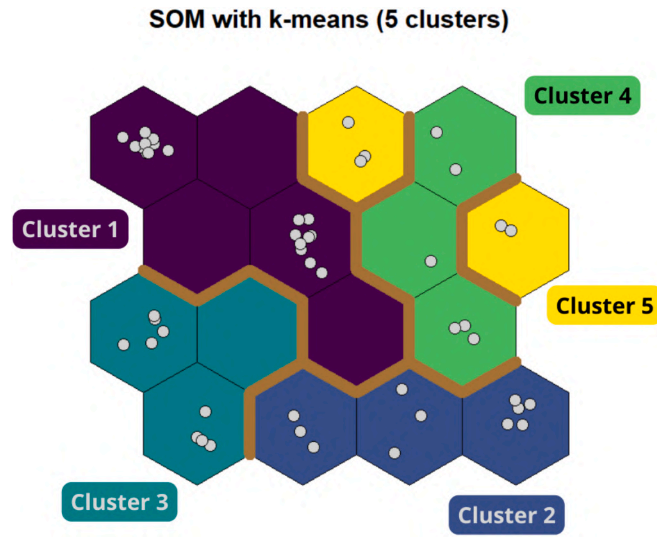

Fig. 15. K-means cluster map.

From the clustering and the intervention reports, one can conclude the following:

- Radiator and towel dryer faults have similar patterns as stroke or level shift. Radiators, however, might display a similar pattern in the energy measurement while the towel dryers do not. This might be

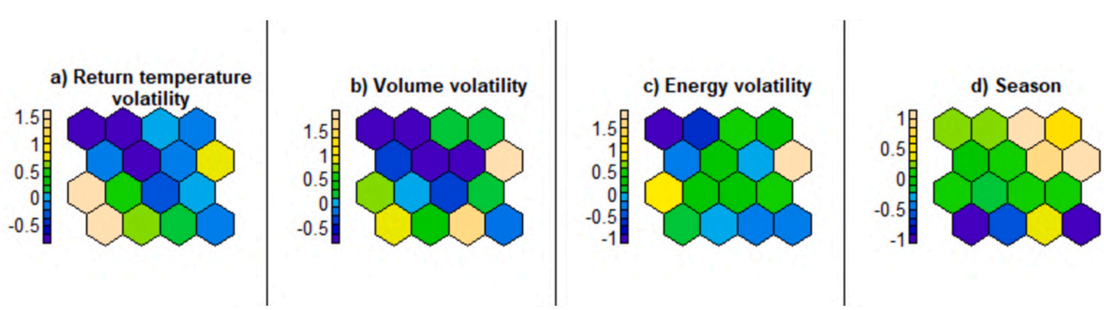

Fig. 14. SOM property plot – Volatility and season features (numeric variables).

Table 6
Summary of the k-means clusters implemented in SOM.

Cluster	Nr. of points	Nr. of nodes	Season	Return temperature		Volume flow		Energy	
				Pattern	Volatility	Pattern	Volatility	Pattern	Volatility
1	19	5	Mid	S	Low	S	Low	S NO	Low Medium
2	11	3	Mid Cold	LS	Medium Low	LS	High Low	LS NO	Low
3	9	3	Mid Cold	D	High Medium	D	Medium	NO D	High Medium
4	6	3	Warm Mid	LS + D	Low	LS + D S LS	Medium Low	NO	Medium
5	5	2	Warm	D LS + D	Low Medium	NO D	Medium High	NO	Medium High

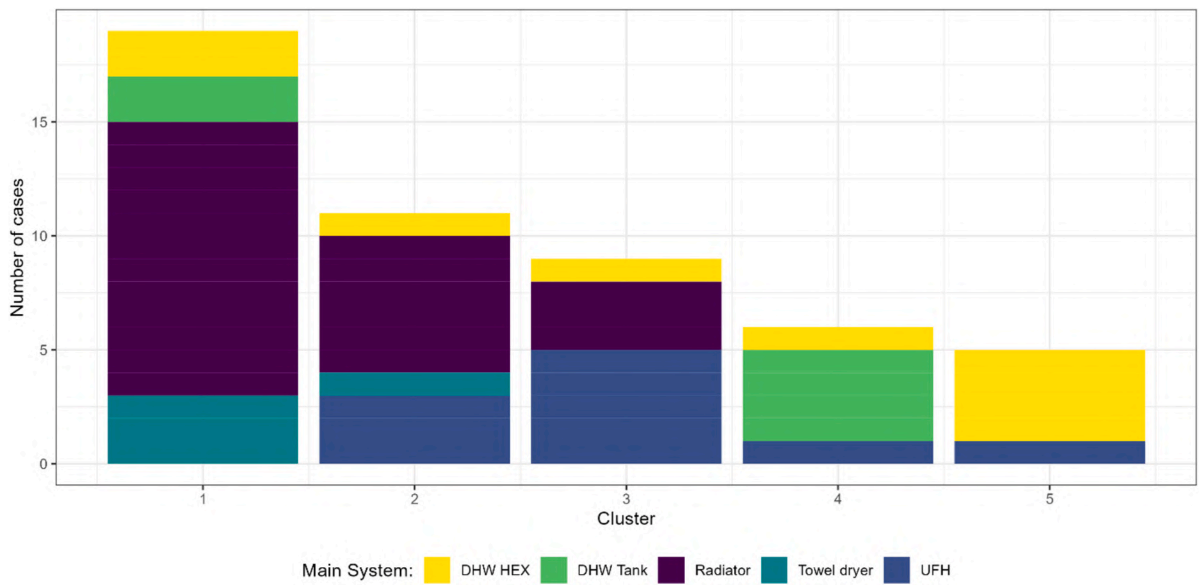

Fig. 16. Association of the main system where the fault occurred with a given cluster.

due to the maximum energy output being generally expected smaller for towel dryers.

- A fault in the UFH system may sometimes display a similar pattern as a radiator (abrupt change) while other times it might display a slower pattern (degradation). However, both these faults cause higher levels of volatility in the measurements.
- The faults occurring in the SH systems seem too often occur in the mid-cold external temperatures season, while faults in the DHW production system usually occur in the summer.
- A fault in DHW production does not seem to cause any impact on energy usage. Nevertheless, the return temperature and water volume flow are negatively affected by it. The results also show that DHW tank faults might display the level shift with a degradation pattern, while a fault in the heat exchanger might cause a degradation pattern.

3.4. Lessons learned and suggestions for further work

This research underscores the necessity for implementing automated FDD methods within DH systems. Since automated FDD methods are crucial for the advancement towards the 4th generation of DH systems, leveraging SHM data that is already available. Following such need, the article closes with some remarks regarding the lessons learned from this research but also proposes several suggestions for further work.

- Expert assessment and dataset limitations:

Due to the small dataset of 50 cases with some ambiguous fault labels, this study heavily relied on expert assessments, analyzing each case individually. This approach, while effective for the study, is impractical for real-world DH networks, which comprise numerous connected buildings. Consequently, the study proposes the use of the BEAST methodology to detect and segment data points exhibiting anomalous behavior, addressing the scalability issue.

- Effective fault measurement:

It was observed that return temperature is the most effective measurement for detecting faults. In all studied buildings, return temperature exhibited abnormal readings during the expected fault periods mentioned in the reports. Conversely, energy usage, despite being a more accessible metric, proved less reliable in detecting all faults. This is because it only identifies faults when the power output is substantially high, such as with radiators.

- Need for high-quality ground truth data:

Integrating and enhancing ML models for fault diagnosis in DH substations require a larger quantity of high-quality ground truth data. The current study, constrained by a dataset of only 50 cases, was insufficient for training robust ML models. Traditional classification algorithms like Random Forest or XGBoost, as well as deep learning models, demand a substantial amount of well-labeled data for effective training.

- Data compilation and sharing:

DH companies should compile, anonymize, and share data to expand the field and develop standardized datasets. This collaboration would facilitate the validation and comparison of different models using a uniform dataset, accelerating advancements in fault detection technologies.

- Handling SHM data issues:

A notable identified issue is the handling of hourly SHM data in Danish utilities, where rounding errors from truncation (rounding down measurements to the nearest integer) processes lead to asynchronous measurements. Although this was mitigated by aggregating data into daily granularity, it is imperative to eliminate these truncation processes to ensure data accuracy. Indeed, it is expected that certain faults might only be detected with high-resolution measurements.

- Practical considerations for clustering analysis:

In this study, the data collected from 50 household substations was used for clustering analysis. While this amount of data allowed for meaningful insights, practical implementations of the clustering model in larger district heating networks would require a significantly larger dataset to ensure comprehensive model training and fault detection. Based on our experience, increasing the number of substations or extending the measurement period would enable the identification of more granular fault patterns. We recommend that future studies focus on collecting high-resolution and long-term data across diverse building types to ensure the scalability and effectiveness of the clustering approach.

- Diverse data types for improved diagnostics:

Incorporating a broader range of data types can significantly enhance diagnostic capabilities. For example, indoor temperature data and radiator heat allocators could identify faults in specific rooms, while water meter data could highlight usage patterns and potential faults in DHW systems. Despite being obtainable with more sensors, these data are not consistently accessible to all customers. Additionally, pressure readings, though underutilized by DH companies, could aid in diagnosing faulty components by analyzing pressure differences.

- Utilizing public household information:

Integrating household area data, such as from the Danish Building and Residence Register (BBR) in Denmark, could help standardize SHM data and enable comparisons of faults across different buildings. This holistic data collection and analysis approach would significantly improve the accuracy and efficiency of fault diagnosis in DH substations.

- Predictive fault detection for future time series predictions:

One potential improvement for future studies involves implementing predictive fault detection algorithms, such as next-hour or next-day predictions, to enhance the system's ability to anticipate faults. To achieve this, train and test datasets would need to be defined by segmenting historical time series data. The input data for these predictions would include key features such as return temperature, volume flow, and energy measurements. The clustering algorithm would then produce outputs indicating whether a fault is likely to occur in the near future. This approach could be valuable in enabling real-time fault prediction, allowing for more proactive system maintenance and reducing downtime. While not covered in the current study, this is an important avenue for future research, and we will highlight the potential for its application in predictive fault diagnosis.

4. Conclusion

The study initiates with the intricacies of gathering ground-truth data for the enhancement of fault diagnosis models. A significant step forward has been made with the second iteration of reports from Aalborg DH company, moving past the ambiguous nature of initial collections. However, the investigation reveals that issues persist, such as the mention of a single fault in instances of multiple concurrent faults, the premature timing of interventions obscuring full fault pattern development, and a bias towards faults unnoticed by residents.

Despite these hurdles, from an initial batch of 127 reports, 50 cases of household substation faults were analyzed. Due to the scarcity of comprehensive datasets in the literature and the mentioned challenges, the study concentrated on a detailed case-by-case examination. Analysis hinged on segmenting the fault period recorded in maintenance reports, identifying the month of occurrence, observing the fault patterns, their association with measured parameters, their repeatability, and the extent of parameter value changes due to faults. Findings indicate that while return temperature consistently displays a fault pattern and volume flow typically mirrors this pattern, energy usage data does not. Seasonal trends and volatility in fault occurrence were identified as meaningful for diagnosing fault nature, although data was insufficient to thoroughly assess the impact of fault repeatability and measurement variances before and after the fault.

Furthermore, the research advocates for the need for an automated time series decomposition method to segment SHM data to scale this analysis for all DH customers, as case-by-case analysis is unachievable. The segmentation is proposed using the return temperature because this parameter was always affected by the observed faults. The current study suggests the method BEAST [45] as a suitable algorithm for detecting extreme, short-duration, level shifts, and degradation anomalies.

To categorize symptoms and patterns of faults extracted by the segmentation, the study utilized the observed patterns, volatility, and seasonality to apply SOM with k-means clustering. This analysis produces clusters of faults with similar characteristics, revealing that different heating systems might exhibit similar features. The paper endorses SOM as a method to group symptoms for fault diagnosis and to interpret high-dimensional data. By segmenting data indicative of operational faults and clustering into similar groups, the method solidifies its usefulness in advancing towards more effective DH-automated FDD processes and would, therefore, substantially improve the efficiency and reliability of the DH grid.

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CRediT authorship contribution statement

Daniel Leiria: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hicham Johra:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Justus Anoruo:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Imants Praulins:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Marco Savino Piscitelli:** Writing – review & editing, Supervision, Conceptualization. **Alfonso Capozzoli:** Writing – review & editing, Supervision, Conceptualization. **Anna Marszal-Pomianowska:** Writing – review & editing, Supervision, Resources, Conceptualization. **Michal Zbigniew Pomianowski:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

My code is available in my GitHub repository, and the data can be provided upon request to Michal Pomianowski (mzp@build.aau.dk).

Code/Scripts repository (Reference data) (GitHub)

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