

# A Physics-Based Approach to Monitor Substation Performance and Prevent Inefficiencies in District Heating Systems

*Martina Capone<sup>a</sup>, Elisa Guelpa<sup>b</sup>, and Vittorio Verda<sup>c</sup>*

<sup>a</sup> *Politecnico di Torino, Turin, Italy, martina.capone@polito.it, CA*

<sup>b</sup> *Politecnico di Torino, Turin, Italy, elisa.guelpa@polito.it,*

<sup>c</sup> *Politecnico di Torino, Turin, Italy, vittorio.verda@polito.it,*

## Abstract:

The reduction of operating temperatures is a key enabling factor for the decarbonization of district heating systems, as it supports the integration of renewable and low-carbon heat sources and improves system efficiency. In this context, the operational performance of heat exchange substations is critical, as malfunctions and degradation phenomena, such as fouling in heat exchangers or excessively high set-point temperatures, can affect heat transfer, resulting in elevated return temperatures, excessive mass flow rates, and inefficient system operation.

This study aims to propose a physics-based methodological framework to identify non-optimal substation operating conditions that reduce system efficiency and limit the potential for temperature reduction at the network level. In this paper, the analysis is conducted on operational data from a set of user substations connected to a large-scale district heating network in Italy. The network currently operates at high supply temperatures, around 120 °C, and is mainly supplied by cogeneration units, while it is progressively transitioning towards lower-temperature operation and a low-carbon heat supply.

The proposed approach combines the analysis of measurements (temperatures, mass flow rates, and thermal power) with a physical interpretation of substation behavior under varying climatic conditions and heat demand. This approach allows the identification of anomalous operating patterns associated with performance degradation, including increases in primary return temperatures. Based on this analysis, a monitoring framework relying on performance indicators is introduced to support the early detection of substation malfunctions and degradation phenomena.

The results highlight the importance of substation-level performance monitoring to prevent inefficient operating conditions and to facilitate the reduction of supply and return temperatures. The proposed methodology supports the transition towards lower-temperature and more sustainable district heating systems.

## Keywords:

Anomaly detection; district heating substations; fault detection; fouling; malfunctions.

## 1. Introduction

The decarbonization of energy systems is one of the most urgent challenges facing society. In this context, the heating sector plays a key role, as it accounts for more than half of global final energy consumption [1]. In particular, the decarbonization of heat supply for space heating and domestic hot water is a major priority.

District heating networks (DHNs) are widely recognized as an effective solution to support this transition. At present, DHNs cover around 12% of Europe's heat demand, but it is predicted that they will increase their share considerably in the coming decades; by 2050, it is estimated that they will supply up to 5% of the total final energy consumption, with around 77% of the heat they provide being derived from renewable energy sources (RES) [2]. The integration of RES and waste heat (WH) is also supported by European policies, such as the Energy Efficiency Directive, which promotes the progressive increase of RES and WH shares, targeting up to 100% RES+WH in the long term [3].

To achieve these goals, it is necessary not only to expand DHNs, but also to decarbonize existing systems [4]. Many current networks were originally designed to operate at high supply temperatures, often relying on fossil fuels. However, such operating conditions are not fully compatible with the large-scale integration of RES and WH. For this reason, numerous studies have focused on temperature reduction strategies at building,

substation, and network levels [5], [6], [7], aiming to enable the transition toward fourth-generation district heating (4GDH) systems [8].

The successful implementation of low-temperature DHNs requires that all system components operate efficiently. In recent years, increasing attention has therefore been devoted to fault detection in DHNs. Faults may occur both in the distribution network [9], [10] and in substations [11], which are a frequent source of inefficiencies. Although substation faults are often relatively simple and inexpensive to resolve, they may remain undetected for long periods. In many cases, user systems are oversized, and thermal comfort is maintained even under degraded conditions; as a result, users do not report issues, and anomalies are not identified [12]. Nevertheless, these faults can significantly affect network performance by increasing return temperatures [13] and requiring excessive mass flow rates, thus hindering temperature reduction and limiting the integration of RES and WH. The early detection of such faults is therefore essential to enable the transition toward low-temperature DHNs. Additional benefits of fault detection include improved energy efficiency, early intervention by operators, reduced service interruptions, and optimized maintenance planning [14].

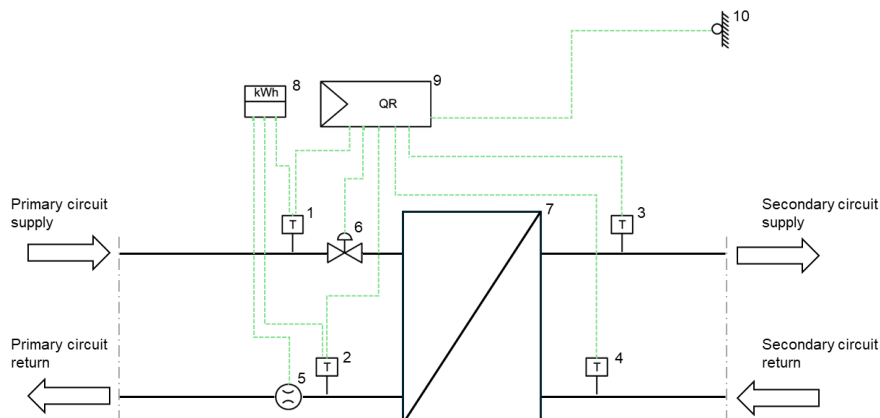
The increasing availability of operational data, driven by digitalization and metering systems, has enabled the development of advanced monitoring and fault detection approaches. Several methods have been proposed in the literature. According to the review by Neumayer [15], anomaly detection methods typically aim at identifying deviations from normal operation and include clustering, regression, and threshold-based approaches, which can be applied even in the absence of labelled datasets. By contrast, fault detection and diagnosis aim at identifying the underlying causes of such deviations and often require domain knowledge or labelled data. In recent years, data-driven approaches have gained increasing attention, both at network level [16] and at substation level [17], [18], [19].

In practical DHN applications, purely data-driven approaches may be difficult to implement due to limited labelled data and complex operating conditions. In this context, this paper proposes a physics-based monitoring approach, where selected variables are interpreted through simplified models to support fault detection and diagnosis. The methodology is demonstrated on a large set of substations from a real DHN in Italy and can serve as a basis for future integration with data-driven approaches.

## 2. Methodology

The monitoring tool presented in this paper was developed for substations equipped with a single heat exchanger and used exclusively for space heating. This choice was motivated by the fact that the available dataset consisted predominantly of substations with this configuration. In the future, however, the methodology could be extended and applied to other substation layouts as well.

The substation configuration considered in this study is shown schematically in Figure 1: the substation consists of a single heat exchanger (7) connecting the primary and secondary circuits. Four temperature sensors (1-4) are installed to measure the supply and return temperatures on both the primary and secondary sides. In addition, a flow meter (5) measures the mass flow rate. These measurements are used both for billing purposes, through the heat meter (8), and for the control of the substation. The control system is based on a heat regulator (QR), which processes the temperature measurements together with the outdoor temperature signal (10). Based on these inputs, the controller modulates a control valve equipped with an actuator (9) on the primary side, thereby regulating the primary-side flow rate and, consequently, the thermal power transferred through the heat exchanger.



**Figure 1.** Schematic representation of the substation layout.

The proposed monitoring approach is based on the following steps:

1. **Data collection.** The data required for the analysis are collected from the substation. These measurements are typically available, as they are used for both billing and control purposes. The dataset includes:
  - a. Supply temperature primary side T1
  - b. Return temperature primary side T2
  - c. Supply temperature secondary side T3
  - d. Return temperature secondary side T4
  - e. Mass flow rate primary side  $\dot{m}_l$
  - f. Heat flux  $\Phi$
  - g. Outdoor temperature  $T_{out}$If not directly available, the heat flux can be computed as  $\Phi = \dot{m}c_p(T1 - T2)$ , while the outdoor temperature can be obtained from external weather monitoring agencies (e.g., ARPA Piemonte).
2. **Data curation.** A data curation procedure is applied to remove outliers, handle missing values, and ensure data consistency.
3. **Identification of quasi-steady conditions.** An algorithm is developed to identify quasi-steady operating conditions, which are then used for the analysis of substation performance. These conditions are defined as periods during which the measured variables vary slowly and without abrupt changes over time, according to predefined tolerance criteria. This step enables the exclusion of transient phases, particularly the start-up period, during which the system variables exhibit significant variations as the building returns to normal operating conditions. In the analyzed case study, buildings are completely shut down during the night; therefore, the morning period is characterized by pronounced peaks associated with system start-up and is excluded from the quasi-steady analysis.
4. **Anomaly detection.** Time series data, together with the identified quasi-steady conditions, are used to detect anomalies in substation operation, defined as deviations from normal behavior (excluding outliers previously removed during the data curation step). Such deviations may indicate malfunctions but can also be associated with changes in user behavior. The methodology associated with this step is described in Section 2.1. Substations exhibiting anomalous behavior are subjected to further analysis in Step 5.
5. **Fault detection and diagnosis.** This step is applied to substations classified as exhibiting abnormal behavior, with the aim of identifying the underlying causes of such behavior and, in particular, assessing the presence of fouling. The analysis is performed under quasi-steady conditions, and specific key performance indicators (KPIs) are monitored to support the diagnosis. The monitored quantities are described in detail in Section 2.2.

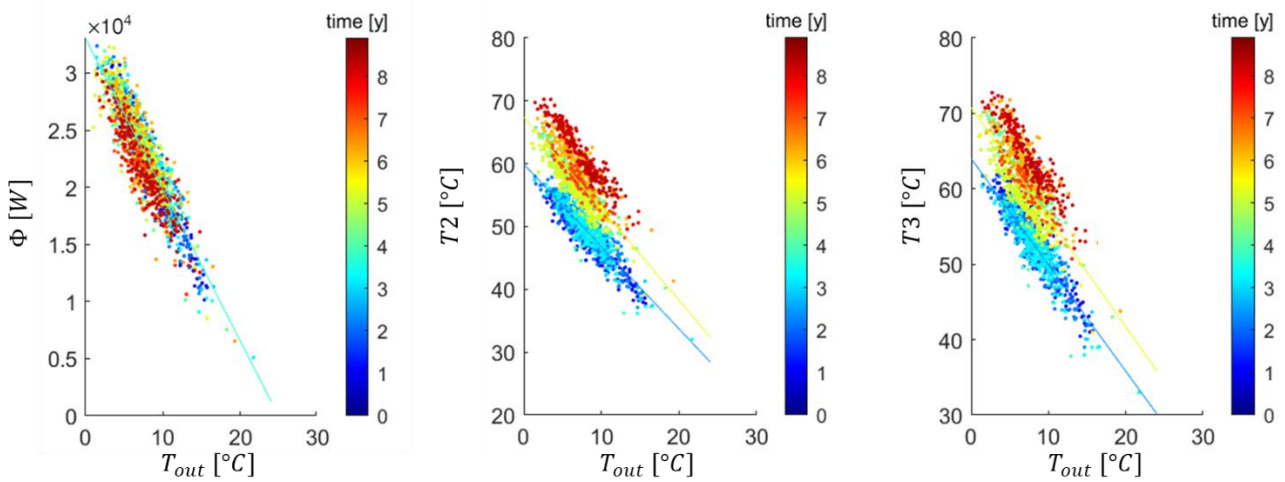
## 2.1. Anomaly detection

Anomaly detection is performed through the analysis of both time series data and quasi-steady conditions, following a two-step procedure:

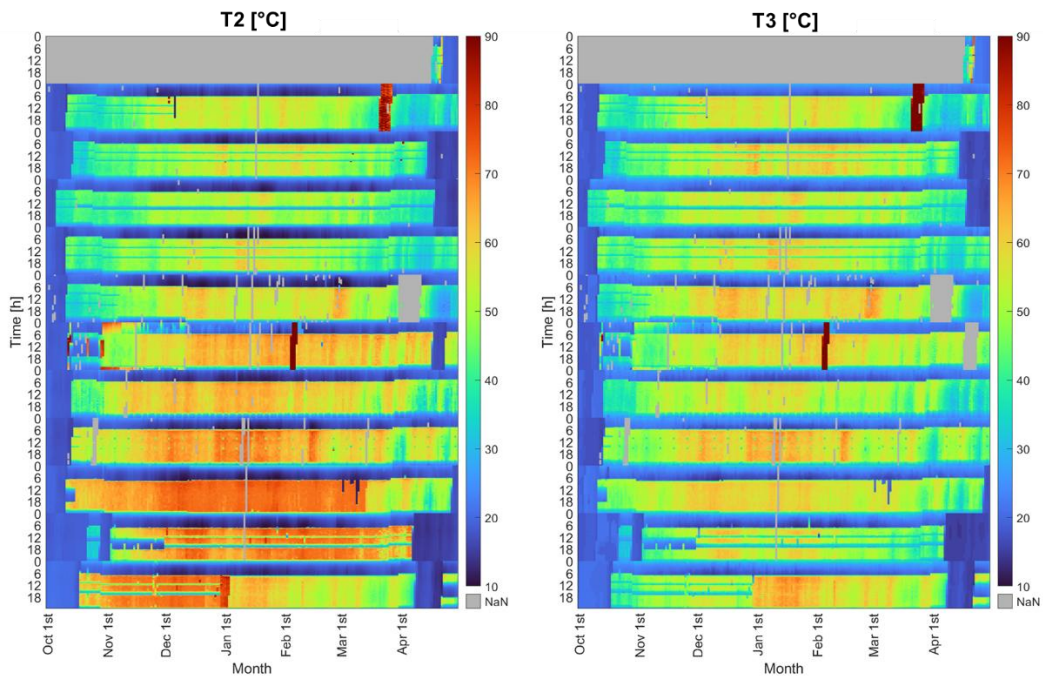
1. The variations of quasi-steady conditions values of  $\Phi$ , T2 and T3 are analyzed with respect to  $T_{out}$ . Under normal operating conditions, these variables exhibit an approximately linear relationship with the outdoor temperature; however, this relationship may vary significantly over time. To capture such variations, quasi-steady data points are visualized using a color scale representing time, allowing the temporal evolution of the relationship to be assessed. A self-developed automatic algorithm is then applied to identify distinct trends and to construct separate characteristic curves, as shown in Figure 2. The figure highlights a case in which the heat demand remains approximately constant over time, while both T2 and T3 exhibit a progressive increase, indicating anomalous behavior.
2. To confirm the anomaly detected in the first step, a manual analysis is conducted using both the quasi-steady plots described in Step 1 and an additional graphical representation, namely heatmaps of the time series over the entire dataset. An example is shown in Figure 3. In this representation, temperature values are displayed using a color scale. The x-axis represents the days of the year; in this case, only the space heating season is considered (from October to April). The y-axis represents the time of day, repeated for each year, with the earliest year at the top and the most recent at the bottom. This visualization enables a comprehensive assessment of temperature variations across different periods and years, providing a clear and intuitive way to identify changes in operating patterns over time. In the example shown in Figure 3, a progressive increase in temperature over time can be observed, visible as a shift toward warmer colors in the lower portion of the heatmap (corresponding to more recent years).

In the present study, this step is performed through visual inspection of the heatmaps. However, future developments may include the adoption of data-driven approaches to automate this process. In particular, transfer learning techniques, which have been applied to similar image-based analyses in the literature (Zhang et al. [20] for the identification of night setback patterns in substations), could be leveraged to enable automated and scalable anomaly detection.

Based on this analysis, users can be classified into three groups: (i) users exhibiting abnormal behavior, characterized by a progressive increase in temperatures over time; (ii) users with normal behavior, for which temperatures remain stable throughout the analyzed period; and (iii) users showing a decrease in return temperature despite stable consumption levels, which may indicate improved performance due to corrective actions or retrofitting measures. Group (i) is the focus of this study, as it aims to investigate the causes of the observed increase in temperatures and of the associated degradation in substation performance.



**Figure 2.** Anomaly detection through the analysis of quasi-steady conditions.



**Figure 3.** Anomaly detection through the analysis of time series heatmaps.

## 2.2. Fault detection and diagnosis

Fault detection and diagnosis aims to identify the underlying causes of the anomalies detected in the previous step, focusing on substations classified in group (i). This step is based on the analysis of quasi-steady conditions to confirm whether the detected anomaly corresponds to an actual fault and to support the diagnosis of its possible causes, with particular attention to fouling.

In a previous work, Guelpa and Verda (2020) [21] developed an automatic tool for fouling detection based on the analysis of the heat transfer coefficient  $UAF$ . This tool proved to be effective; however, it was developed for substations operating with constant secondary-side mass flow rate. This assumption was valid in the past, when fixed-speed pumps were commonly installed on the secondary side, resulting in nearly constant flow conditions. In more recent installations, variable-speed pumps are widely adopted, allowing the secondary-side mass flow rate to vary according to user demand, typically regulated through thermostatic valves. Under these conditions, the methodology must be updated, as the secondary-side mass flow rate significantly influences the evaluation of  $UAF$ . Furthermore, in recent years, thermostatic valves and variable-speed pumps have been installed in buildings that previously operated under constant-flow conditions. In some cases, this transition has been accompanied by changes in user operation, leading to suboptimal system settings. In particular, higher temperature setpoints combined with reduced flow rates have been observed. Such operating conditions can negatively affect the performance of the DHN and should therefore be explicitly considered within the diagnostic framework.

To address these aspects, a set of relevant parameters and key performance indicators (KPIs) is defined and monitored under quasi-steady conditions to support the fault detection and diagnosis process.

### 2.2.1. Secondary-side mass flow rate

The secondary-side mass flow rate is a key variable influencing the heat transfer performance of the substation. However, this quantity is not directly measured in the field and is therefore estimated through a steady-state energy balance, based on first-principles considerations.

Under quasi-steady conditions, the secondary-side mass flow rate  $\dot{m}_{II}$  is calculated as expressed in Equation (1).

$$\dot{m}_{II} = \dot{m}_I \frac{T_1 - T_2}{T_3 - T_4} \quad (1)$$

The temporal evolution of this quantity can be analyzed as a function of the outdoor temperature using a color scale representation, allowing trends over time to be visually assessed. In addition, the temporal evolution of the annual average value of the secondary-side mass flow rate is evaluated, together with its percentage variation with respect to a reference year. This representation provides a clear indication of the magnitude and rapidity of changes in operating conditions.

### 2.2.2. Heat transfer coefficient $UA$

The overall heat transfer coefficient  $UA$  represents the ability of the heat exchanger to transfer heat between the primary and secondary circuits. In this study,  $UA$  is evaluated in a compact form, without explicitly separating the heat transfer area  $A$  from the overall heat transfer coefficient  $U$ . This approach avoids the need for detailed information on the heat exchanger geometry and characteristics, which are typically not available.

Under quasi-steady conditions,  $UA$  is calculated from Equation (2) as:

$$UA = \frac{\Phi}{\Delta T_{LM}} \quad (2)$$

where  $\Delta T_{LM}$  is the logarithmic mean temperature difference between the primary and secondary sides.

The value of  $UA$  is not constant, as it depends on several factors. In particular, it is influenced by the mass flow rates on both sides of the heat exchanger, since variations in flow affect the convective heat transfer coefficients. In addition to this expected behavior, a further decrease in  $UA$  may be associated with fouling phenomena, which introduce an additional thermal resistance between the two sides of the heat exchanger.

Previous work by Guelpa and Verda [21] analyzed the variation of  $UA$  assuming a linear relationship with the primary-side mass flow rate and attributed further reductions to fouling, under the assumption of constant secondary-side flow conditions. In the present study, both primary and secondary-side mass flow rates are considered in order to better isolate the contribution of fouling.

The dependence of  $UA$  on the primary and secondary mass flow rates can be described by the correlation expressed in Equation (3) [22]:

$$UA = \frac{k}{\dot{m}_l^{-q} + \dot{m}_{ll}^{-q}} \quad (3)$$

where  $q$  is an empirical exponent that can be assumed equal to 0.8 in accordance with other studies [17].

As a result, a reduction in  $UA$  at a given primary-side mass flow rate may be caused either by a decrease in the secondary-side mass flow rate or by fouling effects. The proposed methodology aims to distinguish between these contributions and improve the interpretation of the observed behavior.

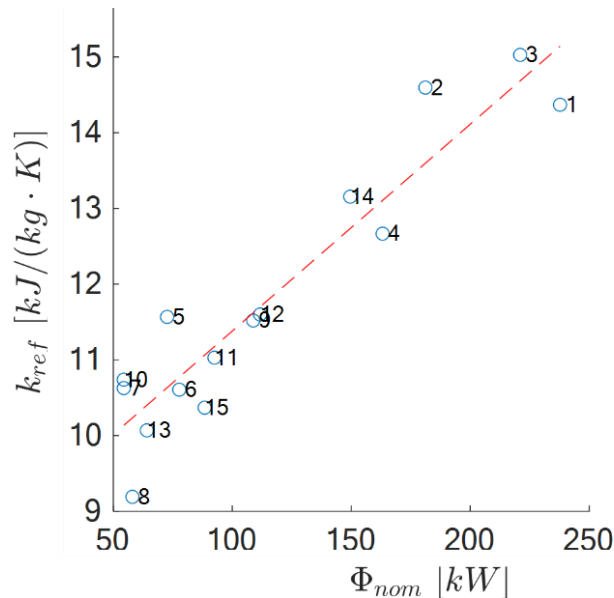
### 2.2.3. Diagnostic heat exchanger parameter $k$

Since Equation (3) accounts for the dependence of  $UA$  on both primary and secondary-side mass flow rates, the identification of the coefficient  $k$  provides a useful diagnostic parameter. The parameter  $k$  accounts for the combined effects of heat exchanger geometry, thermal properties, and operating conditions, while filtering out the influence of mass flow rate variations. Unlike  $UA$ , which reflects also effects related with variations of the mass flow rate,  $k$  allows isolating changes in heat transfer performance. Since geometric and material properties remain constant over time, variations in  $k$  can be associated with degradation phenomena, such as fouling.

This parameter can be obtained through a regression procedure and represents an aggregated indicator of the heat transfer performance of the heat exchanger. The value of  $k$  is estimated by fitting the model in Equation (3) to quasi-steady experimental data using a nonlinear least-squares approach (through the *lsqcurvefit* function in MATLAB). A reference value  $k_{ref}$  is first computed over an initial period representative of nominal operating conditions. Moreover, annual values of  $k$  are evaluated to monitor its temporal evolution.

The analysis of the temporal variation of  $k$  provides a robust diagnostic tool. Stable values of  $k$  indicate consistent heat exchanger performance, whereas a progressive decrease over time suggests a degradation of heat transfer conditions, potentially associated with fouling. Conversely, increases in  $k$  may indicate maintenance actions or improvements in operating conditions.

Moreover, it was observed that the reference value of the reference heat exchanger parameter parameter  $k_{ref}$  is linearly dependent on the substation size. This behavior is illustrated in Figure 2, where the values of  $k_{ref}$  are reported for 15 substations as a function of their nominal thermal power. For this reason, the deviation of the annual value of the diagnostic heat exchanger parameter  $k$  from the trend line is used as an additional monitoring indicator for each substation. The use of the trend line provides a preliminary assessment even in the absence of the initial dataset required to compute  $k_{ref}$ , i.e., when reference (clean) conditions are not available.



**Figure 4.** Relationship between the reference heat exchanger parameter  $k_{ref}$  and the nominal thermal power of 15 substations. The dashed line represents the linear trend used as a reference for performance assessment.

## 2.2.2. Heat transfer coefficient deviation $\Delta UA$ and $\Delta\%UA$

In addition to the analysis of the diagnostic heat exchanger parameter  $k$ , further indicators are defined to support the interpretation of the results. In particular, the deviation of the measured heat transfer coefficient from its expected value is evaluated. The expected value  $UA_{ref}$  represents the heat transfer coefficient that the heat exchanger would exhibit under the current operating conditions (i.e., the measured mass flow rates) if it were operating under reference (clean) conditions. It is computed using the reference parameter  $k_{ref}$  in Equation (3), as expressed in Equation (4):

$$UA_{ref} = \frac{k_{ref}}{\dot{m}_I^{-q} + \dot{m}_{II}^{-q}} \quad (4)$$

Once this reference value is determined, the deviation between the actual and expected values can be used to monitor the heat exchanger performance. The absolute deviation is defined by Equation (5)

$$\Delta UA = UA - UA_{ref} \quad (5)$$

and the relative deviation by Equation (6):

$$\Delta\%UA = \frac{UA - UA_{ref}}{UA_{ref}} \quad (6)$$

These indicators allow quantifying the discrepancy between actual and expected performance under varying mass flow rate. Significantly negative values of  $\Delta UA$  or  $\Delta\%UA$  indicate that the measured heat transfer performance is lower than expected, suggesting a possible degradation of the heat exchanger, for example due to fouling.

Furthermore, the reference value  $k_{ref}$  is used to define a range of expected variability of  $UA$  as a function of the secondary side mass flow rate. In particular, by considering the minimum, average, and maximum values of the secondary-side mass flow rate, a range of expected  $UA$  values can be constructed for each value of the primary-side mass flow rate. This defines a “cone of variability” representing the expected behavior of the heat exchanger under nominal conditions. Measured operating points falling significantly below this region may indicate abnormal behavior and potential degradation of heat transfer performance. This graphical and analytical approach provides an additional tool for distinguishing between variations due to operating conditions and those related to actual faults.

## 3. Case study

The monitoring tool presented in this paper is applied to a set of 126 substations belonging to a large-scale DHN in Italy. All substations are equipped with the configuration previously described and are used exclusively for space heating. The thermal demand profile is characterized by zero demand during nighttime, followed by pronounced peaks and transient conditions in the early morning during system start-up. The dataset consists of measurements with a 5-minute time resolution over 8-12 years depending on the substation, available only during the heating season (October-April).

The DHN currently operates with a supply temperature of approximately 120 °C, while future strategies aim at decarbonization and a reduction of operating temperatures. In this context, the early detection of fouling phenomena is essential to prevent performance degradation that could hinder the transition toward lower supply temperatures.

## 4. Results and discussion

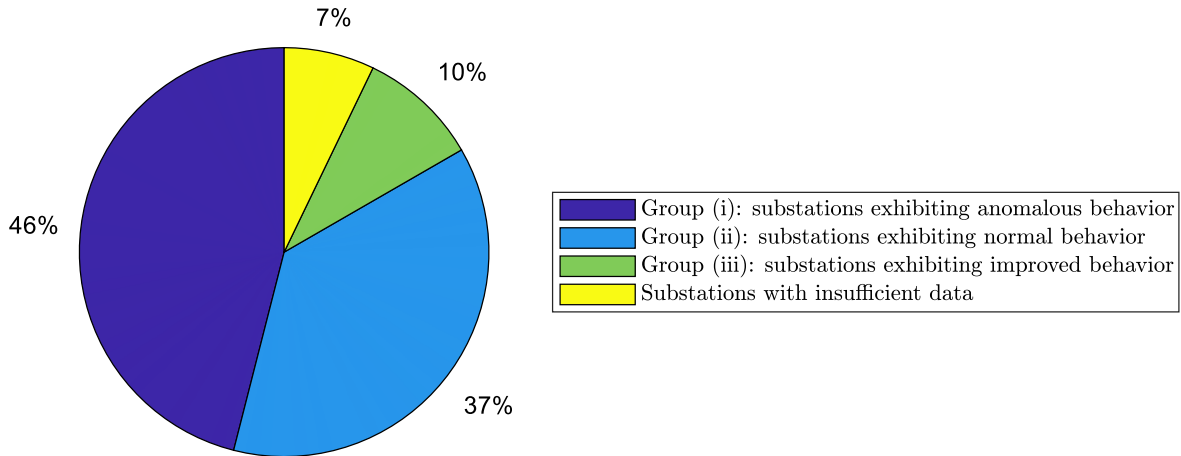
After applying the data collection, data curation, and quasi-steady condition identification procedures to the dataset, the results of the anomaly detection and fault detection and diagnosis steps are presented in this section.

### 4.1. Anomaly detection

The anomaly detection procedure was applied to the full set of 126 substations. Based on the classification criteria described in Section 2.1, the substations were grouped into three categories. The distribution of substations among the three groups is shown in Figure 5.

Overall, 46% of the substations were classified in group (i), exhibiting abnormal behavior characterized by a progressive increase in temperatures over time. A further 37% were classified in group (ii), showing stable

operating conditions throughout the period analyzed. Additionally, 10% of the substations were assigned to group (iii), characterized by a decrease in return temperature despite stable consumption levels. For the remaining 7% of the substations, the analysis could not be performed due to insufficient or unreliable data. Based on this classification, the fault detection and diagnosis procedure is applied to the substations classified in group (i).



**Figure 5.** Distribution of substations among the three groups identified through the anomaly detection procedure.

## 4.2. Fault detection and diagnosis

Substations identified as exhibiting anomalous behavior are subjected to further analysis through the fault detection and diagnosis procedure. The methodology described in Section 2.2 is applied to the entire dataset, enabling the formulation of diagnostic hypotheses for the observed anomalies.

A detailed analysis was then carried out on a subset of 15 substations directly managed by the DHN operator. This allowed the proposed methodology to be validated through direct interaction with the operator, who could assess the hypotheses and perform on-site inspections or operational checks.

The analysis identified several recurring causes associated with the observed malfunctions, which are characterized by increasing return temperatures on the primary side and increasing supply temperatures on the secondary side (associated with the increase in user-side setpoint temperature). The main identified causes are:

- fouling of the heat exchanger;
- suboptimal regulation on the secondary side, often occurring after the installation of thermostatic valves and variable-speed pumps, which allow users to modify flow rates;
- a combination of both effects.

In some cases, the available dataset covered periods in which the anomaly had both developed and subsequently been resolved. Although this information was not initially available, the analysis of the monitoring indicators allowed reconstructing both the occurrence and the resolution of the issue, which was later confirmed by the network operator.

In other cases, the analysis enabled the identification of critical conditions that had not yet been detected by the operator. These findings supported targeted interventions, leading to improvements in the substation performance.

In addition, some malfunctions were also associated with increased user-side temperature setpoints. Once the underlying issue was resolved, a reduction in return temperature was already observed. Subsequently, a decrease in the setpoint temperatures was proposed to the network operator and implemented, leading to further reductions in the return temperature. This highlights the additional potential for performance improvement.

The following subsections illustrate how the proposed monitoring system, based on the interpretation of measured and derived data, supports the identification and diagnosis of different malfunctions. Three representative substations are selected from the analyzed dataset.

### 4.2.1. Substation A

A representative example of a substation (Substation A) is reported in Figure 6. The analysis shows a continuous decrease in the secondary-side mass flow rate over the years, reaching a maximum reduction of approximately 60%. In parallel, the regression-based parameter  $k$  decreases significantly, with a reduction of up to 80%.

The behavior of  $UA$  as a function of the primary-side mass flow rate further supports this trend: for an extended period, the data points fall outside the expected variability region and below the reference surface in the three-dimensional representation. In addition, the deviation of  $UA$  from the expected value is significant.

This overall behavior is consistent with the presence of heat exchanger fouling. The subsequent recovery of the operating conditions is clearly visible in the monitored data, which show a restoration of the expected performance. This interpretation was later confirmed by the network operator, who reported that the heat exchanger had been replaced on that date due to fouling.

The analysis also shows that, if the proposed monitoring system had been applied in real time, the anomaly could have been identified several years in advance, potentially avoiding prolonged periods of elevated return temperatures in the network.

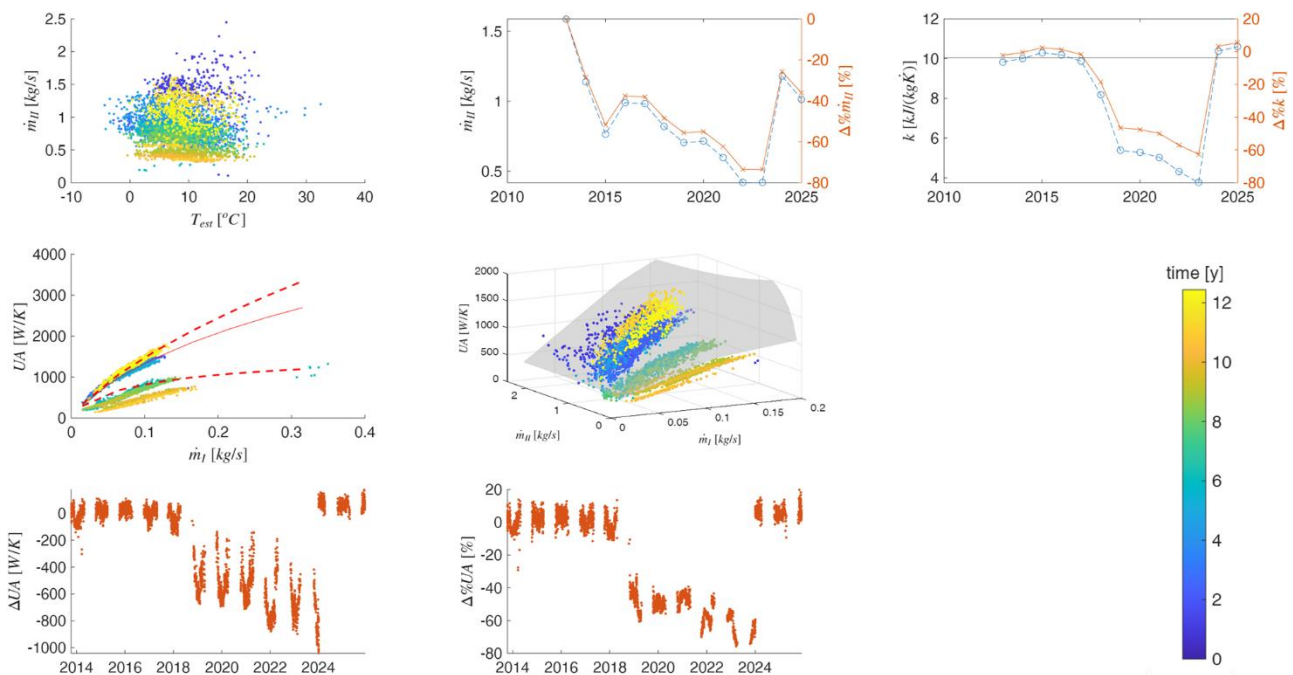


Figure 6. Monitoring tool applied to Substation A.

### 4.2.2. Substation B

A second representative case (Substation B, reported in Figure 7) exhibits a behavior similar to that observed for Substation A. In particular, the secondary-side mass flow rate shows a progressive decrease over time, reaching a reduction of approximately 70%, while the regression-based parameter  $k$  decreases by up to 60%.

The analysis of  $UA$  as a function of the primary-side mass flow rate highlights that, for a significant period, the data points fall outside the expected variability region. Consistently, the deviation of  $UA$  from the expected value reaches a minimum in 2024, indicating a substantial degradation of the heat transfer performance.

Following this period, the indicators suggest a temporary recovery of the operating conditions; however, this improvement is temporary, as the performance rapidly deteriorates again. This behavior is consistent with a recurrence of fouling phenomena.

The substation was therefore notified to the network operator based on the monitoring results. The operator confirmed that a heat exchanger replacement had been carried out in 2024. Following the additional evidence provided by the monitoring system, a further inspection was performed in 2025, leading to the identification of a severely fouled heat exchanger and its subsequent replacement. This intervention resulted in the resolution of the issue.

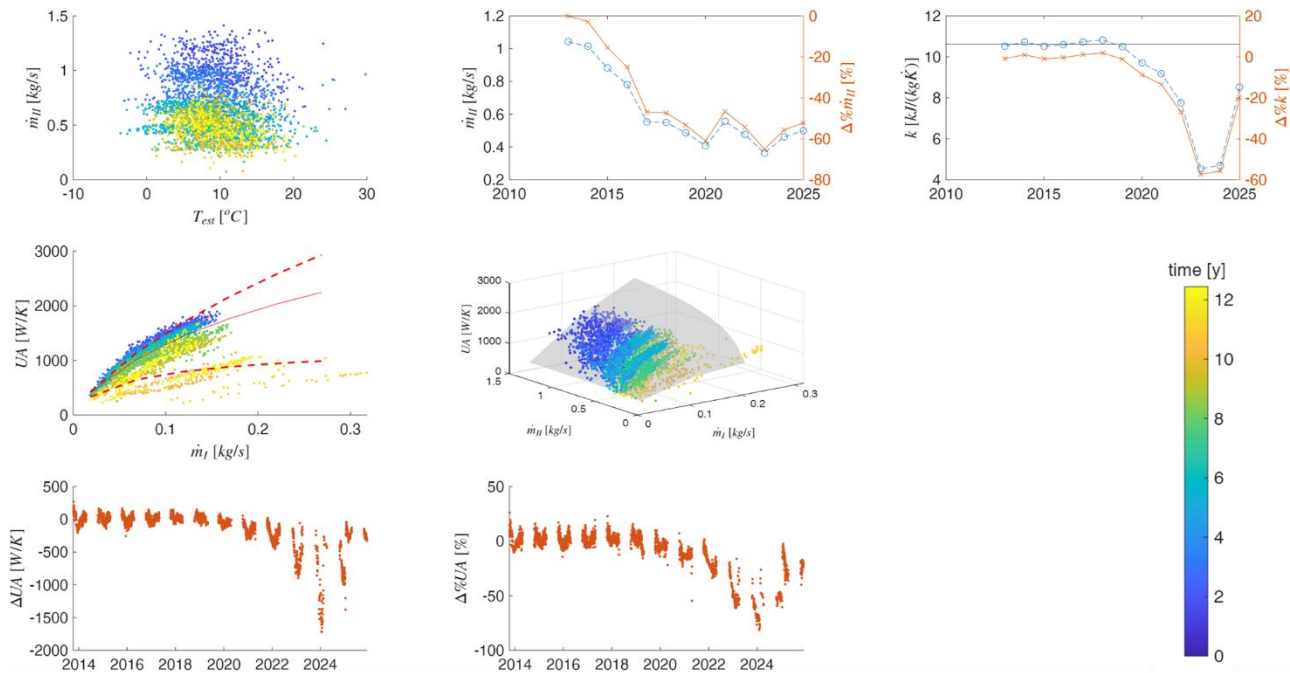


Figure 7. Monitoring tool applied to Substation B.

### 4.2.3. Substation C

Substation C (Figure 8) exhibits a different behavior compared to the previous cases, as shown in Figure 8. In this case, the secondary-side mass flow rate shows a sudden reduction of approximately 70%, after which it remains relatively stable over time. However, the regression-based parameter  $k$  does not show any significant degradation. Consistently, the  $UA$  values remain within the expected variability region, and the deviation from the expected value is limited. This indicates that the heat transfer performance of the exchanger is not affected by fouling.

The increase in primary-side return temperature is instead associated with higher secondary-side supply temperatures, likely due to changes in user-side regulation following the installation of thermostatic valves. The anomaly is therefore attributed to suboptimal operating conditions rather than to heat exchanger degradation. The substation was notified to the network operator, highlighting the potential for improving performance through improved control strategies.

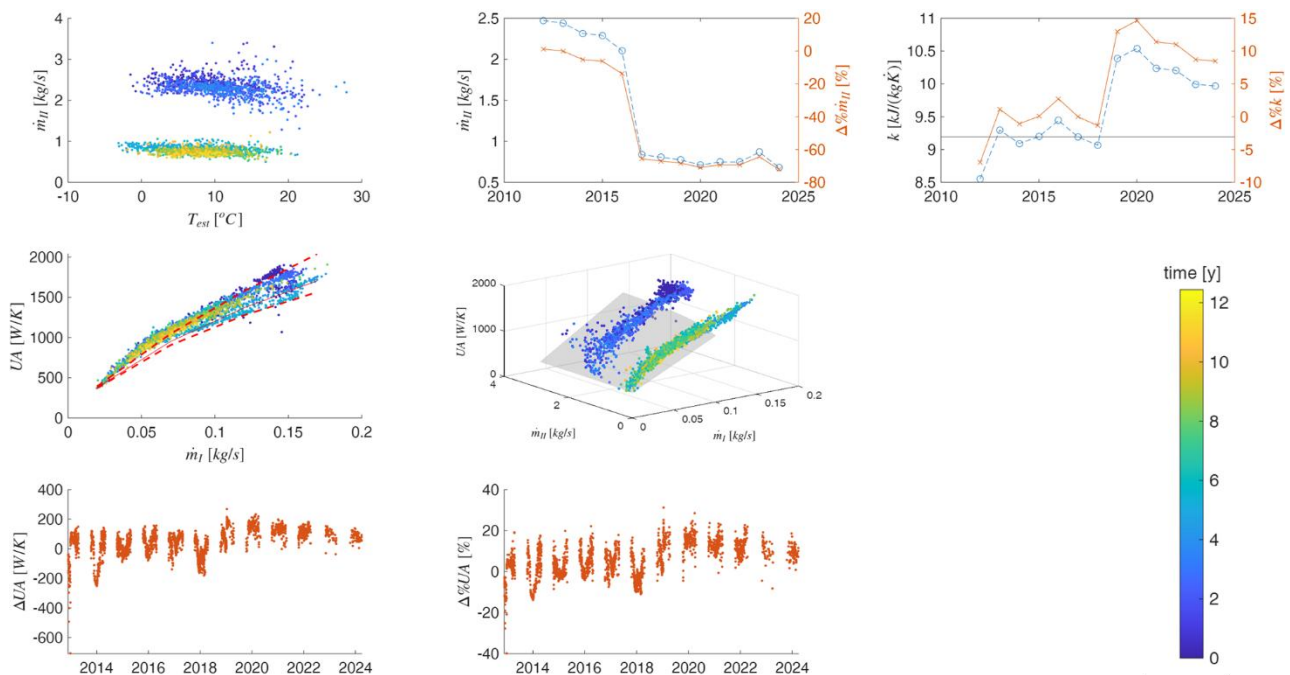


Figure 8. Monitoring tool applied to Substation C.

#### 4.2.4. Lessons learned

The analysis conducted on the investigated substations allowed several general considerations to be drawn.

- In particular, the evaluation of the rate of change of the secondary-side mass flow rate proved to be an effective criterion to distinguish between heat exchanger fouling and anomalies related to changes in operating conditions. A gradual decrease in flow rate, associated with a single cluster of quasi-steady data points, is indicative of progressive fouling, whereas the presence of distinct clusters reflects abrupt changes in operating conditions, typically associated with system modifications such as the installation of thermostatic valves or changes in secondary-side setpoints.
- Among the analyzed indicators, the representation of the overall heat transfer coefficient  $UA$  as a function of the primary-side mass flow rate is particularly effective for identifying fouling. The introduction of the variability region, accounting for the influence of the secondary-side flow rate, represents a significant improvement compared to previous approaches. This allows distinguishing between natural variations due to operating conditions and actual degradation of heat transfer performance, with data points falling outside the expected region indicating potential fouling.
- The analysis of the deviation of  $UA$  from its expected value further enhances the diagnostic capability. Reductions exceeding approximately 30% with respect to a reference period can be considered indicative of significant degradation. This indicator also proves effective in evaluating maintenance interventions, as the restoration of expected  $UA$  values can be observed even with limited post-intervention data.
- Finally, the regression-based parameter  $k$  emerges as a particularly robust and intuitive indicator. Its temporal evolution enables separating the effect of flow rate variations from intrinsic performance changes of the heat exchanger. Based on the analyzed cases, reductions of  $k$  in the range of 10-15% may indicate early-stage fouling, while reductions exceeding approximately 30% are associated with severe degradation. These thresholds, although dependent on the dataset and requiring calibration, provide a practical basis for defining warning and alarm levels within the monitoring system.

## 5. Conclusions

This paper presented a physics-based monitoring approach for the analysis of district heating substations, aimed at identifying non-optimal operating conditions and supporting fault detection and diagnosis. The methodology analyzes available measurements and quasi-steady data through diagnostic indicators derived from heat exchanger analysis.

The proposed framework was applied to a set of 126 substations connected to a large-scale DHN. The anomaly detection procedure allowed the substations to be classified according to their behavior, highlighting that a significant share of the analyzed substations exhibited progressive increases in return temperature and secondary-side supply temperature. These substations were then further investigated through the proposed fault detection and diagnosis procedure. The diagnostic analysis showed that different causes may lead to similar anomalous thermal patterns. In particular, the results highlighted three main situations: progressive heat exchanger fouling, suboptimal regulation on the secondary side following system modifications, and combinations of both effects. The use of derived parameters, including the estimated secondary-side mass flow rate, the overall heat transfer coefficient  $UA$ , the deviation of  $UA$  from its expected value, and the regression-based heat exchanger parameter  $k$ , proved effective in supporting this distinction.

The methodology was further assessed on a subset of substations directly managed by the network operator, confirming the diagnosis and validating the procedure. In some cases, it supported the identification of critical conditions that had not yet been recognized by the operator, leading to inspections and corrective actions. These results confirm the practical value of the monitoring framework as a support tool for maintenance planning and operational optimization.

Overall, the proposed approach demonstrates that substation-level monitoring can provide useful information to prevent inefficiencies, reduce primary-side return temperatures, and support the transition of district heating systems toward lower-temperature and more sustainable operation. Future work will focus on automating the interpretation of heatmap-based anomaly detection, extending the methodology to other substation configurations, and validating threshold values for warning and alarm generation on a larger set of substations.

## Acknowledgments

The authors gratefully acknowledge the operators of the district heating network for providing the data that made this analysis possible.

## References

- [1] European Commission, "An EU strategy on heating and cooling 2016," 2016.
- [2] A. M. Jodeiri, M. J. Goldsworthy, S. Buffa, and M. Cozzini, "Role of sustainable heat sources in transition towards fourth generation district heating – A review," *Renewable and Sustainable Energy Reviews*, vol. 158, p. 112156, Apr. 2022, doi: 10.1016/J.RSER.2022.112156.
- [3] European Union, "DIRECTIVES DIRECTIVE (EU) 2023/1791 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 13 September 2023 on energy efficiency and amending Regulation (EU) 2023/955 (recast) (Text with EEA relevance)."
- [4] P. Caputo, G. Ferla, M. Belliardi, and N. Cereghetti, "District thermal systems: State of the art and promising evolutive scenarios. A focus on Italy and Switzerland," *Sustain. Cities Soc.*, vol. 65, p. 102579, Feb. 2021, doi: 10.1016/J.SCS.2020.102579.
- [5] E. Guelpa, M. Capone, A. Sciacovelli, N. Vasset, R. Baviere, and V. Verda, "Reduction of supply temperature in existing district heating: a review of strategies and implementations," *Energy*, 2022.
- [6] M. Rämä and K. Sipilä, "Transition to low temperature distribution in existing systems," *Energy Procedia*, vol. 116, pp. 58–68, 2017.
- [7] A. Cenian, M. Dzierzgowski, and B. Pietrzykowski, "On the road to low temperature district heating," *J. Phys. Conf. Ser.*, vol. 1398, no. 1, 2019, doi: 10.1088/1742-6596/1398/1/012002.
- [8] H. Lund *et al.*, "4th Generation District Heating (4GDH) Integrating smart thermal grids into future sustainable energy systems," *Energy*, vol. 68, pp. 1–11, 2014.
- [9] L. Manservigi, H. Bahlwan, E. Losi, M. Morini, P. R. Spina, and M. Venturini, "A diagnostic approach for fault detection and identification in district heating networks," *Energy*, vol. 251, p. 123988, Jul. 2022, doi: 10.1016/J.ENERGY.2022.123988.
- [10] H. Bahlwan *et al.*, "Detection and identification of faults in a District Heating Network," *Energy Convers. Manag.*, vol. 266, p. 115837, Aug. 2022, doi: 10.1016/J.ENCONMAN.2022.115837.
- [11] E. Guevara Bastidas *et al.*, "Prioritisation of faults in district heating substations: Towards predictive maintenance and optimised operation," *Energy*, vol. 333, p. 137210, Oct. 2025, doi: 10.1016/J.ENERGY.2025.137210.
- [12] H. Gadd and S. Werner, "Fault detection in district heating substations," *Appl. Energy*, vol. 157, pp. 51–59, Nov. 2015, doi: 10.1016/J.APENERGY.2015.07.061.
- [13] H. Gadd and S. Werner, "Achieving low return temperatures from district heating substations," *Appl. Energy*, vol. 136, pp. 59–67, Dec. 2014, doi: 10.1016/J.APENERGY.2014.09.022.
- [14] D. Leiria *et al.*, "Is it returning too hot? Time series segmentation and feature clustering of end-user substation faults in district heating systems," *Appl. Energy*, vol. 381, p. 125122, Mar. 2025, doi: 10.1016/J.APENERGY.2024.125122.
- [15] M. Neumayer, D. Stecher, S. Grimm, A. Maier, D. Bücken, and J. Schmidt, "Fault and anomaly detection in district heating substations: A survey on methodology and data sets," *Energy*, vol. 276, p. 127569, Aug. 2023, doi: 10.1016/J.ENERGY.2023.127569.
- [16] E. Losi, L. Manservigi, P. R. Spina, and M. Venturini, "Data-driven approach for the detection of faults in district heating networks," *Sustainable Energy, Grids and Networks*, vol. 38, p. 101355, Jun. 2024, doi: 10.1016/J.SEGAN.2024.101355.
- [17] M. A. Jallal, M. Vallée, and N. Lamaison, "Fouling fault detection and diagnosis in district heating substations: Validation of a hybrid CNN-based PCA model with uncertainty quantification on virtual replica synthesis and real data," *Energy*, vol. 312, p. 133590, Dec. 2024, doi: 10.1016/J.ENERGY.2024.133590.
- [18] D. Stecher, L. Ziegler, P. Reiprich, C. Fuchs, A. Maier, and J. Schmidt, "Neural network synthetic dataset generation for fault detection in district heating substations," *Smart Energy*, vol. 20, p. 100206, Nov. 2025, doi: 10.1016/J.SEGY.2025.100206.
- [19] J. van Dreven, A. Cheddad, S. Alawadi, A. N. Ghazi, J. Al Koussa, and D. Vanhoudt, "From bearings to substations: Transfer Learning for fault detection in district heating," *Energy*, vol. 335, p. 138016, Oct. 2025, doi: 10.1016/J.ENERGY.2025.138016.
- [20] F. Zhang, C. Bales, and H. Fleyeh, "From time series to image analysis: A transfer learning approach for night setback identification of district heating substations," *Journal of Building Engineering*, vol. 43, p. 102537, Nov. 2021, doi: 10.1016/J.JOBE.2021.102537.
- [21] E. Guelpa and V. Verda, "Automatic fouling detection in district heating substations: Methodology and tests," *Appl. Energy*, vol. 258, p. 114059, Jan. 2020, doi: 10.1016/J.APENERGY.2019.114059.
- [22] L. Giraud, R. Bavière, C. Paulus, M. Vallée, and J.-F. Robin, "Dynamic Modelling , Experimental Validation and Simulation of a Virtual District Heating Network," in *Proceedings of the 28th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems*, 2015.