Hybrid diagnostic approach for the diagnosis of district heating networks

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Abstract. Decarbonization of the heating sector is a mandatory target towards climate neutrality by 2050. In this framework, District Heating Networks (DHNs) do play an important role since the heat carrier is dispatched from a heat source to end-users.
Reliability of DHNs can be affected by several faults, of which the negative consequences can be prevented by employing diagnostic methodologies to evaluate the health state of the DHN and promptly localize the fault cause.
In the literature, DHN faults are usually detected by means of physics-based and data-driven methodologies, but their drawbacks may hinder their application. Thus, this paper proposes a hybrid approach composed of two steps aimed at detecting the most common faults occurring in DHNs, i.e., water leakages as well as anomalous heat and pressure losses. First, a data-driven diagnostic methodology is employed to assess whether a fault is occurring. Then, a physics-based diagnostic approach identifies the health indices of each pipe of the DHN, the fault position, its type and magnitude. In this paper, the hybrid diagnostic approach is applied to the DHN of the campus of the University of Parma, where different faults were artificially implanted.
The diagnostic approach proves to correctly detect and identify the implanted faults, by also correctly estimating their magnitude even in the most challenging scenarios.

1. Introduction

In the last years, District Heating Networks (DHNs) have been assuming a crucial role to pursue the goal set by the EU commission for climate neutrality. In fact, DHNs may exploit wasted heat to meet thermal energy demand that, currently, is mainly fulfilled by natural gas, coal, and fuel oil [1]. For instance, Italy is promoting and developing novel DHNs to reduce greenhouse emissions [2].

As demonstrated in the literature (e.g., [3]), DHNs may be subjected to several failures, which have to be promptly detected. An extensive review about DHN fault types, causes and diagnostic approaches was reported by some of the authors of this paper in a previous study [4].

In general, DHN diagnosis can be performed by means of physics-based and data-driven models. Physics-based models exploit physics-based equations to calculate each variable of the system, by requiring huge modeling efforts and an in-depth knowledge of the system [5]. Conversely, data-driven models identify the correlation between input and output variables by means of historical data [6]; thus, diagnosis strictly depends on data quality and availability [5].

The novelty of the current study relies on the development of a novel hybrid diagnostic approach that performs a real time evaluation of DHN health state, by providing fault location, type (i.e., water leakages, anomalous heat loss, and pressure losses) and magnitude. As a result, the drawbacks of both physics-based and data-driven approaches can be overcome.

The novel hybrid diagnostic approach is composed of two diagnostic steps.

First, a data-driven diagnostic methodology exploits a NARX neural network as the prediction model to mimic the behavior of the healthy DHN and preliminarily evaluates the DHN health state, by determining whether a fault is occurring.

Second, the physics-based diagnostic approach developed in [4, 7, 8] identifies fault location, type, and magnitude.

The novel hybrid diagnostic approach is validated by means of simulated datasets, in which different faults were artificially implanted within the DHN of the Campus of University of Parma (Italy).

2. Hybrid diagnostic approach

The hybrid diagnostic approach developed in this paper is composed of two diagnostic steps, i.e., a data-driven diagnostic methodology and a physics-based diagnostic approach (figure 1).

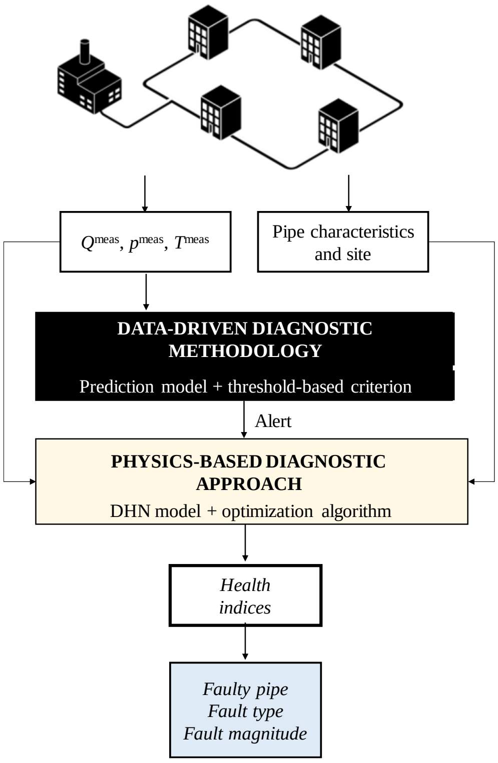


Figure 1. Hybrid diagnostic approach.

The inputs to the hybrid diagnostic approach are the following measurable variables, i.e., the flow rate (Q^{meas}), pressure (p^{meas}) and temperature (T^{meas}) of each power plant (PP) and end-user (EU) of the DHN. Such values can be experimentally acquired or simulated by means of a digital twin (e.g., as made in [9]). These measurable variables Q^{meas}, p^{meas} and T^{meas} feed the data-driven diagnostic methodology, which includes a prediction model and a threshold-based criterion.

The *prediction model* calculates the predicted Q, p, and T of each end-user under both steady-state and transient operating conditions.

The *threshold-based criterion* compares the predicted and the actual values of the measurable variables to assess whether a fault is occurring. If the deviation between the actual and the predicted variables exceeds a threshold, an alert is raised. Afterwards, the DHN should be operated under steady-state conditions. Based on Q^{meas}, p^{meas} and T^{meas} collected under steady-state conditions, the physics-based diagnostic approach calculates the health indices of each pipe. To this purpose, a DHN model and an optimization algorithm are used to provide the faulty pipe, type and magnitude.

The data-driven diagnostic methodology as well as the physics-based diagnostic approach are described in the following.

2.1. Data-driven diagnostic approach

The data-driven diagnostic approach employs NARX neural networks as prediction models and the k-σ rule as the threshold-based criterion for fault detection.

The NARX models are first trained on healthy data to simulate the safe operation of the DHN. Subsequently, the prediction models are tested on new healthy data to assess their prediction reliability and estimate the parameter σ of the k-σ rule.

Then, the trained NARX models coupled with k-σ rule is employed for the real-time prediction of the measurable variables and the detection of any abnormal deviations from the healthy behavior by comparing actual and predicted data of the DHN.

NARX neural networks predict the target variable at the next time step as a function of d previous values of the target series and n predictor (independent) variables. Each EU measurable variable is, in turn, considered as the target variable, while the remaining measurable variables and the ones of the PP are employed as predictor variables. Therefore, for each EU, three simulation models are developed, i.e., one for each measurable variable.

The simulation model employed in the data-driven diagnostic methodology is shown in figure 2. At each time step t, three NARX models are run simultaneously one step at a time, and the delayed predicted values of each target variable are fed back to the input of all models.

The absolute difference between the predicted value and the corresponding true value is compared to the standard deviation σ of the residuals on the tested healthy data. The parameter k is set equal to 3. Thus, if the absolute deviation does not exceed 3σ, then a given data point is labeled as healthy; otherwise, it is labeled as faulty.

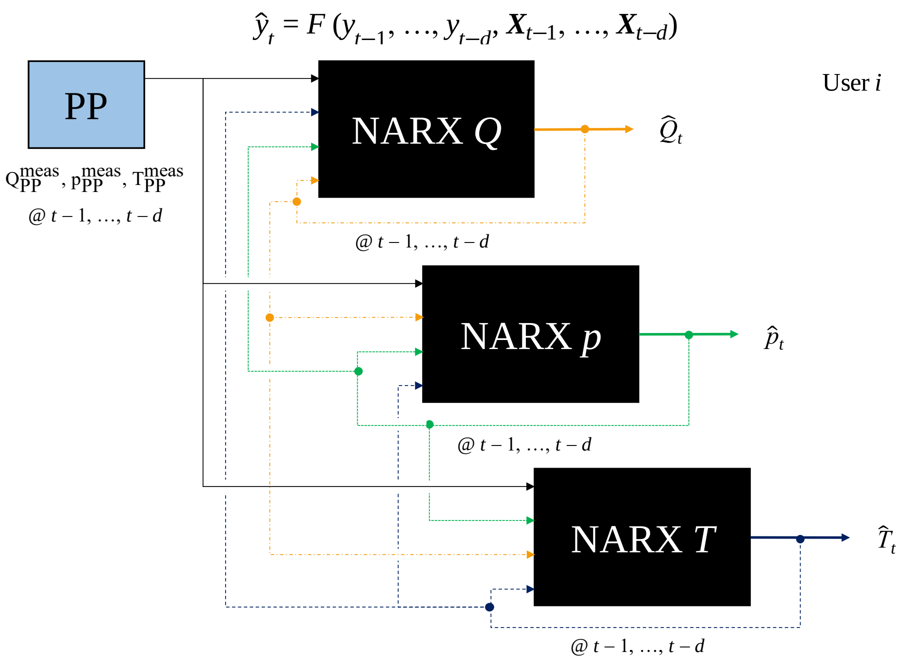


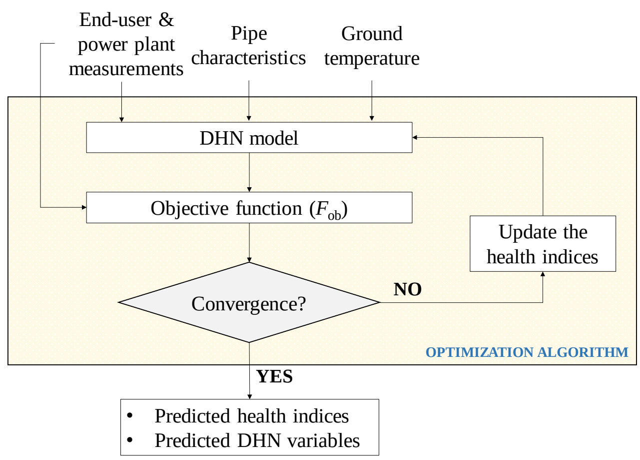
Figure 2. Data-driven diagnostic approach.

2.2. *Physics-based diagnostic approach*

The physics-based diagnostic approach, which is thoroughly described in previous papers of the same authors [4, 7, 8], is aimed at (i) detecting the faulty pipe, (ii) identifying the fault type (i.e., water leakages, anomalous heat losses and anomalous pressure losses) and (iii) estimating fault magnitude. As demonstrated in [7] and [8], the physics-based diagnostic approach detects both single faults (i.e., only one pipe is faulty and the fault cause is unique) and multiple faults (i.e., multiple pipes are faulty or different fault causes occur).

To this aim, each pipe of the DHN is labeled by means of three health indices, i.e., x_Q, x_{Rth} and x_{Rp}, that determine whether leakages, anomalous heat and pressure losses occur, respectively. Each health index varies in the range from 0 to 1. Under healthy conditions, all health indices are equal to one. Instead, when a fault takes place, the health index of the faulty pipe is lower than one; the lower the health index, the more severe the fault.

The rationale of the physics-based diagnostic approach is sketched in figure 3.



$$F_{ob}=\left(\frac{Q_{PP}^{meas}-Q_{PP}}{Q_{PP}^{meas}}\right)_s^2+\left(\frac{Q_{PP}^{meas}-Q_{PP}}{Q_{PP}^{meas}}\right)_r^2+\left(\frac{T_{PP}^{meas}-T_{PP}}{T_{PP}^{meas}}\right)_r^2+\sum_{i}^{N_{EU}}\left(\frac{T_{EU,i}^{meas}-T_{EU,i}}{T_{EU,i}^{meas}}\right)_s^2+\left(\frac{T_{EU,i}^{meas}-T_{EU,i}}{T_{EU,i}^{meas}}\right)_r^2+\left(\frac{p_{EU,i}^{meas}-p_{EU,i}}{p_{EU,i}^{meas}}\right)_s^2+\left(\frac{p_{EU,i}^{meas}-p_{EU,i}}{p_{EU,i}^{meas}}\right)_r^2$$

Figure 3. Physics-based diagnostic approach.

A DHN model calculates mass flow rate, temperature and pressure in all pipes under steady-state conditions, by means of mass flow rate and power balances, and by calculating pressure losses as made in [4, 7, 8]. The DHN model has to be fed with (i) the values of the measurable variables (Q^{meas}, T^{meas}, p^{meas}) of all end-users (N_{EU} in total) and power plant, (ii) pipe characteristics (e.g., the length of each pipe) and (iii) ground temperature.

The predicted variables and predicted health indices are obtained by minimizing the objective function F_{ob} reported in figure 3. For both the supply (subscript “s”) and return (subscript “r”) pipelines, the F_{ob} compares the difference between actual and predicted Q, T and p of each end-user and power plant. An optimization algorithm adjusts the health indices until F_{ob} is minimized.

3. Case study

The hybrid diagnostic approach is tested and validated by considering the DHN of the campus of the University of Parma (Italy), which is sketched in figure 4. The network is composed of both a supply and return pipeline. In the supply pipeline, a power plant delivers heat to twelve end-users. Then, the return water flows get back to the power plant through the return pipeline. As a result, the whole DHN, which comprises both the supply and return pipelines, is approximately 4 km long and is composed of forty-six pipes (twenty-three pipes both in the supply and return pipelines). Thus, since in the physics-based diagnostic approach each pipe is labeled by means of three health indices, 138 health indices (i.e., three health indices multiplied by forty-six pipes) have to be predicted in total.

In this paper, Q^{meas}, T^{meas} and p^{meas} of the power plant and end-users were simulated by means of the digital twin presented in [9]. In this manner, fault location and magnitude, as well as its time of occurrence, are known [10].

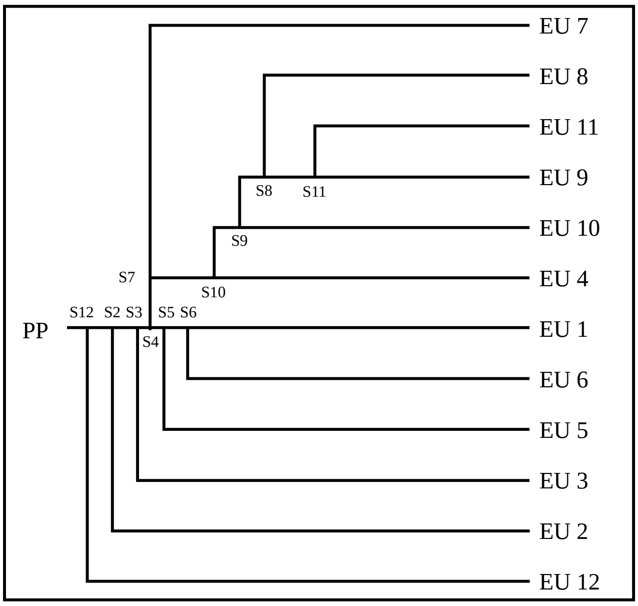


Figure 4. Layout of the DHN.

3.1. Implanted faults

In this paper, the hybrid diagnostic approach is validated by means of two faulty datasets (i.e., Fault #1 and #2), which include anomalous heat losses and anomalous pressure losses, respectively.

The digital twin developed in [9] provided the measurable variables at each end-user and power plant by varying pipe characteristics with respect to the healthy condition. Thus, the thermal conductivity of the insulation layer (λ_{ins}) was increased to mimic anomalous heat losses. Instead, pipe roughness ε and internal diameter D_{int} of the faulty pipe were varied to model anomalous pressure losses due to pipe fouling and corrosion.

In both faulty datasets (table 1), the pipe that connects node S5 to EU5 is faulty. In Fault #1, thermal conductivity λ_{ins} of the faulty pipe is fifty times higher than that under heathy conditions. Such a fault affects the entire pipe length. Instead, in Fault #2 multiple fault causes lead to anomalous pressure losses. In fact, the roughness ε of the faulty pipe is ten times higher than that under healthy conditions and, simultaneously, the pipe internal diameter D_{int} is approximately 2.5 times lower along 10% of pipe length.

Table 1. Implanted faults.

Fault	Effect of the fault	Fault location	Faulty parameter	Health parameter
#1	Anomalous heat losses	S5-EU5 (Entire pipe)	$\lambda_{ins} = 2.00$ W·m^{-1}·K^{-1}	$\lambda^*_{ins} = 0.04$ W·m^{-1}·K^{-1}
#2	Anomalous pressure losses	S5-EU5 (Entire pipe)	$\varepsilon = 1.00$ mm	$\varepsilon^* = 0.10$ mm
		S5-EU5 (10% of the pipe length)	$D_{int} = 0.04$ m	$D_{int} = 0.10$ m

4. Results

This Section discusses the outcome of the diagnosis obtained by means the hybrid diagnostic approach, of which both the data-driven methodology and the physics-based diagnostic approach were implemented in the Matlab® environment [11].

The NARX neural networks were trained by means of Bayesian regularization backpropagation and the maximum number of training epochs was set at 10^3. To improve network generalization, an early stopping criterion was used during training (i.e., minimum validation error).

The physics-based diagnostic approach exploited a gradient-based method to calculate health indices. In fact, as discussed in [7], it proved more accurate than alternative optimization algorithms. The upper and starting values of the optimization were set equal to 1, while the lower bound was set equal to 10^{-3}.

4.1. Data-driven diagnostic approach

The data-driven methodology employs NARX neural networks for real-time simulation of DHN transient operation. In this Section, a time window of twelve hours is analyzed. For such a timeframe, tables 2 and 3 report the fraction of the tested data points whose absolute deviation from the predicted values is higher than 3σ for Fault #1 and Fault #2, respectively.

It can be noted from table 2 that 90% of the actual T data of EU5 exhibit an abnormal deviation from the normal pattern. Figure 5 shows the actual values for the temperature of EU5 and the respective predicted values together with lower and upper boundaries.

Table 2. Fraction of tested data outside the safe boundaries for Fault #1.

EU	1	2	3	4	5	6	7	8	9	10	11	12
Q	58%	0%	0%	0%	0%	2%	15%	8%	3%	35%	12%	0%
p	0%	0%	0%	6%	0%	0%	16%	8%	5%	0%	10%	0%
T	0%	1%	0%	0%	90%	0%	0%	0%	0%	0%	0%	1%

Table 3. Fraction of tested data outside the safe boundaries for Fault #2.

EU	1	2	3	4	5	6	7	8	9	10	11	12
Q	12%	0%	5%	0%	100%	5%	12%	10%	2%	10%	8%	0%
p	0%	0%	0%	17%	100%	0%	15%	11%	19%	0%	20%	0%
T	0%	1%	0%	0%	0%	0%	0%	1%	4%	0%	0%	0%

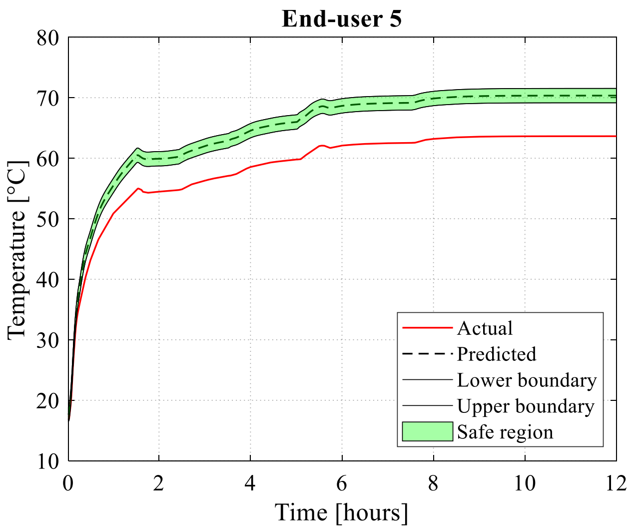


Figure 5. Comparison between actual and predicted data for the variable T of EU5 (Fault #1).

It can be grasped from figure 5 that almost all the actual data points are outside the safe region, which mimics the operation of a healthy DHN. Because of the high number of outliers (significantly higher than 50% of the tested data), the data-driven methodology rises an alert, which should push to operate the DHN under steady-state conditions to further check DHN health state by means of the physics-based diagnostic approach.

Similarly, in Fault #2 (see table 3), the data-driven methodology correctly predicts that a fault is occurring in the DHN. In fact, all tested data points for Q and p of EU5 lie outside the $\pm 3\sigma$ boundary. As a consequence, the data-driven methodology triggers an alert. Conversely, the outlier rate is lower than 20% for the remaining EUs and it is almost null for variable T. This means that the candidate faulty pipe is the one leading to EU5 and abnormal pressure loss is the candidate fault type. This first alert will be subsequently verified by means of the physics-based diagnostic approach.

4.2. Physics-based diagnostic approach

The diagnosis performed by the physics-based diagnostic approach is reported in figure 6, which shows the predicted health indices related to the simulated faults, of which the affected health indices are $x_{\mathrm{Rth,s}}$ (Fault #1) and $x_{\mathrm{Rp,s}}$ (Fault #2).

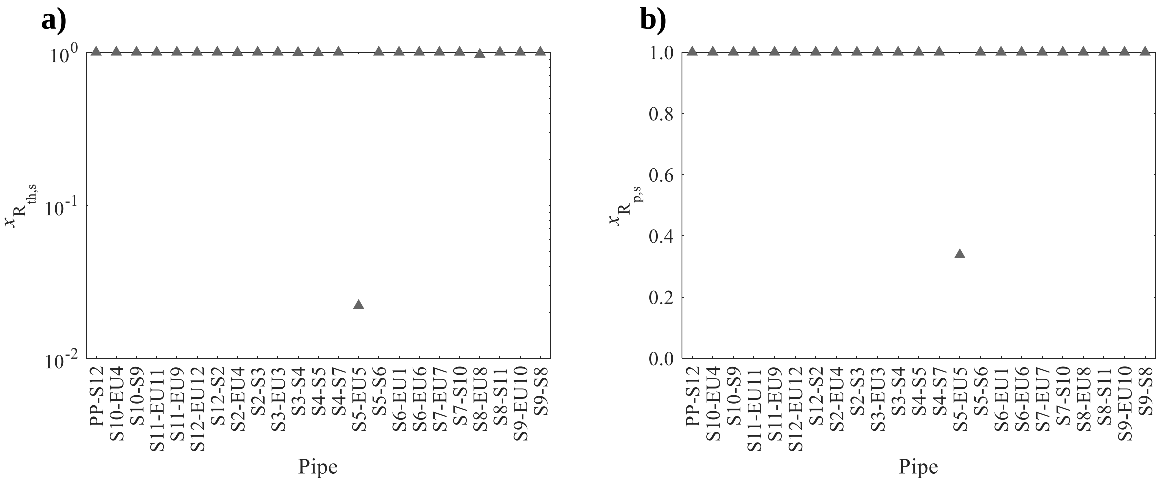


Figure 6. Predicted fault location, type, and magnitude for Fault #1 (a) and Fault #2 (b).

As can be grasped from figure 6(a), Fault #1 is correctly detected, since the faulty pipe (i.e., S5-EU5) is correctly identified and fault type and magnitude are also provided. In fact, all health indices are close to 1 (i.e., healthy pipe), with the exception of $x_{\mathrm{Rth,s}}$ of pipe S5-EU5, which is found equal to 0.022, while the actual (i.e., simulated by the digital twin [9]) $x_{\mathrm{Rth,s}}$ is equal to 0.020.

Similarly, the faulty pipe (i.e., S5-EU5) is also detected in case of Fault #2 (figure 6(b)), since the health indices of healthy pipes are found equal to 1. Instead, health index $x_{\mathrm{Rp,s}}$ highlighted that anomalous pressure losses occur in pipe S5-EU5; in fact, it is found equal to 0.338, i.e., very close to the actual value (0.336).

As a result, the average deviation between actual and predicted health indices in Fault #1 and #2 is lower than 1.3%.

Thus, the hybrid diagnostic approach developed in this paper proved to be a reliable methodology for DHN diagnosis.

5. Conclusions

This paper developed a novel hybrid diagnostic approach aimed at detecting and identifying the most frequent faults, i.e., water leakages, anomalous heat losses and anomalous pressure losses, affecting District Heating Networks (DHNs). The hybrid diagnostic approach includes two steps, i.e., a data-driven diagnostic approach and a physics-based diagnostic approach. The data-driven diagnostic methodology, which comprises a prediction model and a threshold-based criterion, raises an alert when the deviation between actual measurable variables and the corresponding values predicted by NARX neural networks exceeds a threshold. Then, the physics-based diagnostic approach, which comprises a DHN model and exploits an optimization algorithm, calculates the health indices of each pipe under steady-state conditions, by identifying the faulty pipe, as well as fault type and magnitude.

The hybrid diagnostic approach was tested by considering the DHN of the campus of the University of Parma, in which two faults (i.e., anomalous heat and pressure losses) were artificially implanted by means of a digital twin that mimics the DHN under investigation.

For both implanted faults, the data-driven methodology detected more than 90% of tested data points outside the safe region of normal operation and correctly triggered an alert. Moreover, the physics-based diagnostic approach correctly detected the faulty pipe, by also proving the fault type and magnitude; the deviation between actual and predicted health indices was lower than 1.3%.

Acknowledgments

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Nomenclature

D	diameter [m]
d	number of delayed values
F	function
k	parameter of the fault detection rule
N	number
n	number of predictor variable
p	pressure [Pa]
Q	flow rate [kg·s^{-1}]
S	splitting junction node
T	temperature [°C]
t	time step
$\boldsymbol{X}$	predictor matrix
x	health index
y	target variable
ε	pipe roughness [mm]
λ	thermal conductivity [W·m^{-1}·K^{-1}]
σ	standard deviation
Superscripts	
meas	measurable
$\frown$	predicted
$*$	under healthy condition
Subscripts	
EU	end-user
ins	insulation
int	internal
ob	objective

PP	power plant
Q	flow rate
r	return pipeline
R_{th}	thermal resistance
R_p	coefficient of pressure losses
s	supply pipeline
Acronyms	
DHN	District Heating Network
EU	End-User
PP	Power Plant

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