Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira, Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria

doi: 10.3850/ESREL2026061419_esrel26-p26285-cd

Application of Probability and Topological Metrics for Resilience Assessment of District Heating Networks

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The concept of resilience is essential for reducing the effects of high-impact and low-probability (HILP) events, such as extreme weather variations, geopolitical conflicts, and cyberattacks. District heating systems are particularly susceptible to HILP events given their age and hard-to-access nature, however, they are often overlooked, while power systems receive more attention. This research proposes a novel composite resilience evaluation framework for district heating systems based on key resilience metrics: robustness, resourcefulness, and recovery. Each metric comprises several graph topology-based metrics, normalized to ensure positive increments, and aggregated into resilience blocks. Resilience building blocks are combined into a single composite, weighted resilience index, with values ranging from zero to one for easier interpretation. The proposed index is tested on a couple of experimental networks with basic and advanced topologies and later used to evaluate a district heating system in a mid-sized city in Lithuania. Future research goals for expanding resilience-building blocks, including technical aspects of the network, thermal-hydraulic simulation, and network optimization, are described at the end of the article.

Keywords: Resilience, Safety, Robustness, Resourcefulness, Recovery, District heating, Graph theory, Network topology.

1. Introduction

A district heating (DH) system consists of a network of pipes (supply and return lines), consumers (individual houses, apartment buildings, industrial facilities, shops, etc.), and heat generation plants (co-generation plants (CHP), waste-to-energy plants, waste heat recovery from industrial facilities such as data centers, metro stations, and sewage treatment plants (Wheatcroft et al., 2020)). The reliability of this complex network of components is crucial to maintaining livable conditions for people living in northern countries. However, due to factors such as aging components, these systems are prone to failures. Although replacing aging components can be planned without interrupting the system (or with minimal interruptions), the real challenge to reliability and continuous heat supply arises from hard-to-predict disruptions, such as natural disasters, industrial accidents, political conflicts, or cyberattacks in the age of digitalization. Such disruptions are called high-impact and low-probability (HILP) events (Xu et al., 2023).

To measure how well a system is prepared to withstand such disruptions a concept of resilience can be used. There is no single generally accepted definition of district heating system resilience (or energy system resilience in general). On the one hand, such a definition would be impossible, as resilience depends heavily on the system itself (for example, the structural resilience of a material is completely different from the resilience of social networks). On the other hand, a generic definition would help clarify misconceptions about what resilience actually is (Scharte, 2023). There are, however, a few institutions that have their own definition of resilience that follows similar meaning, for example *US Department of Energy* describes resilience as *"The ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions"* (U.S. Department of Energy, 2023). However, in this research a definition by *International Energy Agency - IEA* is used: *"The capacity of the energy system and its components to cope with a hazardous event or trend, to respond in ways that maintain its essential functions, identity and structure as well as its capacity for adaptation, learning and transformation. It encompasses the following concepts: robustness, resourcefulness, recovery"* (Jasiūnas et al., 2021). The definition by *IEA* is used to decompose the concept of resilience into tree key metrics: *robustness*, *resourcefulness*, and *recovery* which are used as building blocks for resilience evaluation in section 3.

The paper is structured as follows: various attempts to measure the resilience of diverse energy and DH systems are presented in section 2. A novel DH system resilience evaluation methodology based on graph topology metrics is described in section 3. The described methodology is applied to evaluate the district heating system of Utena (Lithuania) with results presented in section 4, conclusions in section 5 and future plans discussed in section 6.

2. Related Work

Compared to similar concepts such as energy security or risk analysis, energy system resilience is sufficiently new, with quantitative assessment strategies beginning to emerge in the early 2000s (Bruneau et al., 2003). Therefore, the set of methods developed to evaluate it is still expanding, with majority (related to energy systems) focused more on power grids and other energy networks rather than district heating. The research on DH system security, flexibility, and resilience started to take pace in 2015 (Priedniece et al., 2024).

The lack of a unified definition for system resilience has resulted in absence of an established resilience evaluation framework (Lin and Bie, 2016) and, as a result, it led to a wide spectrum of evaluation methods that apply a plethora of scientific disciplines and fields including statistical and probabilistic approaches, machine learning, modelling and simulation, agent-based modelling etc. (Runje et al., 2021). These methods are usually classified into qualitative (e.g., checklist and questionnaires) and quantitative strategies (e.g., probabilistic methods, graph-theory methods or power flow-based performance simulations)(Lin and Bie, 2016).

Even though qualitative resilience evaluation strategies play an important role in resilient systems, quantitative approaches are generally more frequent and preferred as they can provide numeric values which can be used by policy makers or system managers to better understand a system in question, and to develop strategies to increase the resilience of it. As it was stated before, there exist many different approaches for system evaluation. Early attempts used *resilience triangle* - a curve with its highest values representing a normal system performance and each lower value indicating system performance loss caused by a disruption. Bruneau et al. (2003) used the resilience triangle to represent the expected degradation in system's quality over time and calculated its area to construct a numerical value representing seismic resilience *R*:

$$R = \int_{t_0}^{t_1} [100 - Q(t)]dt,$$

where $Q(t)$ denotes the quality of a community's infrastructure as a function of time, expressed as a percentage. The symmetry problem of the resilience triangle (two completely different systems may have the same resilience index) is analysed by Zobel (2010), where authors propose a way of analysing tradeoffs between two resilience triangle parameters (loss and time) and a new way of visualising them using hyperbolic curves. Later research incorporated new elements to the resilience triangle evolving it into a resilience trapezoid that introduced waiting time before restoration, and later fully fledged resilience curve containing multiple restoration stages as well as post-restoration consideration (return to normal state, slightly degraded state or improved state) (Amiri and Guéniat, 2024).

Probabilistic approach was used by Feofilovs and Romagnoli (2017) to evaluate DH network in Ludza (Latvia) by constructing pipe failure probabilities using Wallenius probability distribution and scores assigned by using findings from literature and expert insights. Monte Carlo simulation was used to simulate different pipe burst scenarios caused by extremely low temperature. Finally, resilience index was calculated as a ratio of scenarios in the resilience limits and a number of total scenarios.

Indicators-based approach is used by Vamanu et al. (2021) with over fifty proposed indicators for the resilience evaluation of energy systems. Composite resilience index is presented by Pakere et al. (2025) and used for evaluation and comparison of DH systems in several municipalities in Latvia by introducing four feature dimensions: technical, economic, environmental, and social covering resilience-related criteria.

3. Methodology

This research applies a graph theory-based approach utilizing a plethora of graph topology and other metrics to assess network preparedness to withstand a disruption caused by a HILP event. Graph topology metrics are used to construct several resilience-defining indicators for each building block: robustness (B_R), resourcefulness (B_U), and recovery (B_V), which are normalized, and aggregated into a single, weighted composite index later.

3.1. *Graph formulation*

DH system is formulated as a graph - network structure consisting of nodes and node connecting lines (edges) where each node refers to either consumers, pipe connections (junctions), or heat producers. Conventional graph formulation uses structure:

$$G = (V, E), \tag{1}$$

here, node set $V = V_c \cup V_p \cup V_h$, $V_c = \{v_{c1}, \ldots, v_{cn}\}$ - a set of consumer nodes, $V_p = \{v_{p1}, \ldots, v_{pm}\}$ - a set of heat producer nodes, $V_h = \{v_{h1}, \ldots, v_{hl}\}$ - a set of pipe junction nodes, and edge set $E = \{(v_k, v_l) \mid k \neq l,\ v_k, v_l \in V\}$ - represents pipes.

3.2. *Robustness*

Robustness is an important aspect of any system, as it evaluates whether the system can (and how well it can) tolerate disruptions until it fails. Shafiei et al. (2025) describe robustness as *"... a system's ability to maintain functionality even when specific components fail or unexpected disruptions occur..."*, where "unexpected disruptions" refer to HILP events. In terms of network topology, Wan et al. (2021) use robustness and resilience terminology interchangeably and define it as the size of the giant component in the network graph. Although suitable for social, biological, or geographical networks, this method may not work in DH networks, as constant connection with a heat producer must be considered.

To assess global connectivity, two graph topology metrics are used: edge connectivity and natural connectivity. Liu et al. (2017) define edge connectivity as *"... the minimum number of edges which must be removed from a connected graph in order to disconnect it."*:

$$\nu(G) = \min_{s,t \neq s \in V} \{\nu_{s-t}(G)\}, \tag{2}$$

therefore, it can be used to measure how much the system is able to withstand fragmentation during a disruption (higher $\nu(G)$ values refer to higher network robustness (Liu et al., 2017)). To normalize edge connectivity we divide it by the maximum node degree in the network:

$$\tilde{\nu}(G) = \frac{\nu(G)}{\max_{v \in V} deg(v)} \tag{3}$$

This way, we get values in the range $(0, 1]$ with values closer to one representing higher robustness. Oehlers and Fabian (2021) define natural connectivity as a measure that can be used to increase *disconnection robustness*. According to Liu et al. (2017), natural connectivity "...*characterizes the redundancy of alternative routes in a network...*" and define it as:

$$\overline{\lambda} = \ln\left(\frac{1}{N}\sum_{i=1}^{N} e^{\lambda_i}\right), \tag{4}$$

where λ_i refers to $i-th$ value of the graph adjacency matrix. The larger the value of the natural connectivity is the more robust the network is.

To normalize natural connectivity we divide it by the maximum natural connectivity as suggested by Bernal and Rey (2019):

$$\tilde{\lambda} = \frac{\overline{\lambda}}{N - \ln N} \tag{5}$$

Finally we calculate consumer and producer connectivity - how many independent routes exist between a producer $v_p \in V_p$ and a consumer $v_c \in V_c$ - $k^{v_p}_{v_c}$ for all producer and consumer nodes and then average them:

$$R_3 = \frac{1}{|V_c|} \sum_{v_c \in V_c, v_p \in V_p} k^{v_p}_{v_c} \tag{6}$$

The normalized variants of Eq. (2), and Eq.(5) are used as a three key robustness metrics in the robustness block B_R:

$$B_R = \omega_{R_1} \hat{R}_1 + \omega_{R_2} \hat{R}_2 + \omega_{R_3} R_3, \tag{7}$$

where $\omega_{R_1} + \omega_{R_2} + \omega_{R_3} = 1$ - are weights with $\omega_{R_3} = 0.5$ as R_3 measures very important metric - heat supply availability during a disaster while $\omega_{R_1} = \omega_{R_2} = 0.25$ as both ω_{R_1} and ω_{R_2} measure global network connectivity.

3.3. *Resourcefulness*

Resourcefulness is the second building block of the composite resilience index and is responsible for evaluation of system's ability to reuse existing network elements to minimise performance degradation and to reduce system's stagnation which is caused by reaction time and preparations before the system recovery. Bruneau and Reinhorn (2006) define system resourcefulness as ... *the capacity to identify problems, establish priorities, and mobilize resources when conditions exist that threatens to disrupt some element, system, or other measures of analysis.*". In terms of topology, such actions could involve re-routing by utilizing ring structures in the network (Jebamalai et al., 2022).

As with robustness, resourcefulness block B_U combines three topology metrics, starting with U_1 - connection availability between a heat producer and a consumer during a disruption. We use Monte Carlo simulation along with spatially correlated failures to simulate disruptions based on selected disruption radius r. To assess how many consumers receive heat after a disruption (network state G') occurs for each iteration of Monte Carlo simulation we calculate fraction of consumers served $S(G')$ (dividing the number of connected consumers after a disruption by the number of consumers during a normal system operation to preserve positive incrementation of the metric). Zhang and Chi (2015) use similar metric to evaluate network robustness by proposing percentage of unserved nodes (fraction of unserved area due to a component failure, calculated as a number of unserved nodes divided by total number of nodes in the network). Since the disruptions are HILP events, we cannot know where a disruption may hit, therefore, disruptions occur at a random point in the network with equal probability (*random removal* as described by Bernal and Rey (2019)) and to account for varying sizes of affection zones (different disruptions may have different magnitude) during a disaster we add severity level $s \in (0, 1]$. After every hit we calculate served fraction $S(G'(s))$ (network state G' with disruption severity level s) and then average it for every severity level s. Finally, we calculate connection availability as the area under resourcefulness curve (AUC) constructed using average served fraction per severity level:

$$U_1 = \int_{S_{min}}^{S_{max}} E(S|s)ds, \tag{8}$$

where S_{max} and S_{min} refers to maximum and minimum severity level accordingly.

Next, we assess network uniformity - whether the network is uniform or consists of interconnected components ("islands"). Uniform network is more resilient than fragmented one as a pipe failure in uniform network may not even affect the performance whereas in fragmented network a single pipe failure could disconnect major group of consumers. To assess uniformity of the graph we calculate edge betweenness centrality, defined by Oehlers and Fabian (2021) as "... *the ratio of shortest paths between two nodes that pass through the considered edge, summed up over all node pairs*" averaged and subtracted from one to maintain positive incrementation of the metric over the whole network:

$$U_2 = 1 - \frac{1}{|E|} \sum_{e \in E} b_e \tag{9}$$

As a final resourcefulness metric we calculate average efficiency to measure how easily nodes can reach each other using shortest paths between them. This is done by averaging inverse of shortest distance between any two graph nodes, defined by Bernal and Rey (2019) as:

$$U_3 = \frac{2}{N(N-1)} \sum_{1 \le i \le j \le N} \frac{1}{d(v_i, v_j)} \tag{10}$$

This symbolizes network flexibility to component failures.

Finally we combine $U1, U2$, and $U3$ into a single resourcefulness metric:

$$B_U = \omega_{U_1} U_1 + \omega_{U_2} U_2 + \omega_{U_3} U_3, \tag{11}$$

where $\omega_{U_1} + \omega_{U_1} + \omega_{U_1} = 1$ are weights, and $\omega_{U_2} = \omega_{U_3} = 0.5$ with more importance given to $\omega_{U_1} = 0.5$.

3.4. *Recovery*

Recovery (or *recoverability*) is arguably the most important aspect of DH or any other system. Even the most robust systems eventually fail, therefore, ability to quickly restore system performance back to the pre-disruption levels can be lifesaving. Kim et al. (2025) define the recoverability as *"... the capacity of engineers and society to implement effective strategies to quickly restore the functionality of a network following a disruption."* and point out that it may cover resourcefulness and rapidity on its own.

For recovery, as with resourcefulness, a Monte Carlo simulation is used to damage the graph (state G'), calculate the fraction of consumers served, and then repair the network based on edge betweenness values before a disruption to restore edges with the highest importance first (high betweenness - more connections to that edge). To assess the speed of recovery, a fraction of consumers served after every repair is calculated and averaged in the end:

$$V_1 = \frac{1}{K} \sum_{k=0}^{K} S_k, \tag{12}$$

where K - total number of repairs done and S_k - fraction of consumers served during a repair k. To assess repair effectiveness we calculate a fraction of average efficiency (defined in subsection 3.3) before $E(G)$ and after $E(G')$ a disruption occurs:

$$V_2 = \frac{E(G')}{E(G)} \tag{13}$$

V_1 and V_2 are used to construct the final building block of the resilience metric:

$$B_V = \omega_{V_1} V_1 + \omega_{V_2} V_2, \tag{14}$$

with weights $\omega_{V_1} + \omega_{V_2} = 1$ and $\omega_{V_1} = \omega_{V_2} = 0.5$.

3.5. *Resilience index*

Finally, after three resilience building blocks are constructed, composite resilience index is calculated as:

$$R = \alpha B_R + \beta B_U + \gamma B_V, \tag{15}$$

here $\alpha + \beta + \gamma = 1$ are weights associated with every building block B_R, B_U, B_V. Resilience index is bounded by 0 and 1 with lower *R* values referring to lower resilience values and higher *R* values referring to higher overall resilience. Weights $\alpha = \beta = \gamma$ and $\alpha + \beta + \gamma = 1$ (individual metric weights were defined over [0, 1] and normalized to sum to unity, with greater weights assigned to metrics of higher importance), however, the future research should consider different distribution since some aspects of resilience may be more important than others.

3.6. *Topological evaluation*

Since the resilience index is based on network topology metrics, to assess the index performance, a couple of test graphs are constructed: branch - a simple connected graph, representing a network with basic topology, and a mesh graph - a fully connected graph, representing a network with complex topology (high redundancy) (Jebamalai et al., 2022).

The data generated based on the selected synthetic graphs are passed as input to the resilience evaluation algorithm along with disruption severity level $s \in (0, 1]$. The results of resilience

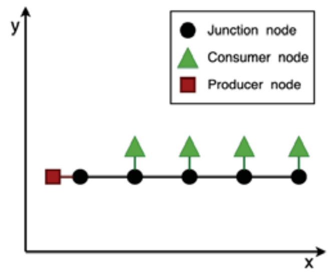

Fig. 1. Branch graph-based network.

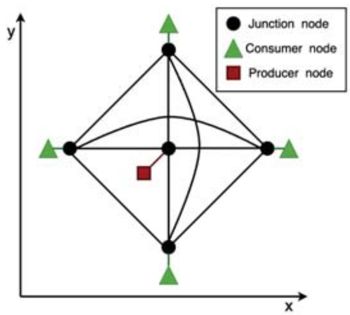

Fig. 2. Mesh graph-based network.

evaluation of branch and mesh networks in table 1 show that the network with a more complex topology returns a higher resilience index than the one with a poorer topology (less redundancy). Also, running the algorithm on a network with a single heat source results in lower resilience index (and resilience metrics) values compared to a network with two (or more) heat sources (*Branch+*). Test graphs demonstrate the methodology's capacity to react to system structure and capture redundancy. This also shows that multiple heat sources (and diversification of heat sources) are important for maximizing system resilience.

Table 1. Branch and Mesh network resilience assessment results.

	Branch	Branch+	Mesh
Robustness	0.6755	0.6755	0.9282
Resourcefulness	0.3908	0,6203	0.6813
Recovery	0.3263	0.5128	0.7056
Resilience	0.4642	0.6029	0.7717

4. Resilience evaluation of Utena DH system

The previously described resilience evaluation methodology is used to assess the resilience of Utena city's district heating system (Lithuania). Data used in this research is *GIS*-based open-access data, which is available on Utena city district heating system web page (`https://www.ust.lt/en/`). Part of data preprocessing was performed using geographic information system software *QGIS* and later - *python* for further preprocessing and calculations. The Utena DH system (see Fig. 3) consists of 1460 pipes, 541 connected consumer buildings, and one heat production plant. Connections between consumers and heat producer were not specified, therefore *kd-tree* algorithm was used to assign consumer nodes (as well a producer) to the nearest junction nodes.

The data gathered was used to construct a DH system graph as described in section 3. After preprocessing, the data was passed to the resilience evaluation algorithm. The evaluation results are presented in table 2. The results show that, overall, Utena DH system resilience is in the second quarter of possible index values, indicating room for improvement, with system resourcefulness and recovery requiring the most attention. It should be noted that the methodology used captures only the system's topology, and a more comprehensive analysis will be conducted in future research using an expanded set of resilience metrics. (as described in section 6).

Table 2. Utena DH system resilience evaluation results.

	Utena DH system
Robustness	0.5626
Resourcefulness	0.355
Recovery	0.1184
Resilience	0.3454

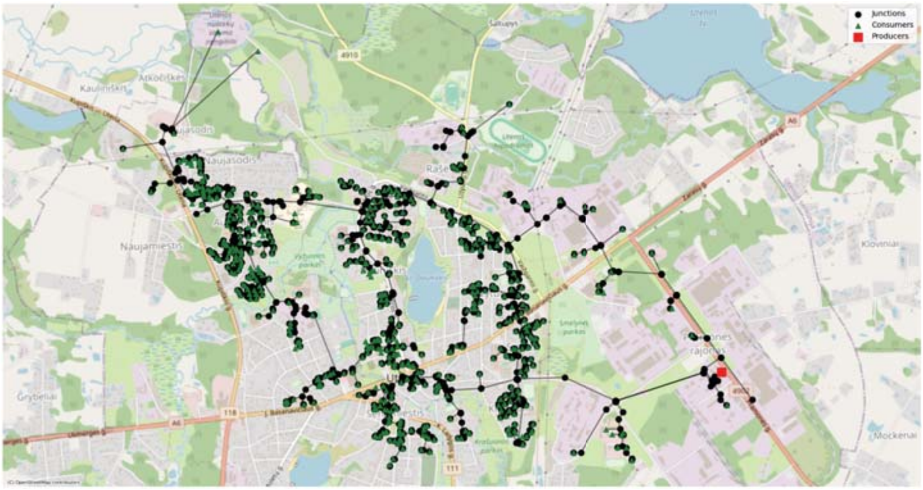

Fig. 3. Utena district heating system.

5. Conclusions

In this article, a novel resilience evaluation framework is proposed, with an emphasis on the importance of graph topology metrics in network-based systems. A composite resilience evaluation index is proposed, using three key resilience metrics - robustness, resourcefulness, and recovery - as building blocks. Each key metric is constructed using several graph topology metrics to capture network topology aspects relevant to that metric. To test the index's performance under topology changes, two basic networks are constructed: a *branch* network representing a simple topology with no redundancy and a *mesh* network with high redundancy. After running the resilience evaluation algorithm, the results align with expectations - a simple topology yields a lower resilience index, while a more complex topology yields a higher one. The resilience of multiple heat sources was also evaluated (*branch*+ network), and the results were compared to the system with one heat source. Results showed that more heat sources lead to higher system resilience, as failures of major connections are mitigated by redundant connections to other heat sources. This aligns with a key aspect of resilience - redundancy and energy diversification. Finally, the resilience evaluation methodology was applied to assess the DH system of Utena (Lithuania). Based on the results, the resilience of the Utena DH system is bellow average, with the greatest attention needed on system resourcefulness and recovery improvements. As noted before, the resilience methodology applied is based on topology of the system, and more detailed analysis will be performed in the future.

6. Future Work

Future research will introduce a broader range of resilience metrics into each resilience-building block. Since DH systems use water as a heat carrier, thermal-hydraulic simulations will be used to account for pressure changes resulting from pipe bursts in the network. Finally, resilience assessment only provides system's state at the time of estimation; therefore, optimization will be performed not only to estimate current preparedness but also to improve it with minimal resources, as redundancy usually entails costs.

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