

Jonatan ZISCHG

# Understanding patterns, dependencies and resilience in complex urban water infrastructure networks

## FINAL REPORT

on the research stay at

Purdue University

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Supervisor at home university:

Assoz.-Prof. Dipl.-Ing. Dr. techn. Robert Sitzenfrei, Department for Infrastructure, University of Innsbruck

Supervisor at host university:

Prof. P. Suresh C. Rao, Lyles School of Civil Engineering, Purdue University

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## General description

This final report describes the outcome of the research visit from Jonatan Zischg at Purdue University from September, 20<sup>th</sup> 2017 to December, 19<sup>th</sup> 2017. During these three months the research collaboration between Purdue University and the University of Innsbruck also beyond the research visit were strengthened. Regular skype meetings and a joint research proposal for future collaboration are considered. Although the time period was restricted, most of the pre-defined goals could be achieved. The main goals of this exchange were defined as follows:

First, the *strengthening of interdisciplinary thinking* in terms of the overall topic of complex networks was sought. This goal included the learning of new approaches and methods, discussions and collaborative working with experts in the field of complex network analysis. The main goal was to identify reoccurring network patterns and network motifs in different types of natural and engineered systems. During the research visit Jonatan Zischg closely worked with Prof. Suresh Rao and his PhD students on the topic of complex network analysis. Among them the collaboration and common research questions with Christopher Klinkhamer, who is working with urban infrastructure networks and their interdependencies, and Soohyun Yang, who is working with natural river networks and engineered sewer networks, were the most promising. Furthermore, also contacts to other groups could be established.

Second, the *understanding urban network evolutions, co-locations and interdependencies* (e.g. street network and water infrastructure) based on the geospatial embedding, the functional topology and other structural graph characteristics, were investigated. The process of network evolution gave insights in the historical development and design and how the network might grow in the future. The investigation of different network types and their interdependencies in one holistic model (the so-called multiplex network theory) was proposed in first investigations.

The third question was to find an answer on what is a *robust and resilient network structure*. By stressing networks with varying topologies (e.g. different districts in a water distribution system – also considering the rich-poor divide), different structural (e.g. network integrity) and functional changes (e.g. supply security) were observed. The hypothesis was that differences in network topologies indicate resilience. With regard of this topic, realistic failure scenarios for the resilience analysis were defined and the expansion of the methodology to various real and virtual (“in-silico”) networks to find a (general and type specific) structural resilience metric was striven. With regard to this topic, first results were obtained, however, the analyses could not be completed due to lack of time.

The last objective was to write a *joint publication* based on the abovementioned research questions. The content of the work is mainly based on the first and second objective. The publication will be submitted to an international journal and builds the basis of this final report. With regard to the third objective of determining the robust and resilient network structure, a methodology was defined to identify critical

components of water supply networks. Thereby not only the criticality of pipes (network edges) can be identified, but also other structural components, like isolation valves (network nodes), are evaluated by means for complex network analysis. The novel methodology is presented in the last chapter of this report.

## **Chapter 1: Understanding urban network evolutions, co-locations and interdependencies**

This chapter presents the first version of the joint publication, entitled “A Century of Topological Co-evolution of Complex Infrastructure Networks in an Alpine City”.

### **Abstract**

In this work, we used complex network analysis approaches to investigate topological co-evolution over a century of three different urban infrastructure networks. We performed network analyses using on a unique time-stamped network data set of an Alpine case study, representing the historical development of the town and its infrastructure over the past 107 years. The analyzed infrastructure encompass the water distribution network (WDN), the urban drainage network (UDN), and the road network (RN). We use the dual representation of the network, with pipes or roads as nodes and intersections as edges. The functional topologies of the networks are analyzed based on the dual graph, providing insights beyond a conventional graph (primal mapping) analysis. We observe that roads, WDN and UDN all exhibit “scale-free” network characteristics [Pareto node-degree distributions,  $P(k)$ ], and evolve with consistent patterns over time. However, structural differences between the three network types resulting from different functionalities are reflected in the  $P(k)$  and the characteristic path lengths. We show the remapping of the dual network characteristics to the spatial map, the identification of criticalities among different network types through co-location analysis and discuss possibilities for further applications.

### **Introduction**

The field of complex network analysis originated in statistical physics at the end of the 20<sup>th</sup> century, and is now widespread among numerous disciplines including natural, technical, and social sciences. In engineering, the focus of network analysis has shifted away from the traditional perspective of investigating individual components to the exploration of topological properties of the networks, taking a holistic view of the entire system (Blanchard & Volchenkov 2008). Many complex systems can be described in form of a network, with recent increases in computing power making it feasible to investigate the topologies of entire networks consisting of high-resolution data (Strogatz 2001). Examples of these types of investigations range from molecular interaction networks (e.g. protein interactions of cells) and social networks (e.g. communication between humans) to global transportation systems and individual human mobility (Assenov et al. 2007; Gonzalez et al. 2008; Uhlmann et al. 2012).

Despite the various types and representations of these networks, important commonalities exist. Most complex networks are neither regular graphs (e.g., perfect grids), nor are they purely hierarchical systems (e.g., trees), but a hybrid of these structures (Louf & Barthelemy 2014). The analysis of complex networks gives insight to structural morphologies, similarities, recurring patterns and scaling laws (Barabási & Albert 1999). The applications are multifaceted: Identification of central nodes; prediction

of future developments and network growth (e.g., information spreading); identification of vulnerabilities to enhance security (Zweig & Zimmermann 2008), and improvement of the network resilience (Sterbenz et al. 2013). Complex network analyses of critical infrastructure, such as water distribution networks (WDNs) and urban drainage networks (UDNs), provide valuable insights beyond the traditional engineering approaches to design and operate systems in a more reliable way, and to help build-up structural resiliency (Yazdani et al. 2011).

In the past, most structural features in complex networks were investigated based on a conventional graph representation (so-called “primal space”), where pipes or conduits are the edges and their intersections the vertices of a mathematical graph (Zeng et al. 2017). Conversely, different approaches, based for example on common attribute classification (i.e., road name or pipe size) or intersection continuity (i.e. maximum angle of deflection), consider the network structure in its “dual space”, i.e. functional components (e.g. pipes with same diameter) which belong together, represent the vertices and their intersection the edges of the graph (Masucci et al. 2014). Further explanations are given in the subsequent section. Unlike the conventional primal representation, dual mapping approaches may also consider the continuity of links (pipes or conduits) over a variety of edges and hierarchy (e.g., pipe diameter; maximum designed flow) for further graph analysis.

Previous studies using the dual mapping approach were mainly performed on road networks (Porta et al. 2006; Hu et al. 2009; Masucci et al. 2014), but an extension to each network type is possible. Masucci et al. (2014) investigated the road network growth for the city of London and found stable statistical properties to describe the topological network dynamics. Krueger et al. (2017) applied the HICN principle for the first time to the evolving sewer networks in a large Asian city with 4 million people. The authors found that sewer network types quickly evolve to become scale-free in space and time. In Jun and Loganathan (2007) a dual mapping approach was used to describe the connectivity of isolation zones in water distribution networks. Klinkhamer et al. (2017) examined the co-location of existing road and sewer networks in a large Midwestern U.S. city, and homoscedasticity of subnets across the city, but did not examine temporal evolution of these networks. In Mair et al. (2017) the geospatial co-location of roads, pipes and sewers was investigated using data set for one time for three Alpine case studies, finding strong similarities between the systems. Studies on the co-evolution of water infrastructure networks (water distribution and urban drainage) and road network are crucial when investigating functional interdependencies and cascading vulnerabilities across different network layers. Examples are the flood induced change in road traffic or the collapse of entire road segments causing flow disruptions in all systems to different extents.

In this work, we present for the first time a topological analysis of three infrastructure networks co-evolving over a century. The results of the dual mapping for a unique dataset of 11 time-stamped water distribution and urban drainage network states and 8 time-stamped road networks of the medium size Alpine case study, as the town and its infrastructure evolved during the last 107 years, and the population tripled from about 40K to about 130K. We investigated network topological metrics using the

Hierarchical Intersection Continuity Negotiation (HICN) dual mapping approach (Masucci et al. 2014). We observe that all infrastructure networks show “scale-free” network characteristics under the dual representation, and evolve with consistent patterns over time. With the presented methodology patterns (e.g. vertex connectivity) and trends for the future network development and engineering design are obtained. The study includes an investigation of the sensitivity of the dual mapping approach, using different criteria to build the new graph. The reflected structural features, such as the backbone of the networks, were uncovered for each network type and remapped to the spatial map. A further analysis shows the pairwise co-location of high node-degree components (“network hubs”) across different infrastructure network types, which builds the basis for analyzing disturbances and structural resilience.

## Data analyses

### *Network connectivity*

Node degree distribution [P(k)] is a significant topological property of complex networks. The degree (k) of a node i in an undirected network describes the number intersecting links, and is calculated through the network’s adjacency matrix A, where the degree of node i is defined by the sum of the i-th row of A. For example, the node degree in social networks represents the number of contacts. Engineered networks show scale-free characteristics, following a Pareto power-law distribution (Klinkhamer et al. 2017; Krueger et al. 2017), with  $P(k) \sim k^{-\gamma}$ ,  $k \geq k_{min}$ . The mean node-degree is defined as  $\langle k \rangle = \frac{2e}{n}$ , where e is the total number of edges and n is the total number of vertices. In the limits a mean degree of 2 indicates a tree-like network structure, grid patterns or cyclic structures have mean degrees around 4 (Barthélemy 2011). Along with the node degree distribution, the characteristic path length  $\langle l \rangle$  (or average path length) is an important and robust measure of network topology. It quantifies the level of integration/segregation throughout the network. In water infrastructure and power grid networks energy losses are dependent on the characteristic path length. It is calculated by the average shortest path distance between all couples of nodes as follows:

$$\langle l \rangle = \frac{1}{n \times (n - 1)} \times \sum_{i \neq j} d(v_i, v_j),$$

where n is the number of vertices and  $d(v_i, v_j)$  denotes the shortest path between vertex  $v_i$  and  $v_j$  (Assenov et al. 2007). The probability density function of the path length, P(l) can, for example, be considered as the approximation of the travel-time distribution with a nearly consistent distribution of flow velocities.

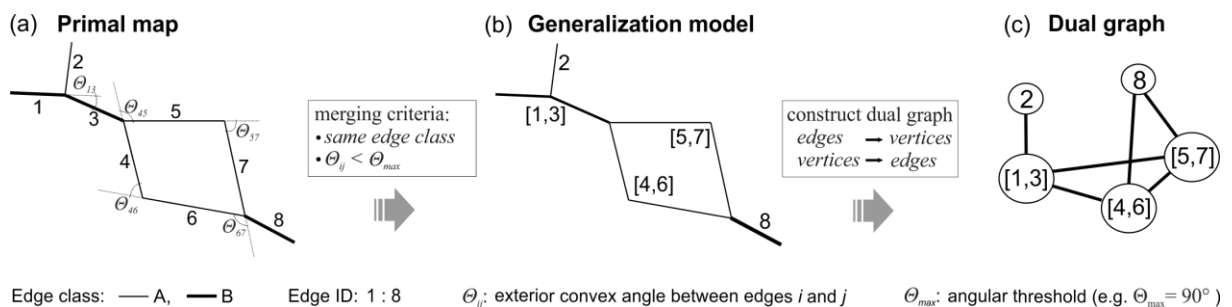
The local clustering coefficient  $C_i$  of node i describes the connectivity (number of edges m) among its k neighbors. A perfect cluster/cliq (  $C_i = 1$  ) indicates a full connection of all nodes/individuals. If an

isolation of one node in the cluster occurs, the other nodes remain connected. Conversely, a  $C_i = 0$  indicated that node  $i$  holds together all its neighboring nodes. Regarding infrastructures, a higher clustering coefficient indicates more loops and alternative flow paths in the network. In an undirected graph  $C_i$  is defined as follows:

$$C_i = \frac{2 \times m}{k_i \times (k_i - 1)}$$

### HICN Principle for Dual Mapping

The HICN approach emphasizes the functional topology of the network by aggregating components (e.g., pipes, conduits, roads) with identical attributes (e.g., pipe diameter, road type), while also maintaining a certain level of straightness (e.g., road sections) (Masucci *et al.* 2014). After reducing the network complexity with this “generalization model,” the aggregated edges are converted into vertices and the intersections are converted into edges. The resulting graph is the so-called “dual” (mapped) representation of the “primal” graph (see Figure 1). In addition to the edge class, the angular threshold  $\Theta_{max}$  is a second criterion used for the generalization model. It defines the maximum exterior convex angle of connected edges being merged (Porta *et al.* 2006).



**Figure 1:** HICN method to construct the dual graph from the primal map. Resulting dual graphs are dependent on the generalization model (adapted from Zischg *et al.* (2017a) with permission from ASCE).

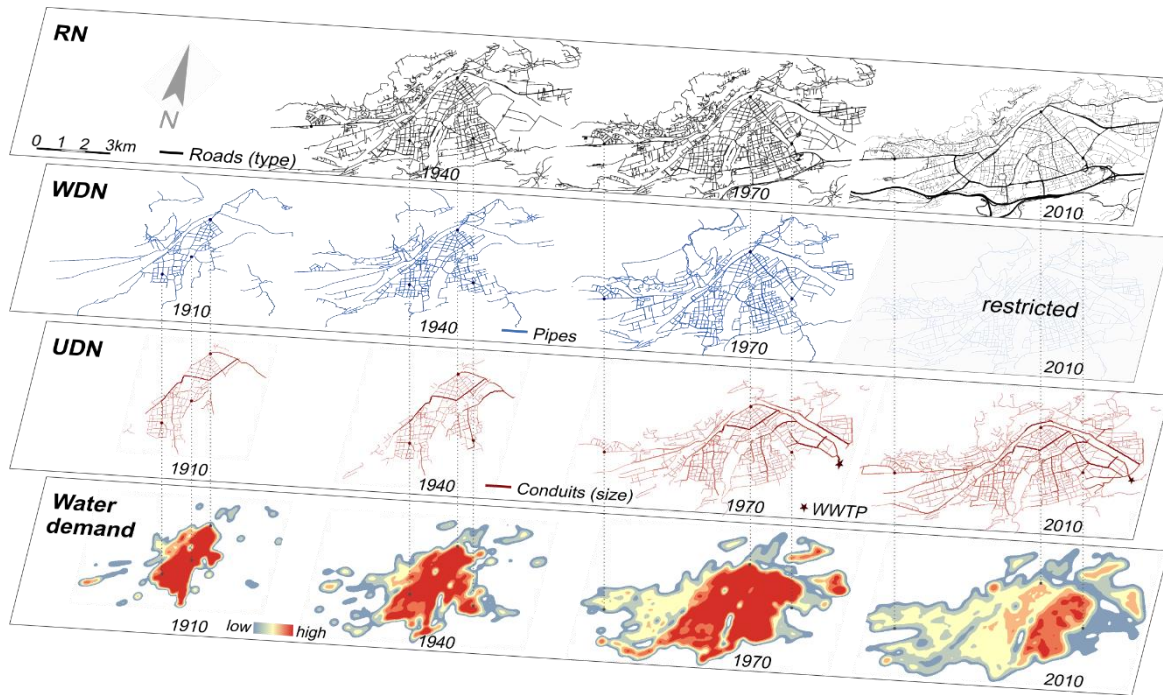
The HICN allows for reducing the network complexity of the primal map and considers the hierarchy of network elements (e.g., different level of detail of the pipe representation). Identical cohorts of edges are considered as a single component, the dual node. Take for example the same pipe segment (identical diameter) mapped with differing criteria: On the one hand, it is described with 2 vertices (start vertex + end vertex) and, on the other hand, is described with 10 vertices (start vertex + end vertex + 8 intermediate vertices). The resulting graph characteristics in primal representation are significantly different (e.g. mean degree of 1 and 1.8), which shows the important effect of network simplification before the complex network analysis. However, the dual-mapped network circumvents this issue through generalization and still preserves the connectivity information of the original network. Another advantage is the detachment from the geographical embedding, allowing the network to be non-planar.

With this methodology, the underlying hierarchy (e.g. highly connected components) of the network can be uncovered.

### **Alpine case study**

To investigate the co-evolving topology of three urban infrastructure networks with the HICN dual mapping methodology, we utilize available, high-resolution network data for a medium size alpine city. The temporal evolution of the urban infrastructure networks is defined through time-stamped system states at 10-year intervals, starting with the year 1910 for water distribution and urban drainage networks. The road network data starts with the year 1940, since historical orthophotos to reconstruct the network were only available from that time. The city has grown from approximately 40,000 inhabitants in 1910 to 130,894 in 2016. The historical data set describes the expansion of the networks, and includes pipe rehabilitation, changing source (e.g. reservoirs) and sink nodes (e.g. sewer outfalls), altering population densities, and variations of water consumption patterns of the water distribution and urban drainage systems. The detailed description of the network reconstruction for this case study can be found in Sitzenfrei et al. (2015) and Glöckner (2017). Figure 2 shows the time-stamped networks at chosen stages in the primal map. For the UDN a greater thickness and a darker color of the edges indicates a larger conduit size, which connect to one large waste water treatment plant (WWTP) in the eastern part of the city after the 1970s. Before the wastewater was directly discharged to the river, outside the urban areas at the eastern parts of the city. When actually building the WWTP, there were no major changes in the network necessary. The old outlets were transferred to combined sewer overflows (CSOs). For security reasons the pipe diameter for the WDN cannot be shown. The color shading at the road network in 2010 indicates the different road types, ranging from residential (light grey), tertiary, secondary, primary roads, and motorways (black).





**Figure 2:** Time-stamped co-evolution of the water distribution network (WDN), the urban drainage network (UDN) and the road network (RN) of an Alpine city.

Table 1 gives a short narrative introduction on the history of the infrastructure networks of the investigated case study during the last century.

**Table 1:** Narrative changes of the infrastructure networks (Schulze 2012; Gloeckner 2017).

Years	Narrative
before 1910	WDN for about 23,000 inhabitants; total population 49,727 in 1900; design demand 150 liters per capita and day
1910 - 1929	maximum recorded water consumption of 500 liters per capita and day in 1927; 30% of the current WDN structure existed already in 1910
1930 - 1949	2 world war; infrastructure mainly unaffected; reduction of water consumption below 300 liters per capita and day through information campaigns
1950 - 1969	construction of the WWTP (mechanical treatment) in 1966; strong UDN expansion in western and eastern direction; biggest growth rates for the WDN between 1960-70.
1970 - 1989	380 liters per capita and day; construction of the highway (70s); construction of the biological treatment at the WWTP in 1974; connection of neighboring villages to the WWTP; maximum loads of 330,000 people equivalents (PE) in 1987
1990 - 2009	Further connection of neighboring villages; expansion of the WWTP to 400,000 PE; minor network expansions, increased pipe and sewer rehabilitation
2009 - present	About 250 liters per capita and day (domestic water demand is app. half of it); Reduction of people equivalents to 270,000 PE (2011); Roads:476 km; WDN: 320 km; UDN 244 km.

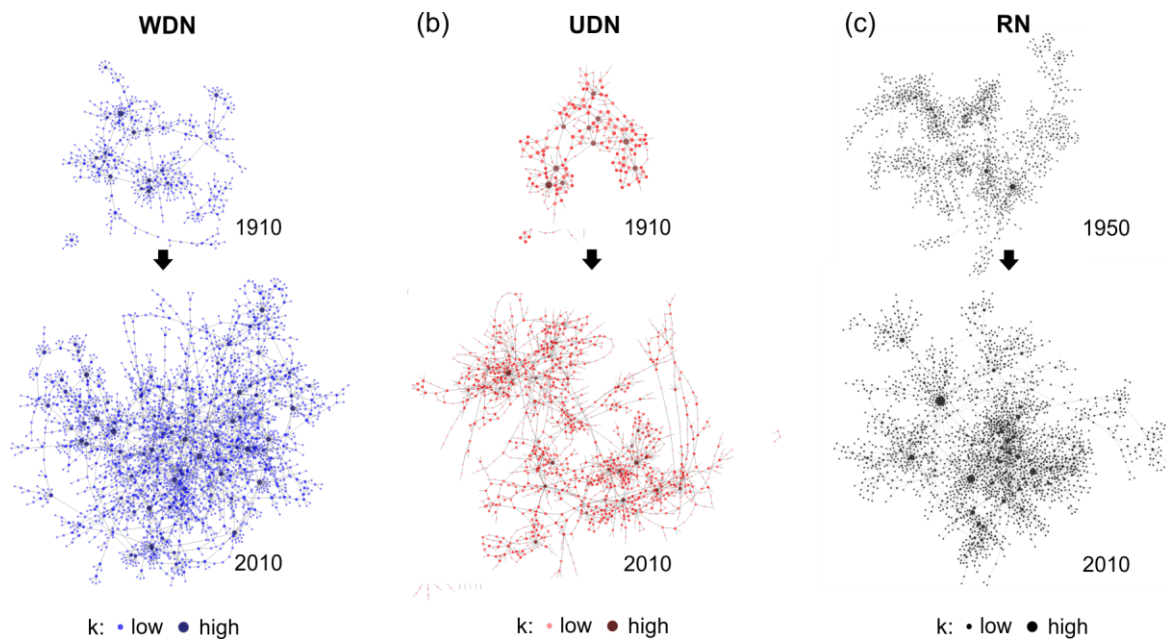
## Results and Discussion

In this section, we present the results of the historical co-evolution dual representation of the three infrastructure networks (WDN, UDN and RN), followed by a sensitivity analysis of the HICN dual

mapping. In this analysis, a parameter variation of the angular threshold, the edge class, and the network partition (entire network vs. largest connected component (LCC)) is performed, while investigating the parameter sensitivity on the node degree distribution. We also show the remapping of dual network characteristics to the primal map, investigate correlations between dual node degree and edge class (e.g. road type) and identify pairwise spatial co-locations of dual nodes among the three network types.

### Dual mapping

The application of the HICN dual mapping to the historical infrastructure networks for the first (year 1910 for WDN and UDN, and 1940 for RN) and last stage (year 2010) is illustrated in Figure 3. The dual graphs show the node degree (darker and larger nodes represent central network “hubs” with high node degree). For the application of the HICN method to the water infrastructure networks, identical pipe diameters (WDN) and conduit sizes (UDN) are used for the edge class criterion in combination with an angular threshold  $\theta_{max}$  of 180 degrees; i.e., we ignore the curvature of pipe/conduit segments. On the other hand, for the dual mapping of the road networks, we used the  $\theta_{max}$  of 45 degrees (Zhan *et al.* 2017) and the road type as criteria for the generalization model. We further discuss the application of different parameter values in the section Dual Mapping Sensitivity.



**Figure 3:** Dual mapped co-evolution of the infrastructure networks: (a) WDN, (b) UDN and (c) RN. The color shading and size of the node indicates its degree.

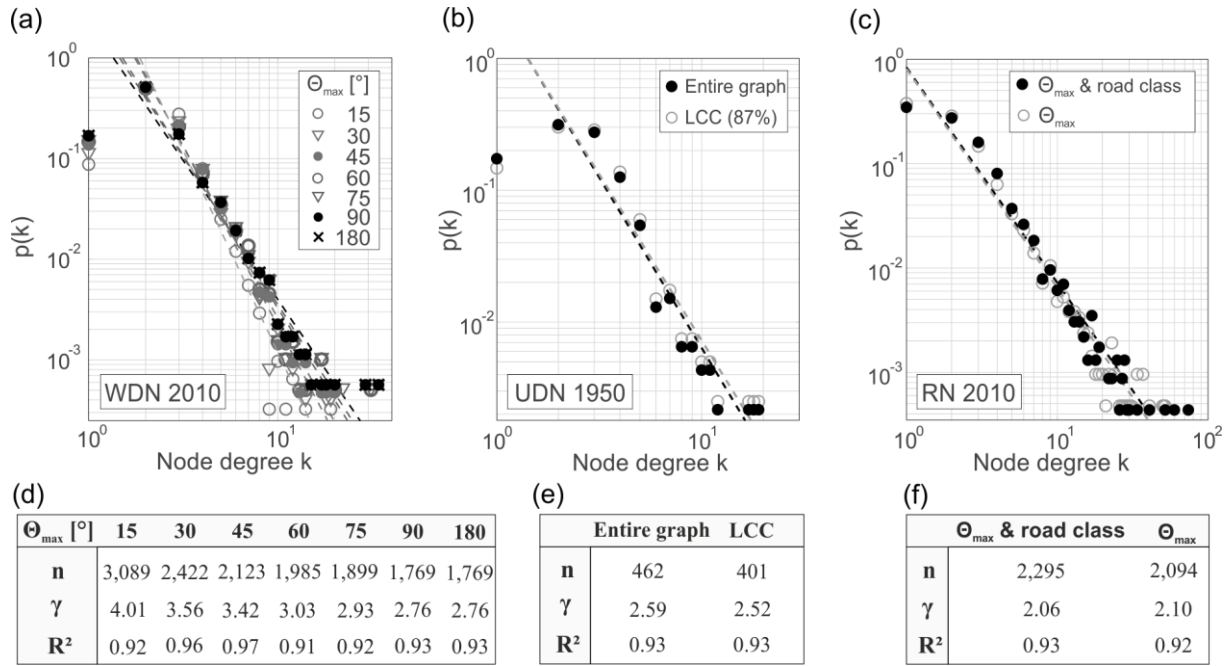
### Sensitivity of the dual mapping

For the HICN approach different angular thresholds and edge attributes can be considered to construct the dual graph. In Figure 4 we show the results of the sensitivity analysis on the node degree distribution for three parameters used for the HICN approach. First, we identify the sensitivity of the angular threshold  $\theta_{max}$  using the WDN of 2010 as reference. Second, we choose the UDN 1950 with 10 sub-

networks and investigate the graph characteristics for the entire network and the largest connected component (LCC) only. Finally, we show the effect of neglecting the edge class criterion (road type) for the RN in 2010 as reference. The black nodes represent the network configuration as presented in the previous section.

With increasing angular threshold  $\Theta_{max}$  we observe that more pipes (of the same class) are merged together and therefore the size of the dual graph is reduced (see Figure 4 a). For example, the reference network has 7,392 edges in the primal space, which are generalized to 3,089 and 1,769 dual nodes for angular thresholds of 15 and 180 degrees, respectively. Figure 4 (d) shows the outcome of 7 variations of the angular threshold  $\Theta_{max}$  from 15 to 180 degrees. All resulting node-degree distributions follow truncated power-law distributions, with increasing slope for lower threshold angles. The results using angular thresholds of 90 and 180 degrees are identical, meaning that no sharp inner angles between connected pipes of the same class are found in the graph. Unlike for road networks, where  $\Theta_{max}$  also is a criterion for visibility, we suggest that restricting  $\Theta_{max}$  in WDNs and UDNs is less important to find and aggregate pipe segments with unique identity because of their underground locations. We conclude that for investigating the node degree distribution of the historical networks, the angular threshold  $\Theta_{max}$  is of minor importance, but must be consistently applied between the types and the states of the networks. Figure 4 (b) shows the results when investigating the entire graph (all sub-networks) and the largest connected component (LCC), which contains 87% of the total nodes. For the reference network UDN 1950, no significant changes in the power law exponent are seen (see Figure 4 e). Finally, the neglection of the road class as additional criterion for the HICN method slightly decreases the size of the network, but has a low effect on the probability density function (see Figure 4 c and 4 f). This can be interpreted with the low incidence of changing road types across straight road segments.

In this study, we used the pipe diameter to identify functionally identical pipe segments. However, any geometric or hydraulic parameter could be used, but (potentially) leading to different outcomes. Examples could be the age or the material of the pipe, but also classified (design) flows or (measured or modeled) head losses. The advantage of using the pipe diameter is that it is a surrogate measure of the flow and is independent of a hydraulic simulation.

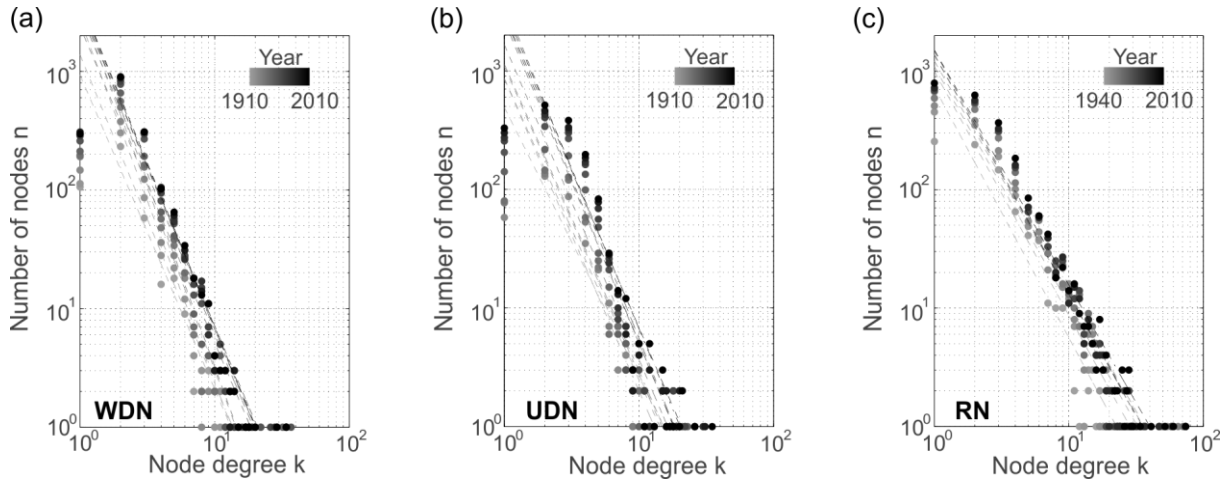


**Figure 4:** Sensitivity of the HICN approach on the node degree distribution of the WDN 2010

#### Characteristics of the dual graph

Resulting nodal-degree distributions,  $P(k)$ , for the WDN, UDN and RN in the dual space are presented in Figure 5, plotted for all network types on log-log axes for the time-stamped states. A darker node color indicates a younger and more mature network state. We observe emergence of a consistent pattern, namely, a truncated power law distribution  $p(k) \sim k^{-\gamma}$ ,  $k \geq k_{\min}$ , with  $k_{\min}$  equal to 2 for all three network types. For the WDN (mean:  $2.82 \pm 0.18$ ) and UDN (mean:  $2.63 \pm 0.14$ ) larger slopes and a stronger decrease of the number of leaf nodes ( $k = 1$ ) are found compared with the RN (mean:  $2.15 \pm 0.09$ ). A possible explanation of the truncation could be the missing house (low-degree) connections for both water infrastructure networks. The exponent  $\gamma$  values fall in the range between 2.65 and 3.12 for WDN, 2.27 and 2.84 for UDN, and 2.06 and 2.35 for RN (see Table 1). The goodness of fit is described with the coefficient of determination  $R^2$  and is based on log-log linear regression values (see Table 1).

The truncated power law [Pareto] distribution also indicates that the probability of finding nodes with many connecting links (“hubs”) is much lower than of nodes with few connections (terminal dual nodes). According to the literature this behavior is typical for scale-free networks, which are dominant in most natural networks. The “scale-free” characteristics, within the observed range  $[k_{\min} \leq k \leq k_{\max}]$ , are also indicated with the significant higher maximum degrees  $k_{\max}$  (representing a “network hub”) compared to the mean degree  $\langle k \rangle$  (see Table 1a).



**Figure 5:** Dual node degree distribution over time of (a) the WDN, (b) the UDN and (c) the RN. The color shading from light grey to black indicates the evolution of the network.

Although the mean degree  $\langle k \rangle$  of the UDN is larger than that for the WDN, the maximum degree  $k_{max}$  of both water infrastructure networks are similar. One reason for that are fewer changes in the conduit diameters, resulting in the aggregation of more conduits and thus having higher connectivity. The highest connectivity is found for the road network, indicated a high  $k_{max}$  and  $\langle k \rangle$  (see Table 1b).

**Table 2a:** Topological dual mapped properties over time for the WDN, UDN and RD.

Year	n			$\gamma$			R <sup>2</sup>		
	WDN	UDN	RN	WDN	UDN	RN	WDN	UDN	RN
1910	451	223	-	2.65	2.27	-	0.92	0.93	-
1920	577	321	-	2.77	2.63	-	0.92	0.90	-
1930	745	354	-	3.06	2.54	-	0.87	0.91	-
1940	968	436	849	3.07	2.60	2.35	0.94	0.91	0.87
1950	1,056	462	1,278	3.12	2.59	2.20	0.94	0.93	0.89
1960	1,223	715	1,420	2.66	2.65	2.14	0.92	0.89	0.93
1970	1,513	1,042	1,716	2.72	2.72	2.08	0.90	0.92	0.94
1980	1,641	1,236	1,937	2.73	2.84	2.11	0.92	0.94	0.91
1990	1,719	1,318	1,993	2.69	2.76	2.12	0.94	0.87	0.90
2000	1,764	1,431	2,081	2.76	2.64	2.15	0.91	0.90	0.91
2010	1,769	1,585	2,295	2.76	2.70	2.06	0.93	0.87	0.93
<i>Mean:</i>				2.82	2.63	2.15			
<i>Variance:</i>				0.031	0.021	0.008			

Furthermore, change in slopes ( $\gamma$ ) reveals that secondary pipes connect more likely to “well-connected” main pipes. The growth of the networks in terms of total number of dual nodes  $n$  over time is illustrated in Figure 6 (a). Highest growth rates of the networks are seen in the 1960’s and 1970’s, which can be partly related to the economy boom and the implementation of the waste water treatment plant (Sitzenfrei *et al.* 2015).

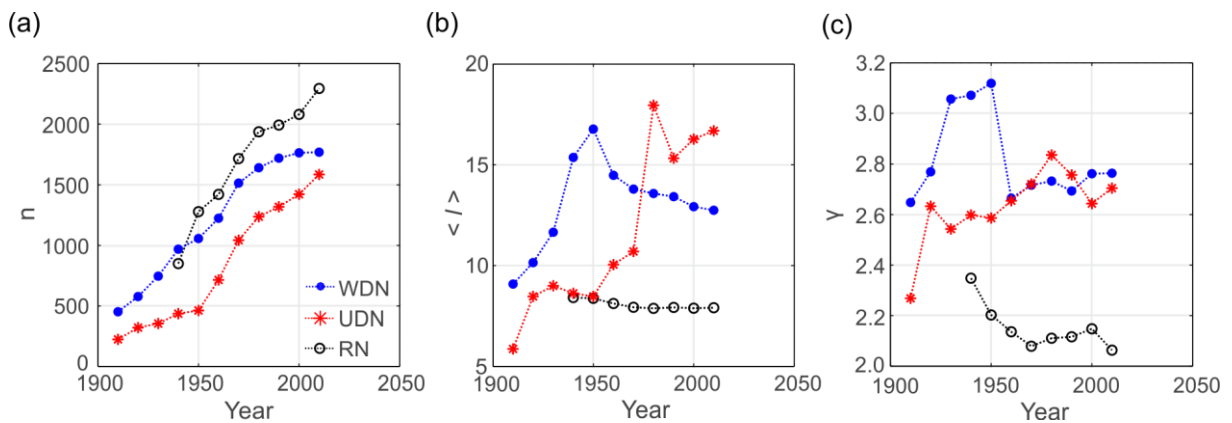
**Table 2b:** Topological dual mapped properties over time for the WDN, UDN and RD.

Year	$\langle k \rangle$			$k_{max}$			$\langle l \rangle$		
	WDN	UDN	RN	WDN	UDN	RN	WDN	UDN	RN
1910	2.37	3.19	-	15	16	-	9.09	5,87	-
1920	2.44	2.91	-	22	19	-	10.15	8,47	-
1930	2.43	2.88	-	14	19	-	11.65	9,00	-
1940	2.42	2.93	3.03	17	19	32	15.36	8,63	8.41
1950	2.43	2.93	2.92	17	19	52	16.77	8,47	8.38
1960	2.47	2.82	2.95	32	23	54	14.47	10,05	8.12
1970	2.53	2.77	3.00	37	22	65	13.79	10,70	7.93
1980	2.56	2.75	3.05	34	22	71	13.57	17,95	7.88
1990	2.56	2.76	3.05	34	30	74	13.42	15,32	7.93
2000	2.58	2.77	3.05	34	31	74	12.92	16,28	7.89
2010	2.59	2.81	3.03	34	35	74	12.74	16,68	7.91

The characteristic path length  $\langle l \rangle$  of the network states is shown in Table 1b and Figure 6 (b). In the dual representation, the path length defines the number of changing edge attributes (e.g. diameter changes) between two dual vertices. We observe that the  $\langle l \rangle$  value is much smaller than the number of vertices, which is an indicator for a “small world” property of the graph, meaning that every vertex is connected to every other through a very short path. In general,  $\langle l \rangle$  increases with expanding geographical boundaries of the network (Figure 6 b). During the 1980’s there is a significant increase of  $\langle l \rangle$  for the UDN, possibly because the tree-like connections of peripheral zones and neighboring villages to the central wastewater treatment plant. In contrast,  $\langle l \rangle$  for the WDN decreases during the past few years, as a result of the WDN densification and the construction of alternative flow paths (loops) for redundancy purposes. Furthermore, it is remarkable that  $\langle l \rangle$  for the UDNs at the early stages of the 20th century is lower compared to that for WDNs. One reason for that is that the UDN at the historical center of the Alpine case study had fewer alterations of conduit diameters (see Figure 2, middle left), resulting from the coarse design concepts and material limitations at that time. As the road network grows over time, we observe the lowest values for  $\langle l \rangle$  a nearly constant trend over time, indicating a high network integrity. To compare the results with the physical shortest path length (e.g., in km) in the original geographical embedding, the same analysis should be repeated in the primal representation of the network.

Figure 6 (c) presents the slopes  $\gamma$  of the node-degree distributions  $[P(k)]$  over time. When comparing  $\gamma$  with previous studies in the literature, similar ranges between 2 and 3 are reported (Porta *et al.* 2006; Klinkhamer *et al.* 2017; Krueger *et al.* 2017). In this study, the lowest exponents are reported for the RN compared to those for the WDN and UDN. Peaks of  $\gamma$  are found during the 1930’s and 1950’s for the WDN and around 1980 for the UDN. This can be explained with the tree-like expansion of the network to new parts of the city (also indicated with larger characteristic path lengths) and without a strong network densification at those times. During the last part of the 20<sup>th</sup> century the all infrastructure networks evolved with a homogeneous pattern, namely a network growth with a nearly constant power

law exponent  $\gamma$ . This could indicate that the networks are now topologically “mature”, i.e., a similar behavior is expected when the network grows further.



**Figure 6:** Topological properties of co-evolving WDN, UDN and RN: (a) Number of vertices  $n$  over time; (b) characteristic path length  $\langle l \rangle$  over time and (c) power law exponent  $\gamma$  over time.

Possible further applications of the historical network evolution could be applied to future scenarios and an automated network growth algorithm. Furthermore, the generation of virtual networks, using the determined scale-free characteristics (e.g., node-degree distributions,  $P(k)$ ) as additional design criteria, could be subject to further studies. A first step towards more resilient networks is already proposed by Mair *et al.* (2014) and Zischg *et al.* (2017b), who used a subset of the co-located road network with strong similarities to generate virtual WDNs. Moreover, future studies should emphasize on the investigation of many other water infrastructures with different climatic, geographical, topological, and political characteristics. Previous studies showed that understanding the network structure gives insights to vulnerabilities and structural resilience of the systems. Scale-free networks are found to be highly resilient against random failure, but are vulnerable to targeted attacks (Zweig & Zimmermann 2008; Bao *et al.* 2009).

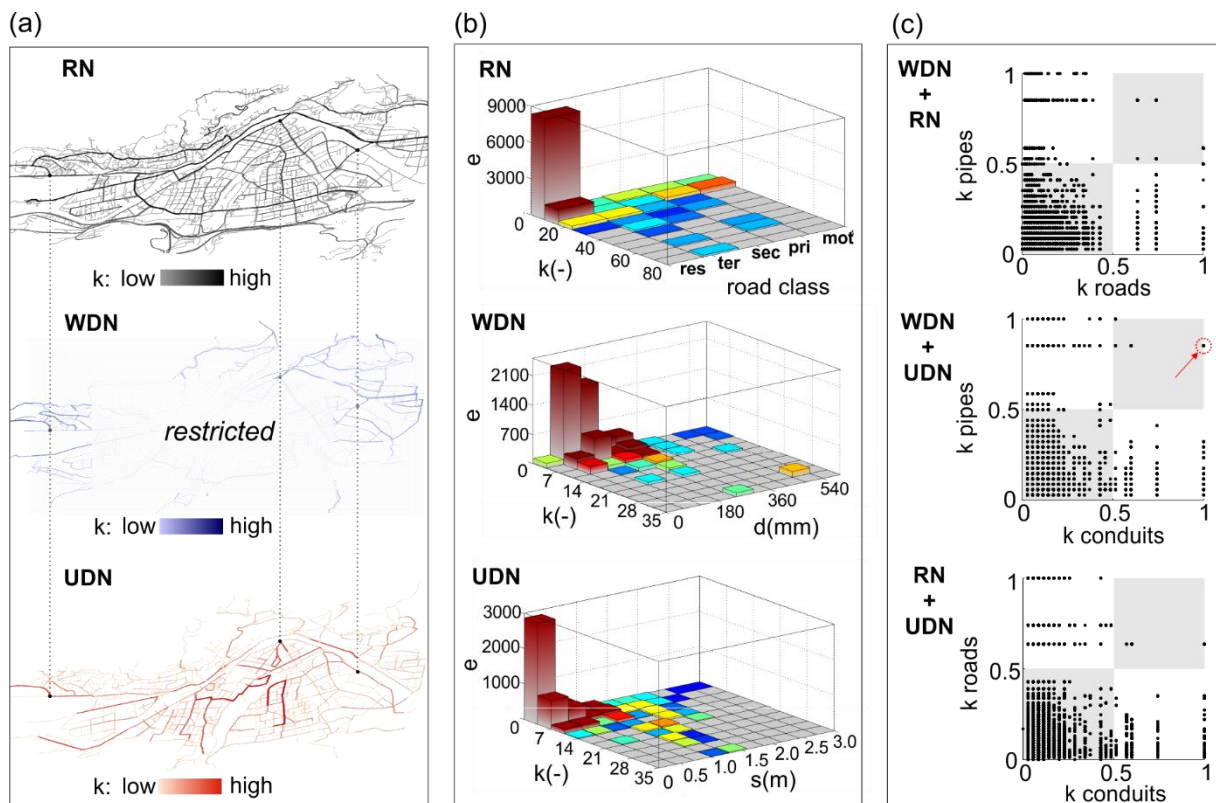
#### *Remapping from dual to primal space*

Remapping the dual graph characteristics to the primal graph representation allows for a geo-referenced visualization and further spatial analyses among the different network types. Figure 7 (a) shows the example of remapping the dual (node) degree to the original physical embedded infrastructure networks at year 2010. The highlighted bold edges represent the dual network “hubs”, i.e. the elements with the most interconnections. The comparison of the dual degree and the edge class (pipe diameter, conduit size and road type) shows that they do not necessarily correlate. This implies that edges with the highest capacity (large diameter in WDN, large conduits sizes in UDN and motorways in the RN), do not have the most intersections. For the RN the “high degree hubs” are identified to be tertiary and primary roads. The reason for this finding for the WDN and UDN is that the source and sink nodes (water sources and WWTP) are located outside the city, requiring “high capacity transmission edges” to the inner parts of

the network, which usually have fewer connections. However, low degree “terminal dual nodes” are mostly found in the edge classes with the lowest capacity (see bivariate histograms in Figure 7 b).

### Geospatial Co-location

We present the results of the geospatial co-location analysis to identify the spatial relationships of dual node degrees among the three network types. Mair et al. (2017) found that approximately 90% of the WDN and UDN are located below the RN for this case study. In Figure 7 (c) the normalized dual (node) degrees of the co-located infrastructure networks are pairwise compared. Nodes in the upper right corner of the scatter plots indicate that high node degree components of both networks are co-located. For example, one conduit segment (UDN) with the highest  $k$  is co-located with one pipe segment (WDN) with the second highest  $k$  (indicated with the circled dot). This could be an indicator for an increased cascading vulnerability when failures occur across multiple networks.



**Figure 7:** Remapping of the dual (node) degree to the primal space for WDN, UDN and RN: (a) Remapped dual degree, (b) Correlation analysis between dual degree and functional edge class describing flow capacity and (c) co-location of dual degree among different network types.

These findings provide a first step towards the assessment of structural resilience and network interdependencies. Besides the identification of the “connectors” (high connectivity), the “carriers” (high capacity) should be further addressed. One future direction of this work could be the analysis of cascading failure across multiple network layer (e.g. a pipe break occurs which affects the water supply, but also influences the co-located road and urban drainage network parts due to traffic rerouting and



additional inflow to sewers). These analyses could provide helpful insights in the resilient (re-)design of networks, providing an integrated view across the usually separated systems.

## **Conclusions**

The historical data set of water distribution, urban drainage and road networks of an Alpine city was investigated using a dual-mapping approach (Hierarchical Intersection Continuity Negotiation method) and metrics of complex network analysis were estimated. The node-degree distributions follow truncated [Pareto] power-law functions,  $p(k) \sim k^{-\gamma}$ ,  $k \geq k_{\min}$  ( $\gamma$  between 2.06 and 3.12;  $k_{\min} = 2$ ) and the characteristic (average) path lengths  $\langle l \rangle$  of the systems are much smaller than the total number of nodes. Therefore, we conclude that, similar to other “self-organized” networks, all investigated infrastructure networks also evolve to exhibit scale-free properties, which describe the neighborhood connectivity of the vertices. Furthermore, change in power-law slopes ( $\gamma$ ) reveals that secondary edges connect more likely to “well-connected” main edges.

Previous studies showed that scale-free networks are highly resilient to random failures, but have high vulnerabilities to targeted attacks. With the presented dual-mapping methodology, patterns (e.g., vertex connectivity) and trends for the future network development and engineering design were obtained. Furthermore, the reflected structural features, such as the “highly connected” components of the networks, were uncovered and remapped to the primal map. It was shown that the “highly connected” components do not necessarily correlate with “high capacity” components. Through the pairwise comparison of the dual degree of different network types, we identified the location where “high degree” components are co-located. These findings could be a measure of assessing the interdependencies and cascading vulnerabilities across multi-layer networks.

## **Chapter 2: Robust and resilient network structure**

This chapter presents the development of the novel methodology to determine a robust and resilience network structure, focusing on water distribution networks, their isolation valve distribution, and different failure regimes. Although no specific results were obtained at this stage, this methodology builds the basis for future investigations and collaborations.

### **Introduction**

Networks are the basic structures of many natural and engineered systems which describe structural and functional relationships. Water distribution networks (WDNs) are part of critical infrastructure whose security and safe operation are essential for the functioning of modern societies. To fulfil those high requirements at all times, the infrastructures must be carefully planned and regularly monitored, to minimize the impacts caused by different failure regimes (e.g. targeted vs. random attack). In this context the term resilience is used, which defines the immediate loss of performance after a failure and the time the system needs to reach again a stable state (Mugume *et al.* 2015; Klammler *et al.* 2017). Furthermore, the legal developments in the handling of critical infrastructure were recently exacerbated (e.g. Austrian Program for Critical Infrastructure Protection - APCIP) aiming to protect such infrastructures from potential threats, such as terroristic attacks. The resilience enhancement of critical infrastructures and optimization in terms of network function are the key challenges for future system design.

Failures in water distribution networks can have multiple origins which propagate through the network and affect the required water quality and/or the water quantity by the user. The failure magnitude depends not only on the impact, but also on the capacity of the network to deal with different disturbance regimes, while still guaranteeing a proper functioning to the users at the same time. Thereby, the network structure is of importance by means of providing alternative flow paths, the number and placement of structural components (flow control and shut-off devices), and the number of (alternative) water sources which can be used in emergency situations. Isolation valves are necessary to mitigate the dispersion of contaminants and to temporally isolate WDN parts to make a repair of failed components possible. The nature of a large number of WDN components in real-world systems, their dependencies and the natural and anthropogenic fluctuations lead to a complex problem, which requires new methods to understand the driving forces in functional dynamics. For similar problems, network theory is applied in various fields ranging from natural networks to internet-based social networks, a relatively new and promising object of network research. Even though network theory has been developed on a basic level for WDN analysis in recent years, process understanding of functional dynamics, e.g. how networks react of external disturbances and recover, has not been investigated sufficiently until now.

In every engineered system a deviation from an ideal (planning) state occurs during a certain time period. Planned operational disruptions are rehabilitation works, where old network components are replaced or renewed. Unplanned disruptions are e.g. pipe breaks, contaminations or failures of other structural

components, such as valves. To make a repair or a replacement possible, those malfunctioning components have to be temporarily disconnected from the main system which is constantly pressurized, through the closure of distributed isolation valves. Due to improper maintenance and infrequent utilization of those isolation valves even these can fail, which leads to much more severe performance declines. For economic reasons the number of isolation valves is usually much smaller than the number of pipes. Furthermore, a proper design depends on factors such as the pipe network topology, the demand distribution, the distance from the water source, the frequency of pipe failure etc., which makes an appropriate placement a complex problem. The dependencies can be assessed with algorithms from complex network theory, as used in the analysis of social networks. The final goal is to get new insights in complex relations for an improved valve network design to enhance the system resilience.

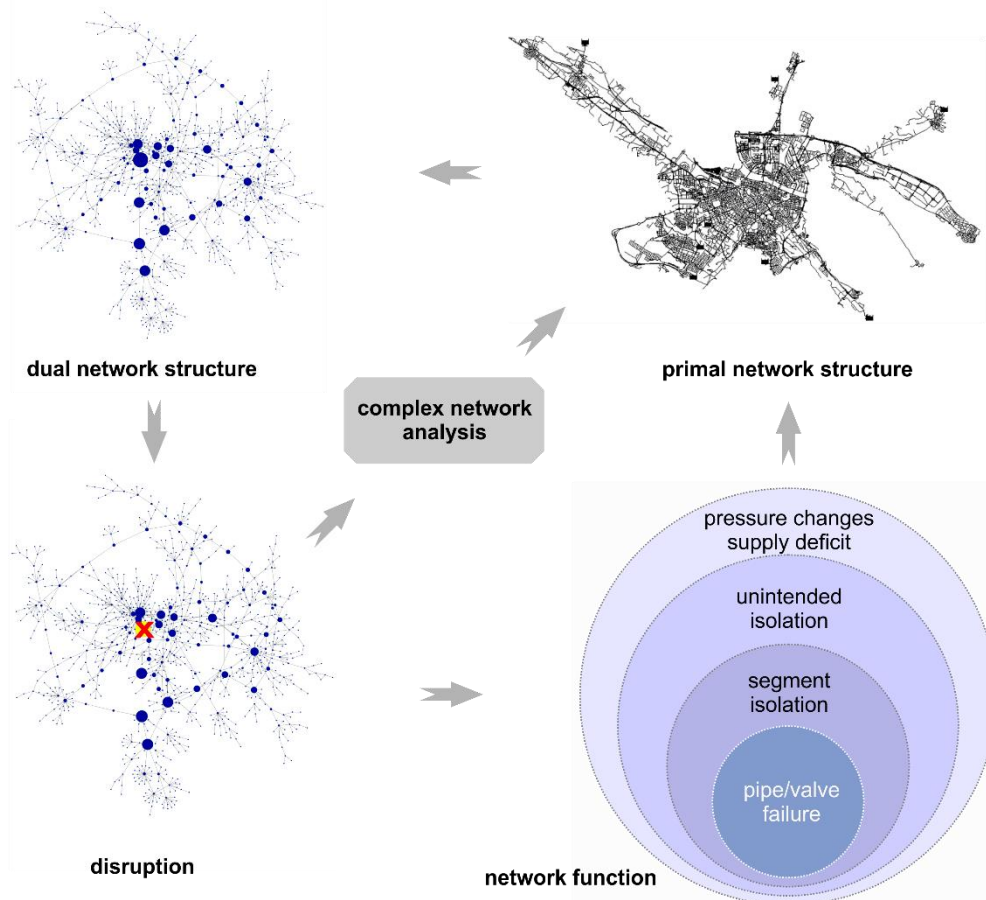
### **Work description**

Alike most social or natural networks, also water distribution systems can be described as a mathematical graph, consisting of edges and vertices. Generally, there exist different ways of representing the network. Traditionally, the pipes are considered as edges and the junction as vertices. This is also called the primal representation of the graph. Alternative network representations, investigate the network in its information space, i.e. functional related components are aggregated to “supernodes” and considered as a single element. In this process a so-called dual graph is created, where groups of pipes are considered as nodes and the intersections as edges. Such dual graphs were recently often used for road network analysis, using the street name or the curvature of connected street segments as criteria for creating the new dual network (Zhan *et al.* 2017). In first studies, different algorithms for the dual graph creation are presented which were then analyzed with metrics from complex network analysis (e.g. degree distribution, scaling laws, centrality measures). Results show that same system described with different network representations (primal vs. dual), leads to completely different results and thus gives new insights in its functional topology (Klinkhamer *et al.* 2017; Krueger *et al.* 2017; Zischg *et al.* 2017a). Some of the main advantages of the creation and analysis of (functional) dual graphs are:

- Simplification of complex network topologies through functional aggregation
- Identification of hierarchical system components (“backbone”)
- The restriction of the geographical embedding of the primal network is repealed
- Preservation of the network connectivity
- New insights in the network structure and new interpretation of metrics from complex network analysis

In this work we apply for the first time complex network analysis on the dual representation of water distribution networks, using data on the pipe layout and the isolation valves as input. In addition, we perform a comprehensive component failure analysis to determine the structural resilience of the valve

and pipe topologies. Finally, we compare and discuss the results of the complex network analysis with those determined by a hydraulic simulation. Figure 8 illustrates the general relation between network structure and its function when a failure occurs (edge and/or vertex failure). Generally, when failures are detected the malfunctioning parts of the network have to be temporarily disconnected from all sources through the closure of distributed isolation valves, which causes a disruption from water supply. Thereby, not only the isolated network parts are affected, but also other WDN parts may notice functional performance loss. Reasons are the unintended isolation and the pressure losses caused by the changing flow patterns.



**Figure 8:** Relations between network structures (primal and dual), complex network analysis and affected network function when subjected to various failure mechanisms (e.g. pipe break or valve malfunctioning). Adjusted from Jun (2005).

The novelty of this work is the application of network theory to functionally aggregated virtual (benchmark) and real-world water distribution networks in their so-called information space. Based on the given information of network topology and isolation valve data, a new network (the so-called dual graph) is created. After the complex network analysis is performed on the dual graph, the attributes are re-mapped and visualized in the primal (traditional) mapped network. It is hypothesized (and first test are promising), that with the re-mapped attributes valuable insights in the structural and functional behaviour of water distribution networks can be obtained.

## State of the Art

The mathematical modelling of WDNs and its response to failure is state-of-the-art for decades already (Walski 1993; Rossman 2000; Möderl *et al.* 2011; Diao *et al.* 2016). More recent research focused on the consideration of WDNs as mathematical graphs and the application of metrics known from complex network theory (Yazdani *et al.* 2011; Hwang & Lansey 2017; Zeng *et al.* 2017). Complex network analysis originated in statistical physics at the end of the 20<sup>th</sup> century, and is now widespread among numerous disciplines including, natural, technical and social sciences. In the field of water distribution system analysis, algorithms from complex network theory are used for graph partitioning and district metered areas (DMAs) planning (Di Nardo *et al.* 2015), identification of vulnerabilities (Agathokleous *et al.* 2017), structural robustness and resilience increase (Yazdani *et al.* 2011; Yazdani & Jeffrey 2012) or for optimizing contamination warning sensor placement (Nazempour *et al.* 2016). All those studies were performed on the primal representation of the network, where e.g. heavily frequented edges (“bottlenecks”) or clustered components were identified. However, most studies did not consider the network function sufficiently, which is crucial especially when investigating failures and structural resilience. Therefore, in this study we suggest to use a dual representation to the graph, where functional topology of the WDN is considered through the combination of the pipe topology and the distribution of isolation valves.

Already at the beginning of the 1990s Walski (1993) emphasized the importance of isolation valves in connection with the redundancy of water distribution systems. For the first time a concept for creating a new network is presented, where parts of the WDN (hereinafter referred to as “segments”) are considered as nodes and the valves are the links among them. A segment is defined as a part of the WDN whose aggregated pipe length is a minimum and, at the same time, can be disconnected from the source(s) through the closure of one or more valves. This idea was pursued by Jun & Loganathan (2007) and an algorithm for creation of the segment-valve diagram ( $\cong$  dual network) was shown. Also the topics of unintended isolation (disconnection of other segments besides the failed segment) and valve failure were addressed. In this context a valve failures describe a valve which cannot be closed. Reasons for that are diverse. For example, valves may not be found due to surface coverage (e.g. snow), inaccessibility or a malfunctioning of the component itself (Jun 2005). Existing studies mostly focused on pipe failure and did not consider the interaction and propagation of pipe and valve failure. When considering complex real-world systems computer-based methods are inevitable. Until now, most studies on the optimal isolation valve system design suggest mathematical optimization algorithms which are generally very computationally intensive (Giustolisi & Savic 2010; Alvisi *et al.* 2011; Giustolisi *et al.* 2014). In this work we aim to apply algorithms from complex network theory as a more efficient and productive alternative.

The complex network analysis of “functional” dual networks, was already performed on different network types by several authors. First studies were presented for road networks (Porta *et al.* 2006; Masucci *et al.* 2014; Zhan *et al.* 2017), but also for sewer and water distribution networks (Klinkhamer

*et al.* 2017; Krueger *et al.* 2017; Zischg *et al.* 2017a). However, the criteria for aggregating components to identical functional units (“supernodes”) and the creation of the dual graph is different from case to case and always depends on the research question. Exemplarily for WDNs, pipe cohorts with identical pipe diameter or WDN segments, which can be isolated through valves, might be two different criteria for creating the dual graph. While with the first criterion the elements (pipe cohorts) with the highest connecting pipes are revealed (“connectors”), in this work the latter criterion is applied to analyse pipe and valve failures.

Although the analysis of the WDN is performed in the information (dual) space of the network, the obtained results can be re-mapped from the dual to the primal (georeferenced) representation of the network, which allows for easier localization of weak points and better visualization (Zischg *et al.* 2017a). Resulting performance indicators are mapped to the components (pipe and valves). Those indicators can be calculated based on hydraulic simulations (Möderl *et al.* 2011; Yoo *et al.* 2012) or graph-theoretical approaches (Yazdani & Jeffrey 2012). Studies comparing the results of hydraulic simulations and complex network analysis are lacking until now. Möderl *et al.* (2011) presented various concepts of mapping performance indicator to individual WDN components, which ultimately aim to support decision makers in improving the re-design and resilience enhancement of the system.

### **Research questions**

First investigations of complex network analysis in the dual network representation of urban infrastructure systems were shown in Zischg *et al.* (2017a). Thereby the temporal dynamics in the functional topology of real world urban infrastructure networks were investigated on a very basic level over a period of one century. In the current work the idea of creating the dual network combined with algorithms from complex network theory is continued and enhanced, with the main focus on water distribution networks at their reaction to disturbances. Thereby, also new criteria for creation of the dual graph are used. The following lists the main questions of this work:

- How can **complex systems be simplified** through **functional aggregation of components** and visualized in a simpler way?
- Which **metrics from complex network theory** can be applied to a newly created “dual” graph (WDN segments are the nodes and the isolation valves the links) and what are the gained insights compared to the traditional network representation?
- How can a vulnerable network structure be identified and what are possible **strategies for structural resilience enhancement**?
- To what extent can a **complex network analysis replace a hydraulic simulation** when assessing an overall system?

First, a general evaluation system for WDNs is developed and then related to the corresponding functional responses caused by different component failure mechanisms. The method is then applied to numerous virtual benchmark systems (Zischg *et al.* 2017b) but also real-world WDNs with different topologies (degree of loops, valve densities, etc.). The ultimate aim is to get new insights on network

design and management, and optimization in terms of resilience. In this context the failure propagation (cascading) of structural components (pipes and valves) is investigated. Based on these findings, also additional goals like the mutual interference of networks (interdependencies) can be address in further studies.

## **Methods**

The following describes the proposed methodology in five steps.

Step 1: First, the data of the WDN must be checked for plausibility and converted into a hydraulic EPANET2 model (Rossman 2000). In most cases the geospatial information on isolation valves is available as GIS (Geographical Information System) point data. In the hydraulic model those valves are considered as zero-demand-nodes, and are marked as isolation valve in the [TAGS] section of the input-file.

Step 2: Second, a simple algorithm for segment identification is developed. In this process parts of the WDN are identified which can be (temporally) disconnected from the water source by valves based on a minimal distance (Jun & Loganathan 2007; Alvisi *et al.* 2011).

Step 3: In addition, those segments are considered as „supernodes” with aggregated attributes such as the water demand, total pipe length, water sources etc. A new network is created where the vertices are the “supernodes” and the link are “isolation valves” the of the graph.

Step 4: Different metrics from statistics and complex network analysis are applied to evaluated the dual graph. Among others, the following attributed are investigated:

- The **degree**  $k$  of a vertex describes the number of connected edges. For example, in case of the dual graph the degree corresponds to the amount of isolation valves which have to be closed for a temporal isolation of the “supernode”. Besides the node degree  $k$  and its distribution  $P(k)$ , centrality measures (closeness or betweenness) and cycle indicators give insights on the functional network topology of WDN.
- The **assortativity** originates from social network analysis. It characterizes the tendencies of vertices to be connected with vertices of similar sort or being of opposing sort (Newman 2002). Nodes in networks with a high assortativity tend to connect to nodes with similar attributes (e.g. similar node degree). In the example of the proposed dual network this attribute is of high interest, especially when considering valve failure and its propagation.
- Another indicator is the determination of **non-useful valves** in the network. Due to the complexity and the cyclic structure of most WDNs in combination with a limited number of isolation valves, the installation of a valve at certain places does not have the desired effect. The simplest example is the implementation of a single valve in a loop, which causes a flow re-routing when closing it, but no isolation.

- Statistical indicators assessing the **inequality** of the “supernodes” (e.g. total demand) are investigated. One example is the Gini coefficient, which is a measure of statistical dispersion usually applied to quantify the wealth distribution of a nation’s residents.

Step 5: Finally, the above presented methodology of (intended and unintended) segment isolation is coupled with a hydraulic simulation. In doing so, also the effects of flow re-routing and the associated pressure changes are investigated and a supply performance indicator is calculated for every “super-node”. Thereby, the magnitude and the geospatial influences on the overall hydraulic performance are compared with the indicators determined by the complex network analysis. The result from both, hydraulic simulation and complex network analysis, are visualized in the primal representation of the network, to easily communicate the findings for decision makers.

The following describes the envisaged algorithm for the creation of the dual graph (Step 2 and Step 3). In the literature, there exist different algorithms for this purpose (Porta *et al.* 2006; Jun & Loganathan 2007; Masucci *et al.* 2014). The central idea is that identical “functional” components of the network (e.g. road, pipe, conduit etc.) are of the same class (e.g. road name, pipe diameter, pipe segment, etc.), while in some cases also maintaining a certain level of straightness (e.g. for street section analysis). To create the dual graph a combination of the Hierarchical Intersection Continuity Negotiation (HICN) Method (Masucci *et al.* 2014) and a breath first search (BFS) algorithm is proposed and explained in Table 3.

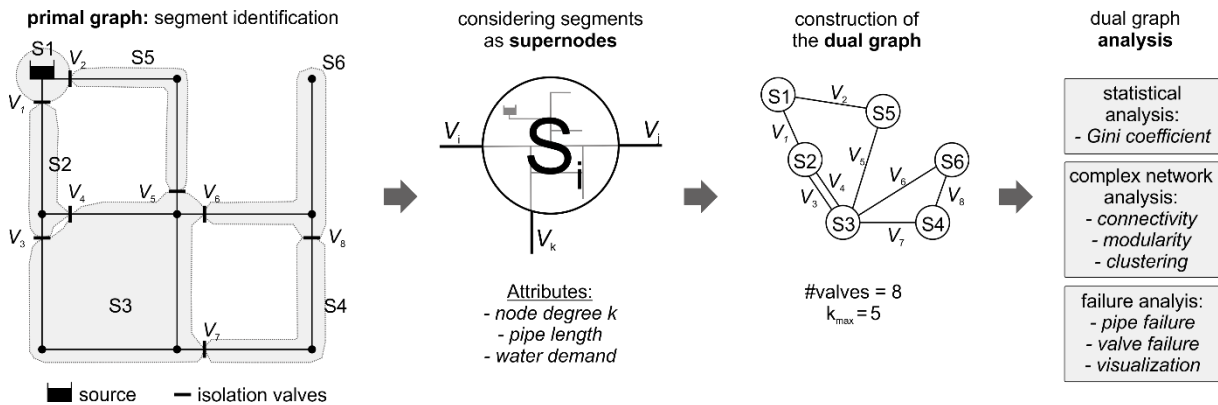
**Table 3:** Proposed pseudocode for the dual graph creation

- 
1. Scan the primal network, put all primal edges into the unused edge set  $E_N$  and let the used edge set  $E_U = \emptyset$ .
  2. If  $E_N \neq \emptyset$ , pick a primal edge  $e_P$  from  $E_N$ , create a candidate dual edge  $e_{CD} = e_P$ ; otherwise go to step 4
  3. Grow  $e_{CD}$  by recursively performing the following until  $e_{CD}$  cannot be extended further:
    - i) inspect the two end points of  $e_{CD}$ . For each of the end points, check if neighbour edges  $e_i \in E_N$  exist, where  $i = 1, 2, \dots, n_{e_{CD}}$  is the index of all such edges.
    - ii) Merge  $e_{CD}$  and  $e_i$  if they are not separated by an isolation valve.
    - iii) If  $e_{CD}$  and  $e_i$  can be merged, then  $e_{CD} = e_{CD} \cup \{e_i\}$ ,  $E_N \setminus e_i$ ,  $E_U = E_U \cup \{e_i\}$
    - iv) If none of the two end points of  $e_{CD}$  can be grow any further, then  $v_D = e_{CD}$  and assign it with a unique dual vertex ID. Go back to step 2.
  4. Construct the dual graph. Let the dual vertices in the dual graph be all the dual vertices  $v_D$ . For every two dual vertices  $v_{D_i}$  and  $v_{D_j}$  represented as a set of primal edges, if they contain primal edges that intersect with each other, construct a dual edge  $e_{D_{ij}}$  between  $v_{D_i}$  and  $v_{D_j}$ .
- 

The basic idea of this methodology was applied in Zischg et al. (2017a), however, with a different criterion for the dual graph generation for water distribution and urban drainage networks. The proposed methodology for this work is explained in Figure 9. On the left the primal graph of the WDN including

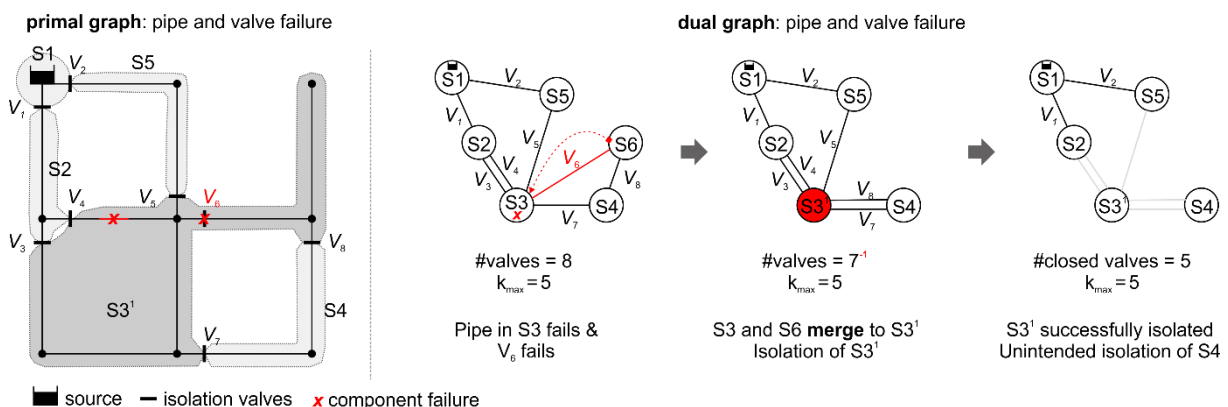


source nodes, pipes, junctions, isolation valves and the associated segments are shown. In addition, all segments (parts of the WDN) are considered as “supernodes”. Then the dual graph is constructed where the “supernodes” are the vertices and the isolation valves are the edges of the graph. Finally, the dual graph is analysed with metrics from statistics and complex network theory and the results are re-mapped from the dual to the primal network and visualized in the form of georeferenced maps.



**Figure 9:** Segments of a WDN in primal mapping (left); aggregation of the pipe(s) into a “supernode” and construction of a dual graph (middle); and analysis of the newly created dual graph with metrics from statistics and complex network theory.

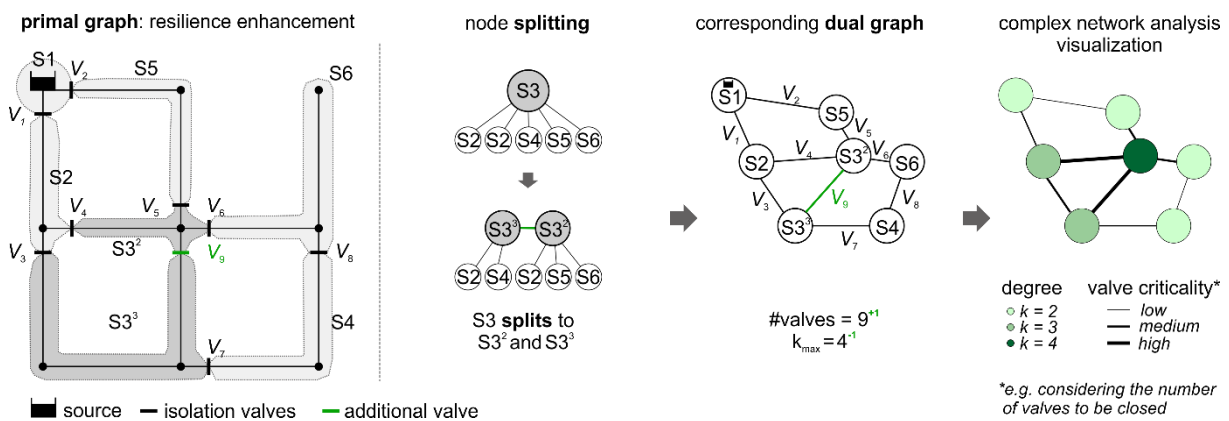
Different WDNs will be analysed in their information space by the creation of the dual graph, combining the information of network topology and the distribution of isolation valves. Figure 10 shows a simple example of two component failures. The network on the left represents the WDN and its sections. When a pipe failure occurs in S3 the section must be isolated. Therefore, V<sub>3</sub>, V<sub>4</sub>, V<sub>5</sub>, V<sub>6</sub> and V<sub>7</sub> must be closed. In case a valve is malfunctioning (e.g. V<sub>6</sub>), the section cannot be isolated directly and the adjacent section (e.g. S6) must be isolated as well. After the direct isolation some WDN parts can be isolated unintentionally, depending on the network structure and the valve distribution (e.g. S4). In case V<sub>6</sub> is fully functioning for the shown example, S6 will not merge with S3, but still be affected by unintended isolation (interrupted connection to S1 which includes the water source).



**Figure 10:** Example of a pipe and valve failure (left). The segment S3 be isolated increases due to the valve failure of V<sub>6</sub> (S3 and S6 are merged). In order to repair the malfunctioning components V<sub>3</sub>, V<sub>4</sub>, V<sub>5</sub>, V<sub>7</sub> and V<sub>8</sub> are closed. This also causes an unintended isolation of S4.

Figure 11 shows a potential strategy of valve retrofitting for enhancement of the networks structural resilience. By introducing an additional valve, the size of the section could be reduced and the structure of the dual graph be changed. In case of a potential pipe failure in S3<sup>2</sup> this section could be isolated without causing an unintended isolation, unlike in the previous case.

The valve criticality shown in this example considers the node degree of the two connected nodes. Connections between two high degree nodes are considered as more critical, because in the case of a valve failure a higher number of valves have to be closed in addition. In this simple example, the water demand of the section, the effect of unintended isolation or the risk of pipe failure in a supernode are not considered. A real water distribution system for a mid-sized town (e.g. 150,000 inhabitants) consists of several thousand interlinked segments, pipes and valves, making the need for efficient assessment and providing a reliable method for strategy testing and placement optimization of valves inevitable.



**Figure 11:** Resilience enhancement through strategic isolation valve retrofitting. Assessment and visualization of the dual graph with complex network metrics. Other strategies could address the provision of additional (decentral) water sources.

### **Chapter 3: Outlook**

The presented work is a first step towards the analysis of interdependent infrastructure networks. Thereby not only the structural correlations (i.e. co-locations), but also the functional relationships (i.e. interdependencies) between different type of networks are of great interest. In urban areas, the interaction between transport networks, power grids, water supply and urban drainage networks is crucial for a well-functioning of modern societies. New requirements for smart, resilient and sustainable cities require new design approaches taking into account a holistic view on related systems, beyond the traditionally separated disciplines. From a graph theoretical perspective, this results in the consideration of multiple network layers, which often are overlapping in space and depend on each other. The dynamic failure analysis of so-called multiplex networks allows for significant implications on their performance, which will be investigated in the future.

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