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A simulation-based failure classification method for water distribution systems

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ABSTRACT

This paper presents a simulation-based method for classifying failures in water distribution systems according to their impact on network operation. The method combines hydraulic simulation, element criticality assessment, flow-path analysis, valve-isolation analysis, and repair-time estimation to assign reported failures to three operational impact classes. The input data include a calibrated hydraulic model of the analysed water distribution system, valve allocation, failure type and location, and the location of critical infrastructure. The output is a classification of failures into classes representing high, moderate, and low operational impact. The method was implemented using WNTR, the EPANET solver, Python, and parallel computing tools, and was tested on a hydraulic model of a real water distribution system in Środa Wielkopolska, Poland. The classification results were compared with assessments prepared by domain experts and operators. The comparison shows high agreement, while disagreement cases indicate the need for further validation under broader operational and demand conditions.

Keywords: water distribution system, failure classification, hydraulic simulation, WNTR, EPANET, critical infrastructure, decision support system.

INTRODUCTION

Water distribution systems (WDSs) are among the most critical components of urban infrastructure. Their importance results not only from their extensive spatial structure, but also from their fundamental role in ensuring continuous access to drinking water for individual consumers, public institutions, and critical facilities [1,2]. The reliability of water supply is therefore directly related to public safety, health protection, and the continuity of basic municipal services. In addition to accidental technical failures, WDSs may also be exposed to intentional contamination, natural hazards, or other emergency events that can interrupt water delivery and affect large groups of consumers. A prolonged interruption in access to basic utilities, such as water or electricity, may also have social and behavioural consequences. Studies in cognitive psychology and crisis behaviour indicate that the inability to satisfy basic needs may lead to stress, loss of balance between an individual and the environment, and undesirable reactions in crisis situations [3]. When such disturbances affect not only individual consumers but entire districts or cities, the operational consequences become significantly more serious. For this reason, maintaining the continuity of water distribution and quickly assessing the severity of failures are essential tasks for water utilities and crisis-management teams. In the event of a failure in a water supply network, operators must identify the location and type of the failure, secure the affected area, determine whether water distribution must be interrupted in a given section, and assign repair resources. When only a small number of failures occur, such decisions can often be made on the basis of expert knowledge and routine operational procedures. However, in emergency situations involving multiple simultaneous failures, limited repair crews, and possible damage to critical infrastructure, a systematic assessment of the operational impact of each failure becomes necessary. In such cases, the key challenge is not only to detect failures, but also to distinguish those that have a significant impact on the functioning of the WDS from those whose influence is moderate or limited. Emergency situations may result from inappropriate routine actions, technical failures, or natural disasters [4, 5]. In the case of floods, earthquakes, or large-scale infrastructure failures, water supply networks may be exposed to multiple simultaneous damages. Regardless of the probability of a specific catastrophic event, tools that support the assessment of WDS failures can help operators manage emergency response, plan repairs, and reduce the time needed to restore normal network operation. Several software tools and computational approaches are available for modelling and analysing water distribution systems under different operating conditions. Examples include the EPANET solver, the Water Network Tool for Resilience (WNTR), TEVA-SPOT, and Water Protector. These tools enable hydraulic simulations, contamination analysis, resilience assessment, and the modelling of atypical scenarios such as pipe breaks, leaks, or power outages. However, evaluating many possible failure configurations manually or by preparing separate simulation models for each scenario can be time-consuming, especially for large real-world networks. Moreover, simulation results must be translated into operationally meaningful information that can be used by water utility operators. EPANET-based hydraulic simulation has been widely used in studies concerning water distribution system analysis and failure assessment. For example, EPANET was used to simulate hydraulic parameters in the water distribution network of Surat City [15]. A combination of GIS, EPANET 2, and descriptive statistical analysis was used to assess failures in a real water distribution network [16]. A case study of pipeline failure simulation in a selected water supply system was presented in [17]. These studies confirm that hydraulic simulation is a useful tool for analysing the behaviour of water distribution systems under failure conditions. However, the objective of the present paper is different from studies focused mainly on hydraulic parameter simulation, failure statistics, or the consequences of selected pipeline failures. In this study, hydraulic simulation is used as one component of a broader decision-support procedure intended to assess the operational impact of reported failures. This paper proposes a simulation-based method for classifying failures in water distribution systems according to their operational impact. The method is intended to support operators in identifying failures that may significantly affect hydraulic performance, water delivery, or access to critical infrastructure. The proposed approach combines several analytical components. First, the elements of the WDS are classified according to their influence on network operation. Next, water flow paths from sources to selected demand nodes or critical infrastructure facilities are analysed. The method also identifies valves that should be closed when it is necessary to isolate a damaged section or reduce pressure in a failed pipe. Finally, reported failures are assigned to one of three operational impact classes: C1 (denotes high-impact failures that may significantly disturb water distribution, affect critical infrastructure, or require complex repair actions), C2 (denotes moderate-impact failures that noticeably affect network operation but do not cause severe system-wide consequences under the analysed conditions), or C3 (denotes low-impact failures whose hydraulic and operational consequences are limited). The main contribution of this paper is the development of an integrated simulation-based failure classification workflow for water distribution systems. The novelty of the approach does not consist in the use of EPANET alone or in the separate application of previously developed algorithms, but in integrating several analytical components into one operational classification procedure. In particular, the method links hydraulic consequences, element criticality, flow-path analysis, valve isolation, expected repair time, historical failure intensity, and the impact on critical infrastructure. As a result, the method transforms simulation and operational data into failure impact classes that can be directly interpreted by water utility operators. The proposed method should be interpreted as a failure classification and decision-support component, rather than as a complete repair scheduling system. It does not determine the final order of repair works or assign repair crews to tasks. Instead, it provides structured information about the operational severity of reported failures. Such classification can be used as an input to further decision-making processes, including repair planning, resource allocation, and crisis-management procedures. This paper is based on selected results obtained during the author's doctoral research [2]. The doctoral dissertation provided the broader methodological background and preliminary development of the algorithms. However, the present paper reformulates these results as an integrated failure classification method and evaluates the complete workflow using real-network scenarios and expert assessments. One component of the method, namely the valve-isolation and flow-analysis procedure, was described in detail in previous work [12]. In the present paper, this component is used as part of a broader operational impact classification framework. A prototype implementation of the proposed method was developed using WNTR, which incorporates the EPANET solver, and the Python programming language (the source code is available at https://github.com/Arillos/WDSAlgorithms/). The implementation was tested on a hydraulic model of a real water distribution system operated by the Miejskie Przedsiębiorstwo Energetyki Cieplnej, Wodociągów i Kanalizacji Sp. z o.o. in Środa Wielkopolska, Poland. The test scenarios were prepared with the support of domain experts and operators working at the company. The classification results obtained by the proposed method were compared with expert assessments in order to evaluate its suitability as a decision-support tool for failure impact assessment in WDSs.

RESEARCH METHODOLOGY

EPANET, a publicly available tool developed by the U.S. Environmental Protection Agency's Water Supply and Water Resources Division in the 1990s, is one of the most widely used tools for the analysis of water supply networks. One of its key features is the ability to perform simulations under different initial and boundary conditions, including various water demand scenarios. Initially developed as an educational and research tool, EPANET gained popularity because it enables the analysis of hydraulic behaviour and water quality processes in water distribution systems. Its functionalities include hydraulic and water quality simulation, modelling the mixing of water from different sources, calculating water age throughout the system, tracking contamination spread, and estimating chlorine residual losses. These capabilities make EPANET useful for understanding and analysing the operation of water distribution systems [6].

The WNTR, a Python package, complements EPANET by providing enhanced capabilities for simulating and analysing the resilience of water distribution networks. In addition to standard hydraulic simulations, WNTR facilitates the modelling of atypical and emergency scenarios, such as power outages, incidental contamination events, pipe breaks, leaks, and earthquakes. The WNTR library includes two simulation engines: *WNTRSimulator*, primarily used for hydraulic simulation with the option to choose between demand-driven and pressure-dependent demand approaches, and *EpanetSimulator*, which enables hydraulic and water quality simulation using the EPANET demand-driven approach [7–9].

In this study, WNTR and the EPANET solver were used to perform the hydraulic simulations required by the proposed failure classification method. To reduce the computation time, the Ray Python library was used to parallelize independent simulation tasks. In particular, simulations performed for different network elements or failure cases were distributed among available workers [10].

The description of the proposed method is presented using the artificial topology of the water supply network shown in Figure 1. The sample network consists of 30 nodes, including one reservoir and two tanks, 42 links, including two pumps, and 31 valves. The nodes are marked with the letter J (Junctions), the links are marked with the letter P (Pipes), and the valves are marked with the letter V (Valves).

Classifying water supply network elements algorithm

Knowledge about the structure and hydraulic behaviour of a water distribution system is a basic requirement for assessing the operational impact of failures occurring in it. In the proposed method, the classification of network elements is used as one of the inputs to the final failure classification procedure. The purpose of this stage is to determine how important individual elements are for the hydraulic performance of the analysed WDS. To determine the criticality of network elements, an element classification algorithm was proposed, hereinafter referred to as Algorithm 1 (attachment Algorithm 1). The algorithm performs hydraulic simulations of the water supply network in which selected elements are removed,

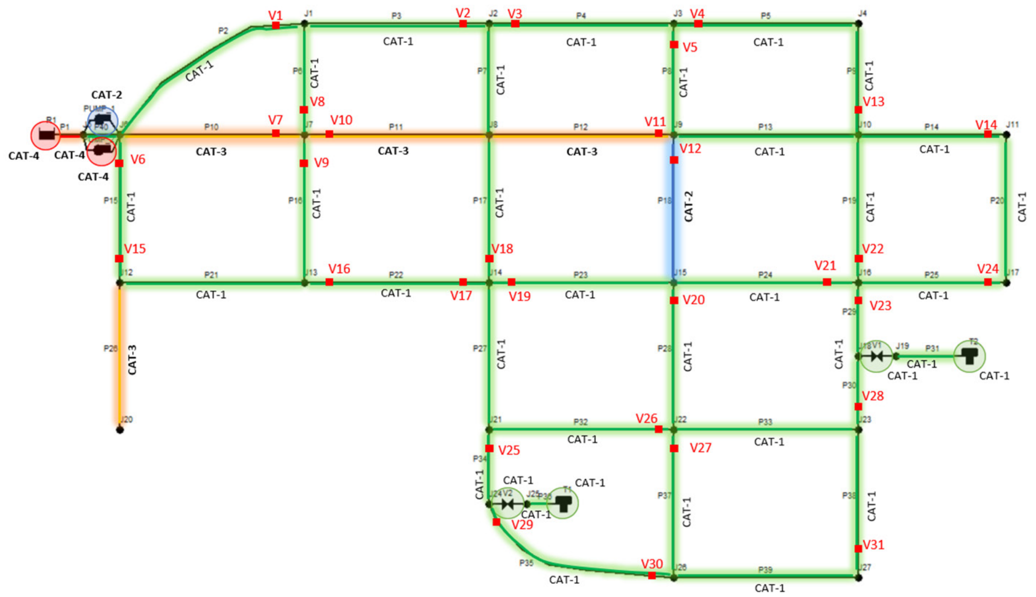

Figure 1. Example of water network topology
(with graphical representation of the results of Algorithm 1) [2]

disabled, or replaced, and compares the obtained results with the reference simulation [2].

The input to Algorithm 1 is the hydraulic model of the water supply network and a set of rules used to assign elements to criticality categories. These rules are expressed in terms of differences between selected hydraulic performance indicators obtained from the reference model and from the modified model without the considered element. The analysed indicators may include flow, demand, pressure, and the height of the liquid column at individual nodes. Therefore, the algorithm is not limited to one hydraulic variable. In the example presented in this section, the classification is illustrated using the daily flow ratio, but the same procedure can be applied to other indicators, such as minimum pressure, demand deficit, peak-hour flow, or the number of nodes below the required pressure threshold.

For every considered element, the algorithm outputs the simulation results, the comparison with the reference simulation, and the assigned element criticality category. The first step of the algorithm is to run the reference simulation, whose task is to represent the normal operating state of the water supply network, without analysed failures or removed elements. The results of the reference simulation are saved to a CSV file. Depending on the selected indicator, the file may store information about flows in individual pipes, daily or peak-hour flow values, pressure in nodes, minimum pressure in nodes, water consumption, demand deficits, and a simulation report generated by the EPANET solver.

Once the reference simulation is completed, a list of elements of the analysed hydraulic model is generated. It contains information about the number and identifiers of reservoirs, tanks, pumps, valves, and pipes. In the next step, for every element that is to be classified, a modified hydraulic model is created and simulated. The modified model represents the network state without the considered element or with the considered element replaced according to the procedure described below. All simulation results are saved to CSV files. For the simulation to work correctly, it is necessary to ensure the topological correctness of the hydraulic model. Simply removing an element from the model would not always yield a topologically correct model.

Instead of directly deleting elements from the model, a special procedure must be employed. If the element to be removed is a node in the model, such as a reservoir or a tank, it is replaced with a junction with zero demand. For links, the procedure depends on their type:

- valves and pumps – the element is replaced with a pipe whose diameter and length correspond to the diameter and length of the removed element;
- pipes – the pipe is removed, and if there is a node that does not have a connection to another pipe, that node is also removed, and

the corresponding information is recorded in the simulation results.

Once all the simulations are completed, the algorithm compares the modified simulation results with the reference results and assigns an element criticality category. Table 1 presents an excerpt from the output of Algorithm 1 applied to the network from Figure 1. The first column contains the simulation identifier, for example PipP10, indicating the classified element. The next columns contain the daily flow rates for selected pipes. The third column from the end contains the sum of daily flows, and the penultimate column is the percentage of this sum relative to the reference simulation. The last column contains the assigned criticality category of the element.

The example in Table 1 presents the flow-based variant of the classification. In this variant, the effect of removing an element is assessed by comparing the sum of daily flows in the modified simulation with the corresponding value from the reference simulation. For a selected hydraulic indicator H, the relative performance of the network after removing or replacing element e can be expressed as:

$$R_H(e) = \frac{H(e)}{H_{ref}} \cdot 100\% \tag{1}$$

where: H_{ref} is the value of the selected indicator in the reference simulation, and $H(e)$ is the value obtained in the simulation performed for the modified model.

For indicators describing deterioration of service quality, such as demand deficit or the number of nodes below the pressure threshold, the interpretation is reversed. In such cases, higher values indicate a stronger negative impact on the operation of the WDS. The thresholds for such indicators should therefore be defined separately, according to the operational requirements of the analysed water utility.

In the considered example, the network is analysed in terms of the impact of WDS elements on the flow of water in the network, and four categories were defined:

- CAT-1: if the result of daily water flow is at least 90% of the reference results. The absence of the element has a limited impact on network operation.
- CAT-2: if the result of daily water flow is in the range from 75% to 89% of the reference results. The absence of the element has a moderate impact on network operation.
- CAT-3: if the result of daily water flow is in the range from 50% to 74% of the reference results. The absence of the element has a high impact on network operation.
- CAT-4: if the result of daily water flow is below 50% of the reference results. The absence of the element causes severe deterioration of network operation.

Table 1. A sample output of Algorithm 1

ID	P1	P10	P11	...	P24	P28	Sum	%	Cat.
(RefSim)	1.95	1315.21	1005.45	...	-131.68	290.22	6938.67	100	CAT-1
(ResR1)	-6E-08	-222.08	467.50	...	848.05	-71.4	1082.56	15.61	CAT-4
(TanT1)	1.95	1315.21	1005.45	...	-131.68	290.22	6938.66	100	CAT-1
(TanT2)	1.95	1315.20	1005.42	...	-131.69	290.28	6938.80	100	CAT-1
(PipP1)	0	-222.08	-467.50	...	848.05	-71.46	1082.58	15.61	CAT-4
(PipP10)	1.83	0	490.78	...	-58.34	243.96	5100.31	73.51	CAT-3
(PipP11)	1.91	883.89	0	...	-85.07	194.92	4427.63	63.81	CAT-3
(PipP12)	1.95	1228.98	743.55	...	-90.41	109.58	4577.74	64.25	CAT-3
(PipP15)	1.95	1702.69	1216.43	...	-122.58	336.9	7316.92	105.45	CAT-1
...	...	...	...	...	...	...	...	...	...
(PipP22)	1.95	1341.31	1148.38	...	-124.93	310.2	7192.02	103.65	CAT-1
(PipP23)	1.95	1317.76	1014.20	...	-123.53	262.89	6879.09	99.14	CAT-1
(PipP18)	1.95	1289.69	926.92	...	86.78	156.53	6223.74	89.7	CAT-2
(PipP29)	1.95	1315.16	1005.29	...	-113.39	310.44	6951.21	100.18	CAT-1
(PipP40)	1.95	1315.21	1005.44	...	-131.63	290.28	6938.87	100	CAT-1

Note: The table contains information about the daily flow in individual pipes [l/s].

The values of the thresholds and the number of categories can be changed in the algorithm input. The same classification structure can also be applied to pressure- or demand-based indicators after defining appropriate operational thresholds. For example, a pressure-based variant may classify elements according to the number of nodes below the minimum acceptable pressure or according to the minimum pressure decrease during peak-demand hours. A demand-based variant may use the total unsupplied demand or the number of nodes without sufficient water supply.

Figure 1 presents the results of executing Algorithm 1 on the sample water supply network. In this figure, CAT-1 indicates elements whose absence slightly affects the operation of the network, CAT-2 indicates elements with a moderate impact, CAT-3 indicates elements with high criticality, and CAT-4 indicates elements without which the network operation is severely deteriorated. The presented network has a backbone structure, which makes it relatively fault-tolerant. In the case of a single pipe failure, other pipes may still be able to meet the required demand and supply water to all nodes.

Algorithm 1 assumes the valve states specified in the hydraulic model. However, in real emergency conditions, operators may change valve states during isolation or repair activities. Such changes can influence the hydraulic behaviour of the network and, consequently, the assigned element categories. Therefore, if valve states are changed, the hydraulic model should be updated and the element classification should be recalculated for the new network state. This assumption is important because the element categories are later used as one of the inputs to the final failure classification procedure.

Algorythm 1

```
"""
      Name:    Algorithm 1 - Klasyfikacja elementów sieci wodociągowej
     Author:   Ariel Antonowicz
  Last update:   24.02.2022
"""
import wntr
import copy
import pandas as pd
import os, glob
from config import Configuration_data


class Algorithm_1:

  def __init__(self):

    self.init_config = Configuration_data()

    self.inp_file = self.init_config.networks_path + self.init_config.inp_file_name + '.inp'
    self.nodes_csv_file = self.init_config.results_path + self.init_config.nodes_csv_file + '.csv'
    self.links_csv_file = self.init_config.results_path + self.init_config.links_csv_file + '.csv'

    self.link_file = open(file=self.links_csv_file, newline='', mode='a')
    self.node_file = open(file=self.nodes_csv_file, newline='', mode='a')

    self.sum_of_flow = 0
    self.sum_of_pressure = 0
    self.sum_of_demand = 0
    self.sum_of_head = 0
    self.links_results = {'flow': list()}
    self.nodes_results = {'head': list(), 'demand': list(), 'pressure': list()}
    self.isolated_nodes_list = list()

    self.wn = wntr.network.WaterNetworkModel(self.inp_file)
    self.wn.options.time.duration = self.init_config.sim_duration
    self.sim = wntr.sim.EpanetSimulator(wn=self.wn)

  def __del__(self):
    for filename in glob.glob("temp*"):
      os.remove(filename)

  def run_simulation(self, wn):
    simulation_results = list()

    sim = wntr.sim.EpanetSimulator(wn=wn)
    for step in range(0, self.init_config.sim_duration + 1, 1):
```

The analysis of network elements from the point of view of demand, pressure, and hydraulic head proceeds in the same way as in the case of flow. However, when pressure is used as the classification indicator, both excessive pressure decreases and excessive pressure increases should be monitored. Significant pressure drops may cause service interruptions, while excessive pressure increases may increase the risk of further damage to the network.

Water flow trace algorithm

Knowledge about the route of water flow from a source, or a group of sources, to a selected node supports the classification of failures in emergency situations. In particular, it makes it possible to determine whether a failure affects the hydraulic connection between water sources and selected demand nodes or critical infrastructure facilities. In the case of multiple simultaneous failures, such information is important for assessing the operational impact of each failure. The purpose of the Water Flow Trace Algorithm, hereafter referred to as Algorithm 2 (attachment Algorithm 2), is to determine the primary route of water from the source to the indicated destination. The algorithm may also indicate secondary routes of water supply to the selected node, for example from other sources. The algorithm works as follows:

Algorithm 2

```
"""
     Name:   Algorithm 2- Algorytm wyznaczania tras przepływu wody
    Author:  Ariel Antonowicz
 Last update:  26.02.2022
"""
import wntr
import copy
import os, glob
from config import Configuration_data


class Algorithm2:

  def __init__(self):
    self.init_config = Configuration_data()
    self.inp_file =

    self.nodes_to_check = list()
    self.results = list()
    self.wn = wntr.network.WaterNetworkModel(self.inp_file)
    self.wn.options.time.duration = self.init_config.sim_duration
    self.sim = wntr.sim.EpanetSimulator(wn=self.wn)

  def __del__(self):
    for filename in glob.glob("temp*"):
      os.remove(filename)

  def run_simulation(self, wn, source):
    simulation_results = list()
    sim = wntr.sim.EpanetSimulator(wn=wn)

    wn.options.quality.parameter = 'TRACE'
    wn.options.quality.trace_node = source

    for step in range(0, self.init_config.sim_duration + 1, 1):
      wn.options.time.duration = step * 3600
      simulation_results = sim.run_sim()

    return {'quality': simulation_results.node['quality'].to_dict('index'),
        'flow': simulation_results.link['flowrate'].to_dict('index')}

  def check_neighbours(self, node_id):
    node_neighbours_list = list()

    for link in self.wn.link_name_list:
      if node_id == self.wn.get_link(link).todict()['start_node_name']:
        node_neighbours_list.append({'node_id': node_id, 'link_id': link, 'start_node_id': node_id,
'end_node_id': self.wn.get_link(link).todict()['end_node_name']})

      elif node_id == self.wn.get_link(link).todict()['end_node_name']:
```

1. For the node for which water flow routes are sought, a list of its neighbours is created. A node is defined as a neighbour when it is connected to the selected node by a pipe, valve, or pump.
2. A hydraulic simulation is performed for the analysed network state.
3. Based on the list of neighbours and the simulation results, nodes in the list are classified as recipients or donors. A node is classified as a donor when it supplies water to the selected node, and as a recipient when it receives water from it.
4. The algorithm is repeated for nodes classified as donors, excluding reservoirs and tanks.
5. When there are no nodes classified as donors, the algorithm is completed.

For example, in the case of node J14 (Fig 1), the neighbouring nodes are J8, connected by pipe P17; J13, connected by pipe P22; J15, connected by pipe P23; and J21, connected by pipe P27. Based on the list of neighbours and the simulation results, the algorithm classified J15 and J21 as recipients, while nodes J8 and J13 were classified as donors. In the next iteration, the set of donor nodes, J8 and J13, is analysed in parallel. Based on the simulation results of the second iteration, new information is obtained. Node J8 has four neighbouring nodes: J2, J7, J9, and J14. Based on the analysis of flow values, nodes J2 and J7 were classified as recipients through pipes P7 and P11, respectively. Node J13 has three neighbouring nodes: J7, J12, and J14. Based on the analysis of flow values, nodes J7 and J12 were classified as recipients through pipes P16 and P21, respectively. Subsequent iterations of the algorithm are performed analogously.

In this way, Algorithm 2 determines the flow route from the selected node towards the source. Figure 2 shows the simulation results, in graphical form, of the Water Flow Trace Algorithm for the analysed example in the first and seventh hours of the simulation. The figure also illustrates that the importance of a pipe in the water distribution process is not constant. It may depend on the

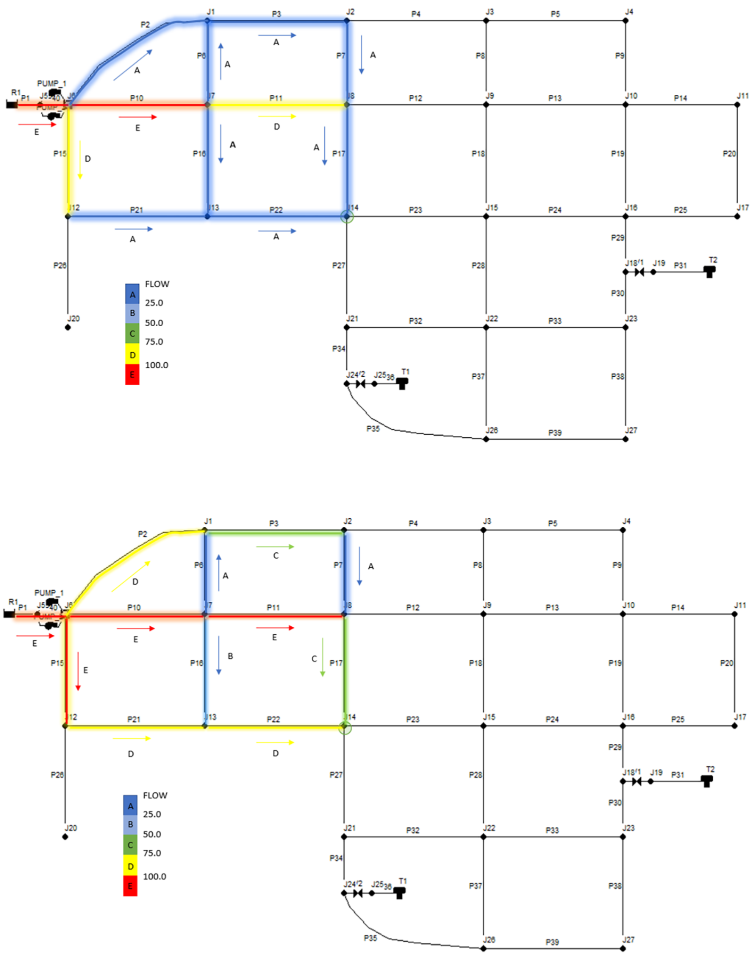

Figure 2. An example of a graphical representation of the Water Flow Trace Algorithm for the first and seventh hours of the simulation [2]

simulation time step, flow direction, and expected water demand. Therefore, in the proposed failure classification method, flow trace analysis can be performed for the entire simulation horizon or for selected critical periods, such as peak-demand hours. When a single operational impact class must be assigned to a reported failure, the hydraulic indicator used for classification should be selected according to the decision context. For conservative emergency assessment, the classification may use the worst-case or peak-demand period. For planning analyses, daily aggregated indicators may be used. If real-time operational data are available, the hydraulic model can be updated to represent the network state at the time when the failure is reported, and the classification can be recalculated for that state. In the case study presented in this paper, the classification was based on the assumed simulation horizon and selected hydraulic indicators, rather than on real-time measurements.

Selecting valves for closure with flow analysis algorithm

The methodology of selecting valves for closure is described in detail in previous research on strategic valve locations in water distribution systems [11]. This approach was supplemented with flow analysis developed by the author in [12], which made it possible to determine a minimal set of valves required to isolate an indicated section. In this paper, this procedure is referred to as the Selecting Valves for Closure with Flow Analysis Algorithm, hereafter referred to as Algorithm 3 (attachment Algorithm 3). The result of the algorithm determining the segments in the analysed water distribution system is shown in Figure 3.

Algorithm 3

```
"""
       Name:    Algorithm 3 - Algorytm typowania zasuw do zamknięcia
      Author:   Ariel Antonowicz
  Last update:  28.02.2022
"""
import wntr
import wntr.network.controls as controls
import pandas as pd
import itertools
import json
import os, glob
import time
import copy
import matplotlib.pyplot as plt
from config import Configuration_data


class Algorithm_3:

    def __init__(self):

        self.init_config = Configuration_data()
        self.inp_file = self.init_config.networks_path + self.init_config.inp_file_name + '.inp'

        self.wn = wntr.network.WaterNetworkModel(self.inp_file)
        self.wn.options.time.duration = self.init_config.sim_duration
        self.sim = wntr.sim.EpanetSimulator(wn=self.wn)

        self.valve_info = self.init_config.valve_info_path + self.init_config.valve_info + '.json'
        self.segments = self.init_config.segments_info_path + self.init_config.segments + '.json'
        self.matrix_a = self.init_config.matrix_path + self.init_config.matrix_a + '.csv'
        self.matrix_b = self.init_config.matrix_path + self.init_config.matrix_b + '.csv'
        self.matrix_c = self.init_config.matrix_path + self.init_config.matrix_c + '.csv'

        with open(self.valve_info, "r") as jsonFile:
            self.valves = json.load(jsonFile)

    def __del__(self):
        for filename in glob.glob("temp*"):
            os.remove(filename)

    def valve_to_pipe_references(self, pipe_id):

        segment = self.find_segment(pipe_id)
        valve_to_pipe_reference = dict()

        for valve in segment['segment_valves']:
            valve_to_pipe_reference[valve] = list()
            for data in self.valves[self.init_config.valve_set]:
                if valve == data['valve_id']:
                    if data['data']['link_id'] in segment['segment_links']:
```

Algorithm 3 is used as a supporting component of the proposed failure classification method. Its purpose is not to optimize the entire repair process, but to determine which valves should be closed to isolate a damaged section or reduce the hydraulic impact of a failure. This information is then used to assess the operational consequences of the failure, including the number of affected nodes, possible pressure drops, and the influence on water delivery to selected parts of the network.

In the proposed approach, the current valve states are taken from the hydraulic model. However, valve operations during emergency response may change the hydraulic state of the network. For this reason, if the state of valves is changed after the isolation of a damaged section, the hydraulic model should be updated and the simulation should be repeated. The updated simulation results can then be used to reclassify reported failures under the new operating conditions. Thus, the method can be applied iteratively as new information about failures or valve operations becomes available.

Failure classification algorithm

The purpose of the failure classification process is to determine the operational impact of individual failures on the water supply infrastructure and on the area in which they occur. In the proposed method, classification is understood as assigning each reported failure to one of the operational impact classes introduced in Section 1: C1, C2, or C3. The classification result is intended to support operators in identifying failures with different levels of hydraulic and operational severity. It should not be interpreted as a complete repair schedule or as the final order of repair works. The correctness of the classification depends primarily on the quality of information available about the WDS, the type and location of the failure, the hydraulic model, and the current operational state of the network.

Based on a literature review and the knowledge of experts responsible for supervising repair crews, three types of failures were identified [2]:

- F1: a failure that does not require interruption of the water distribution process in the analysed section and does not require pipe replacement.
- F2: a failure that requires interruption of the water distribution process in the analysed section, but does not require replacement of the damaged pipe.
- F3: a failure that requires replacement of a pipe section and interruption of the water distribution process in the analysed section.

Based on information about the failure type, it is possible to estimate the expected repair time (ERT), which is one of the indicators used in the classification procedure. Table 2 shows the activities considered in calculating ERT.

In the case of F1 failures, the time required to open and close valves, restore water supply including venting and flushing, clean the pipe, cut the pipe, or install a new pipe section is not considered. In the case of F2 failures, cutting and

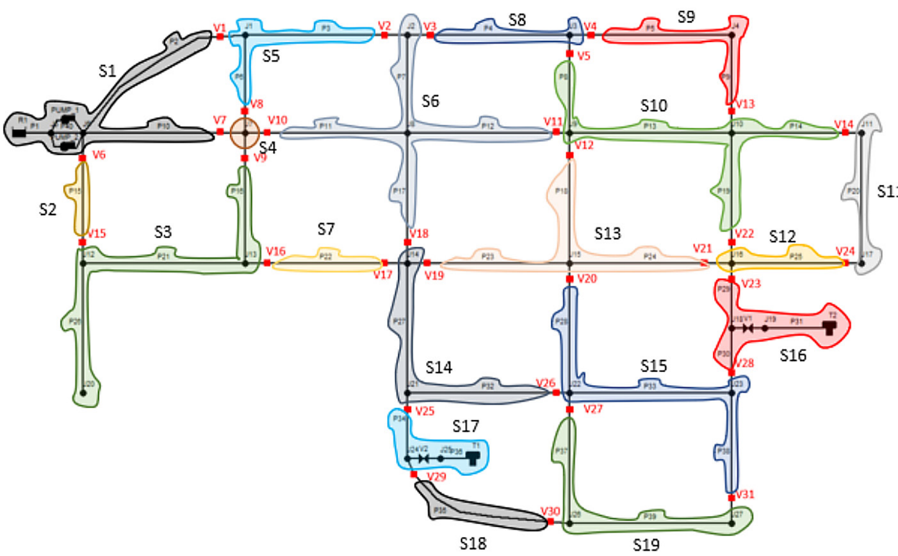

Figure 3. The result of the algorithm determining the segments in the analysed water distribution system [12]

Table 2. Activities considered in calculating ERT

ID	Name of activities	Type of failure		
		F1	F2	F3
1	Opening / Closing a valve	no	yes	no
2	Location of failure	yes	yes	yes
3	Removal of asphalt pavement	yes/no	yes/no	yes/no
4	Pulling down paving slabs	yes/no	yes/no	yes/no
5	Excavation for a pipeline (mechanical)	yes	yes	yes
6	Drainage of water from an excavation	yes/no	yes/no	yes/no
7	Cleaning a pipe	no	yes	yes
8	Installation of a repair band	yes	yes	no
9	Installation of a sealant	yes	yes	yes
10	Excision of a section of a pipe	no	no	yes
11	Installation of a new pipe	no	no	yes
12	Opening the water supply, venting, flushing	no	yes	yes
13	Backfilling of a trench	yes	yes	yes
14	Finishing and cleaning activities	yes	yes	yes

installing a new pipe section are not taken into account. In the case of F3 failures, installation of a repair band is not included, because the damaged pipe section must be replaced. Activities such as removing paving slabs or asphalt depend on the failure location, while drainage of water from the excavation depends on field conditions and the time of starting repair activities. The duration of individual activities can be modified in the algorithm settings.

The classification proceeds based on information about the failure type, place of occurrence, surface type, ERT, the flow value in the failed pipe, the element criticality category obtained from Algorithm 1, the pipe criticality index, and the Damage Intensity Index (DII) [2]. The pipe criticality index is defined as the ratio of the number of failures occurring in a given period to the length of the analysed pipe expressed in kilometres. This indicator reflects historical failure intensity of a given pipe or pipe group.

The Damage Intensity Index uses the results of hydraulic simulations and describes the hydraulic consequences of a failure. Equation 2 shows an example of using information about the state of the network during a pipe failure to determine DII:

$$DII = \frac{D + (N_{WW} \cdot 0.5) + \\ +(N_{LP} \cdot 0.25) + F}{N} \quad (2)$$

where: D – pipe diameter [m]; N_{WW} – the number of nodes in the WDS deprived of access to water; N_{LP} – the number of nodes where the water pressure falls below the assumed threshold; F – flow decrease relative to the reference simulation; N – the total number of nodes in the WDS.

Although the element criticality category may be obtained using the flow-based variant of Algorithm 1, the final failure classification is not based only on daily flow. The DII also includes pressure-related and service-continuity indicators, such as the number of nodes without access to water and the number of nodes where pressure falls below the assumed threshold. Therefore, the final class assignment reflects both the global effect of the failure on water transport and local hydraulic deterioration in the affected part of the network.

Each failure occurring in the water supply network is described by a failure identifier, the type of failure, the identifier of the failed pipe, and the time of failure occurrence. The place of occurrence, for example public or private area, and the type of surface are additional input data that can be provided by the user. If these data are not provided, the algorithm assumes a default scenario: private area and the presence of paving slabs and asphalt. This assumption can be changed in the algorithm settings.

The proposed method classifies reported or confirmed failures. It does not perform failure detection or failure localization. In real emergency situations, information about failures may be incomplete and may appear progressively. Therefore, Algorithm 4 (attachment Algorithm 4) can be applied incrementally. When new information about a failure location, type, or valve state becomes available, the input data and hydraulic model should be updated, and the classification can be recalculated for the current network state.

Before applying the decision rules, the hydraulic indicators used in the classification should be selected for the analysed operational context. The algorithm may use daily aggregated values, peak-hour values, or values obtained for the current network state if real-time data are available. In emergency applications, the use of peak-demand or worst-case values provides a conservative classification, while daily aggregated values may be more appropriate for planning-oriented analyses. After updating the data for all reported failures, Algorithm 4 assigns each failure to one of three available classes according to the following decision rules:

1. A failure is assigned to class C1 when at least two of the following conditions are true:

Algorithm 4

```
"""
     Name:   Algorithm 4 - Algorytm klasyfikacji awarii
    Author:  Ariel Antonowicz
 Last update:  23.03.2022
"""
import numpy as np
import random
from algorithms.algorithm_1.algorithm_1 import *
from algorithms.algorithm_3.algorithm_3 import *


class Algorithm_4:
  def __init__(self):
    self.init_config = Configuration_data()
    self.inp_file = self.init_config.networks_path + self.init_config.inp_file_name + '.inp'

    self.wn = wntr.network.WaterNetworkModel(self.inp_file)
    self.wn.options.time.duration = self.init_config.sim_duration
    self.sim = wntr.sim.EpanetSimulator(wn=self.wn)

    self.classification_results = list()

    self.failures_times = self.init_config.repair_times
    self.failures_types = self.init_config.failure_type
    self.failures_info = self.init_config.failures_path + self.init_config.failures_info + '.json'
    with open(self.failures_info, "r") as jsonFile:
      self.failures = json.load(jsonFile)

  def __del__(self):
    for filename in glob.glob("temp*"):
      os.remove(filename)

  def update_data(self):

    if self.failures[self.init_config.failures_set]['status'] == 'NoUpdated':
      # Element critical factor:
      links_result = Algorithm_1().network_resilience_algorithm()

      for fail in self.failures[self.init_config.failures_set]['data']:
        # Diameter:
        diameter = self.wn.get_link(fail['pipe_id']).todict()['diameter']
        if diameter <= self.init_config.map_pipe_diameter['D3'][1]:
          diam_type = 'D3'
        elif self.init_config.map_pipe_diameter['D2'][0] < diameter <=
self.init_config.map_pipe_diameter['D2'][1]:
          diam_type = 'D2'
        else:
          diam_type = 'D1'
        fail['pipe_diameter'] = {'diameter_m': diameter,'diameter_in': round(diameter * 39.37),
'type': diam_type}
```

- the failed pipe belongs to category CAT-3 or CAT-4;
- the daily or peak-hour flow in the pipe is at least 15% of the total flow in all pipes;
- ERT is greater than 15 hours;
- the criticality index of the pipe is greater than 1.0;
- the failure affects the hydraulic connection to critical infrastructure or causes a significant service interruption.

2. If the analysed failure does not meet the conditions for class C1, it is assigned to class C2 when at least two of the following conditions are true:

- the failed pipe belongs at least to category CAT-2;
- the daily or peak-hour flow in the pipe is at least 10% of the total flow in all pipes;
- ERT is greater than 8 hours and 30 minutes;
- the criticality index of the pipe is greater than 0.5;
- the failure has a moderate influence on hydraulic performance or service continuity.

3. If the failure satisfies neither the C1 nor the C2 rule, it is assigned to class C3.

The above thresholds were developed on the basis of previous research, literature data, and domain expert knowledge [2, 13, 14]. They can be modified in the algorithm settings according to the operational requirements of the analysed water utility. Since the threshold values influence the final classification, their impact should be analysed during method evaluation. In particular, sensitivity analysis can be used to determine whether the assigned classes remain stable under reasonable changes in threshold values and weights used in the DII. Such analysis should quantify the proportion of failures that change their assigned class when thresholds such as the flow share, ERT, pipe criticality index, or DII-related parameters are increased or decreased. In the present study, a full threshold sensitivity analysis was not performed and is therefore indicated as an important direction for future work.

CASE STUDY

The proposed failure classification method was tested using a hydraulic model of a real water distribution system representing the operation of the water supply network of Środa Wielkopolska. The city, with an area of 17.98 square kilometres, is located in the Greater Poland province. The network supplies water to more than 23,000 consumers, and its model was provided by the Miejskie Przedsiębiorstwo Energetyki Cieplnej,

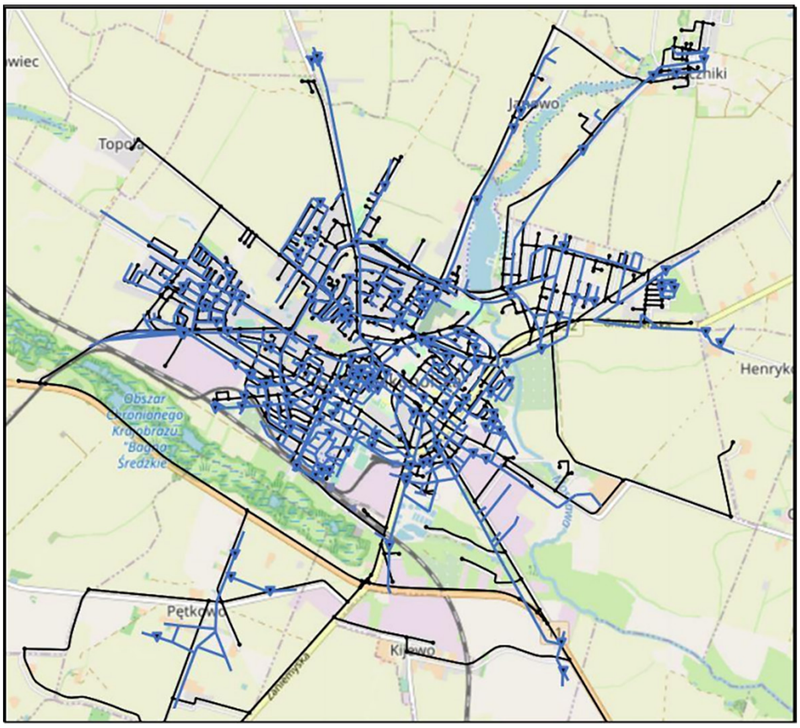

Figure 4. Środa Wielkopolska network topology [2]

Wodociągów i Kanalizacji Sp. z o.o. in Środa Wielkopolska. The analysed water distribution system consists of 1.400 nodes, 7 water sources represented as reservoirs, 1.523 pipes, and 35 valves of TCV and PRV types. Figure 4 shows the topology of the water supply network of Środa Wielkopolska and the surrounding area, as well as the topology of the network together with the road infrastructure of the city.

The hydraulic model was used as the operational representation of the analysed WDS. The model was provided by the water utility operator and includes the basic network structure and demand distribution used for simulation purposes. The head loss factors for all network elements are based on the Darcy-Weisbach formula and SI units. The analysed WDS includes only basic demands; special collection points, such as large industrial plants, were not defined in the model. The network has a centralized structure, in which smaller villages are connected to the municipal water supply network.

Since the proposed classification method depends on hydraulic simulation results, the quality of the hydraulic model is an important factor influencing the reliability of the obtained classifications. In this study, the model was treated as the reference operational model provided by the utility. Detailed calibration records, including measurement points, calibration criteria, and achieved pressure or flow accuracy, were not available to the authors. Therefore, the presented case study should be interpreted as an evaluation of the proposed classification procedure against expert assessments, rather than as a complete hydraulic calibration study. In practical applications, the method should be applied to calibrated and regularly updated hydraulic models.

The lack of detailed calibration records may influence the reliability and stability of the final failure classification. This is particularly important for failures whose classification depends on pressure deficits, flow changes, or the number of nodes affected by service interruption. Errors in pipe roughness coefficients, demand allocation, valve status, or source parameters may change simulated pressures and flows and, consequently, may affect the assigned class, especially in boundary cases between C1 and C2 or between C2 and C3. In this study, no separate robustness tests against hydraulic model miscalibration were performed. Therefore, the obtained results should be interpreted in relation to the operational model provided by the utility, and further validation should include perturbation tests of selected model parameters, such as pipe roughness, nodal demands, and valve states.

Based on the selected water network model, the Python interpreter, and the required libraries, including WNTR and Ray, a set of simulation assumptions was prepared. The simulation horizon was set to 72 hours, and the hydraulic simulation time step was set to 15 minutes. The simulations were performed for the reference network state and for modified network states required by the element classification, flow trace analysis, valve isolation analysis, and failure classification procedures. The computational environment used in the experiments was as follows: CPU -- Intel(R) Xeon(R) CPU E5-2630 v3 @ 2.40GHz (x2), RAM -- 256 GB, operating system -- Linux/Debian 6.12. These details are included to support the reproducibility and scalability assessment of the proposed approach.

To evaluate the suitability of the proposed method for classifying failures according to their operational impact, five test scenarios were developed. Each scenario contains a different number of failures of types F1, F2, and F3, as well as selected critical infrastructure facilities. The scenarios were prepared to represent emergency conditions with multiple simultaneous failures and to test whether the proposed method can distinguish failures with high, moderate, and low impact on the operation of the WDS. The scenarios were prepared with the support of domain experts and operators working at the water utility. They were not intended to reproduce a specific historical event, but to provide controlled test cases for evaluating the classification method. The five scenarios were defined as follows:

- Scenario 1: F1 failures: 8, F2 failures: 1, F3 failures: 10, critical infrastructure facilities: 4.
- Scenario 2: F1 failures: 10, F2 failures: 15, F3 failures: 12, critical infrastructure facilities: 2.
- Scenario 3: F1 failures: 15, F2 failures: 15, F3 failures: 15, critical infrastructure facilities: 3.
- Scenario 4: F1 failures: 4, F2 failures: 2, F3 failures: 9, critical infrastructure facilities: 5.
- Scenario 5: F1 failures: 8, F2 failures: 8, F3 failures: 8, critical infrastructure facilities: 5.

For each scenario, the input data included the failure identifier, failure type, failed pipe identifier, and the location of critical infrastructure facilities. Additional information, such as the place of occurrence and surface type, was included when available or assigned according to the default assumptions described in the methodology. The output of the proposed method was the assignment of each reported failure to one of the three operational impact classes: C1, C2, or C3.

Figure 5 shows one of the generated test scenarios. This example represents a multiple-failure emergency situation. In this scenario, 28 failures were identified, including 8 failures of type F1 with identifiers F1-F8, 10 failures of type F2 with identifiers F9-F18, and 10 failures of type F3 with identifiers F19-F28. In addition, four buildings were classified as critical infrastructure facilities and marked as CI1-CI4. The scenario was used to test whether the proposed method can identify failures that affect hydraulic performance, service continuity, or water delivery to critical infrastructure.

RESULTS

Figure 6 presents the result of Algorithm 3 for the example scenario shown in Figure 5. The figure illustrates the segmentation of the analysed water distribution system and the valves selected for isolating damaged sections. The results of Algorithm 3 were used as one of the inputs to the failure classification procedure, especially when estimating the hydraulic consequences of isolating selected network sections.

For example, for Scenario 1, the classification results were as follows:

- C1: F4, F7, F17, F20, F22.
- C2: F1, F6, F12, F13, F15, F16, F18, F26, F27, F28.
- C3: F2, F3, F5, F8, F9, F10, F11, F14, F19, F21, F23, F24, F25.

In the analysed scenarios, failures located on the primary water route between a source and a critical infrastructure facility were assigned to a higher operational impact class when they caused a significant decrease in delivered water or interrupted the hydraulic connection to the facility. In Scenario 1, two such failures were identified: failure F18, which prevented the transport of water to critical infrastructure facility CI4, and failure F17, which blocked the transport of water to CI3.

Table 3 summarizes the classification results obtained for all five scenarios. Across all scenarios, 149 failures were analysed. The proposed algorithm assigned the same class as the experts in 144 cases, which corresponds to an overall agreement of 96.6%. The agreement was 100%

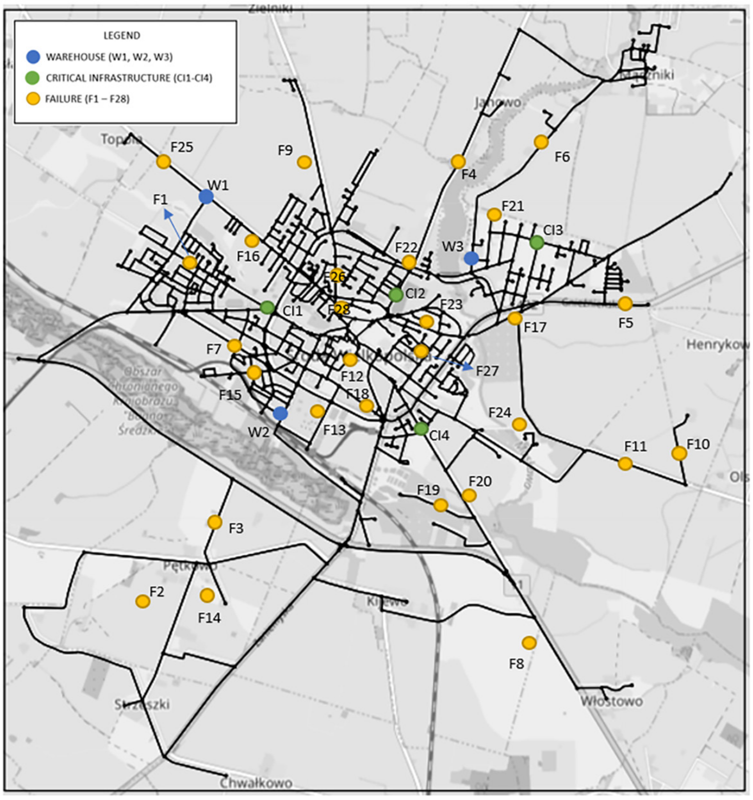

Figure 5. Example test scenario [2]

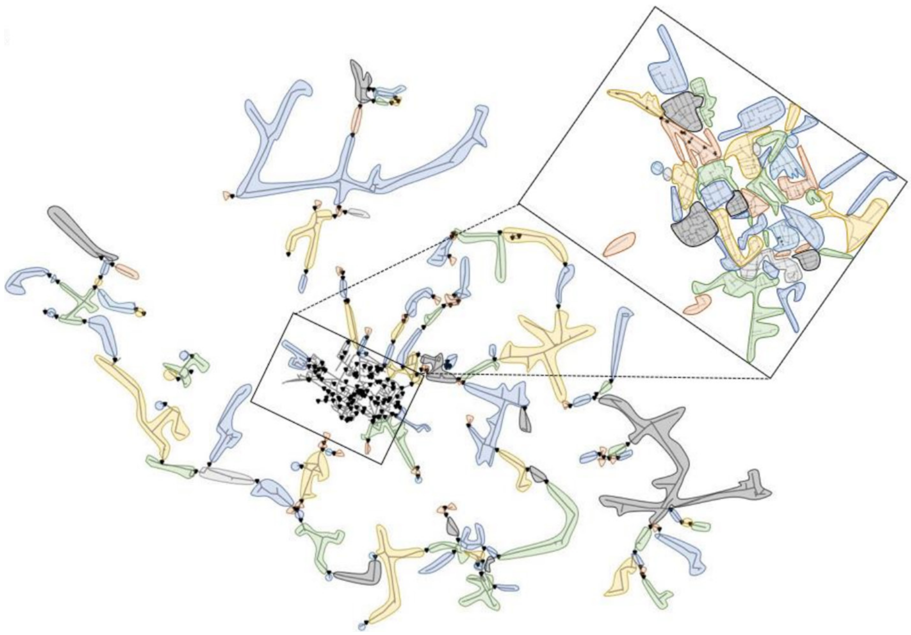

Figure 6. The result of Algorithm 3 for the example scenario from Figure 5 (90-degree rotation) [2]

for Scenarios 1 and 4, 95% for Scenario~2, and 96% for Scenarios 3 and 5.

A direct numerical comparison with previous studies is limited because the analysed networks, input data, failure definitions, and output indicators differ between publications. Earlier EPANET-based studies usually report hydraulic parameters, vulnerable areas, failure rates, or consequences of selected pipe failures. In contrast, the proposed method produces operational impact classes assigned to reported failures. Therefore, the comparison with previous works is mainly qualitative and concerns the scope and decision-support function of the method.

To provide a more detailed analysis of classification differences, Table 4 presents the confusion matrix for all scenarios. Rows represent expert assessments, while columns represent the classes assigned by the proposed algorithm.

Most discrepancies occurred between neighbouring classes, especially between C2 and C3. In Scenario 2, two failures were classified by the algorithm as C2, while the experts classified them as C3. In Scenario 3, one failure was classified by the experts as C1 and by the algorithm as C2, and one failure was classified by the experts as C3 and by the algorithm as C2. In Scenario 5, one failure was classified by the experts as C2 and by the algorithm as C3. Thus, only one discrepancy concerned the boundary between C1 and C2, while the remaining discrepancies concerned the moderate- and low-impact classes.

The discrepancies were analysed by the experts and the authors. In four out of five inconsistent cases, the experts agreed that the classification proposed by the algorithm was acceptable from an operational point of view. The unresolved case occurred in Scenario 3, where the expert assessment assigned one failure to C1, while the algorithm assigned it to C2. This indicates that the boundary between high- and moderate-impact failures requires particular attention in further validation, especially for failures affecting critical infrastructure or causing local pressure deficits.

For each scenario, the execution of the proposed method using the prototype implementation took less than 10 minutes. In comparison, preparing the expert classification required several hours per scenario. This difference indicates that the method may support operators by quickly producing an initial classification of reported failures. However, the result should be treated as decision-support information and not as a replacement for expert judgement, especially in cases with incomplete failure information, uncertain valve states, or insufficiently calibrated hydraulic models.

The obtained results indicate that the proposed method can support the operational assessment of failures in water distribution systems by transforming hydraulic and operational information into failure impact classes. In contrast to studies focused mainly on hydraulic parameter simulation, vulnerable pipe identification, or failure statistics, the

Table 3. Failure classification algorithm results

ID	Algorithm results	Expert assessment	Agreement
Scenario 1	C1: 5 C2: 10 C3: 13	C1: 5 C2: 10 C3: 13	100%
Scenario 2	C1: 4 C2: 13 C3: 20	C1: 4 C2: 11 C3: 22	95%
Scenario 3	C1: 8 C2: 20 C3: 17	C1: 9 C2: 18 C3: 18	96%
Scenario 4	C1: 10 C2: 1 C3: 4	C1: 10 C2: 1 C3: 4	100%
Scenario 5	C1: 7 C2: 8 C3: 9	C1: 7 C2: 9 C3: 8	96%

Table 4. Confusion matrix for all analysed scenarios

Expert assessment	Algorithm classification			Total
	C1	C2	C3	
C1	34	1	0	35
C2	0	48	1	49
C3	0	3	62	65
Total	34	52	63	149

proposed approach integrates several components: hydraulic simulation, element criticality assessment, flow-path analysis, valve-isolation analysis, repair-time estimation, historical failure intensity, and critical infrastructure information. This integration is the main advantage of the method, because it provides operators with concise information about the relative severity of reported failures.

The comparison with expert assessments showed high agreement, which suggests that the proposed decision rules reflect the operational reasoning used by practitioners in most analysed cases. However, the discrepancies observed between neighbouring classes, especially between C2 and C3, indicate that the classification boundaries require further validation. This is particularly important for failures located near critical infrastructure or in parts of the network where local pressure deficits may occur. Therefore, the proposed method should be treated as a decision-support tool rather than as an automatic replacement for expert judgement.

The stability of the classification depends on the quality of the hydraulic model and on the adopted decision thresholds. In particular, inaccurate pipe roughness coefficients, demand allocation, valve states, or source parameters may affect simulated pressures and flows. This may influence the final class assignment, especially for failures located close to the boundary between two classes. Similarly, changes in threshold values used for C1 and C2 classification may alter the number of failures assigned to each class. For this reason, future work should include robustness tests based on perturbations of hydraulic model parameters and sensitivity analysis of the classification thresholds. Such tests would make it possible to determine how many failures change their class under plausible model and parameter uncertainties.

A direct numerical comparison with previous studies is limited because the analysed networks, input data, failure definitions, and output indicators differ between publications. Earlier EPANET-based studies usually report hydraulic parameters, vulnerable areas, failure rates, or consequences of selected pipe failures. In contrast, the proposed method produces operational impact classes assigned to reported failures. Therefore, the comparison with previous works is mainly qualitative and concerns the scope and decision-support function of the method.

Diurnal variability is another important factor influencing failure classification. Flow directions, pipe importance, pressure deficits, and demand satisfaction may change during the day. Therefore, the assigned class should be interpreted in relation to the hydraulic conditions used in the simulation. A classification based on peak-demand conditions may represent a conservative emergency assessment, whereas a classification based on daily average indicators may better reflect general operational importance. In real-time applications, the method should be applied iteratively using the current demand pattern, valve states, and failure information available at the time of analysis.

From a practical perspective, the method may be useful for water utilities during emergency response, especially when several failures occur simultaneously. It can help operators identify failures that require particular attention because of their hydraulic consequences, expected repair time, valve-isolation requirements, or influence on critical infrastructure. At the same time, practical implementation requires a reliable and up-to-date hydraulic model, information about valve states, failure locations and types, and operational validation by domain experts. These requirements should be considered when adapting the method to other water distribution systems.

CONCLUSIONS

The proposed solution requires up-to-date knowledge of the analysed facility. The hydraulic model representing the analysed network should be calibrated and correctly designed in terms of the topological requirements necessary to run hydraulic simulations. This is important because the correctness of the obtained classifications depends on the reliability of the information available about the water distribution system, including network topology, demand distribution, valve locations, valve states, and failure data.

The results obtained for the analysed scenarios indicate that the proposed algorithms can serve as a foundation for decision-support systems in the field of water distribution system failure management. The method combines hydraulic simulation, classification of WDS elements, water flow trace analysis, valve isolation analysis, and repair-time estimation. On this basis, reported failures are assigned to operational impact classes that distinguish failures with high, moderate, and low influence on the functioning of the water supply network.

The proposed method should be interpreted as a failure classification component rather than as a complete repair scheduling system. Its output is not a final repair order, but a structured classification of reported failures into classes C1, C2, and C3. Such classification can support operators and crisis-management teams in identifying failures that require particular attention, especially those affecting hydraulic performance, service continuity, or critical infrastructure. However, final operational decisions should also take into account additional factors, such as repair crew availability, spare parts, traffic conditions, field accessibility, and the current priorities of the water utility.

The effectiveness of the proposed approach depends on its integration with broader decision-support and failure-management procedures. The reliability of such systems depends not only on the classification algorithm itself, but also on the quality of input data, the currentness of the hydraulic model, and the way in which simulation results are incorporated into operational workflows [2].

A prototype implementation of the proposed algorithms was developed and made available under an open-source AGPL license. One advantage of this approach is the absence of licensing fees and the possibility of further development by researchers and practitioners. Each algorithm was implemented in a modular form, which enables future extensions and modifications, for example adding new hydraulic indicators, alternative classification thresholds, or additional failure types.

One limitation of the proposed method is the assumption that the locations and types of failures are known or reported. In real disaster situations, such as earthquakes, floods, or large-scale infrastructure failures, knowledge about failures is often incomplete and may evolve over time. Therefore, the method should be applied iteratively when new information becomes available. Updating the failure list, valve states, and hydraulic model can change simulation results and, consequently, the assigned failure classes.

Another limitation is the dependence on predefined thresholds and weights used in the classification rules and in the Damage Intensity Index. Although these values were selected on the basis of previous research, literature data, and expert knowledge, their influence on the final classification should be examined further. Future work should therefore include a broader sensitivity analysis, robustness tests related to hydraulic model uncertainty, additional demand and seasonal conditions, and validation using historical failures and real operational decisions.

An important direction for further development is the integration of the proposed classification method with a task-scheduling algorithm for repair crews. Such an extension should consider crew availability, vehicle capacity, repair-team skills, warehouse inventory, travel times, and other operational constraints. This would make it possible to transform the classification component into a more comprehensive decision-support tool for crisis management in water distribution systems.

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