Generating Virtual Water Distribution Networks for valve manipulation via reinforcement learning

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Abstract

In this paper we present an algorithm for generating very big numbers of virtual models of water distribution systems. These models will be used for training a reinforcement learning agent. The goal being for the agent to learn to manipulate valves in the system to isolate sectors for rehabilitation work, while maintaining continuity of service for the other sectors in the network.
The algorithm is of two parts; the first uses available street network data for generating the layout of WDN and the elevation of the nodes. The second part concerns the placement of reservoirs on the network and the sizing the pipes. We will present examples of the networks generated by this algorithm and compare the networks characteristics to reference WDN's from literature.

Part I. Presenting the algorithm:

1 Algorithm steps:

Our objective is to generate a very large number of random WDN's that are hydraulically 'realistic' i.e having mean pressure and velocity within usual intervals. This is obtained by penalizing pressures and velocities outside those intervals (see section 1.6. pipe sizing).
Here we present an overview of the algorithm. These steps will be discussed in more detail in the following sections.

Algorithm 1 Generate a random model of water distributing system

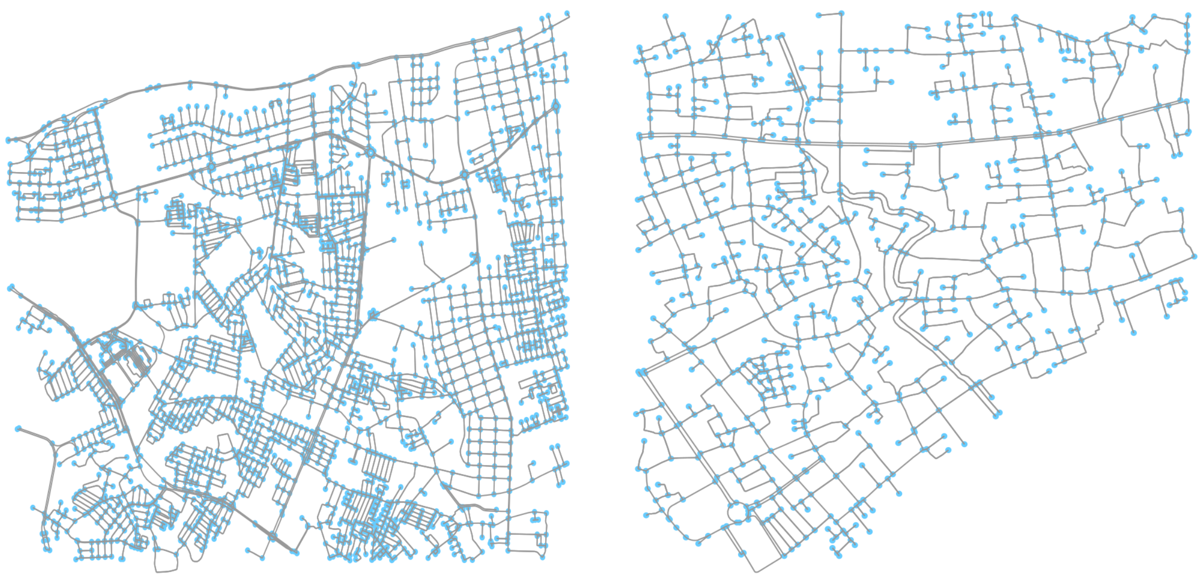
```
BEGIN
  Generate a random layout G(E,V) from street network data
  Add elevation values to the nodes of G
  Clean the graph from clustered nodes, self loops and parallel edges
  Add water demands to the nodes
  Create the main distribution network
  Add reservoirs as nodes and connecting them to the main distribution network
  Add pipe roughness to the edges
  Pipe sizing
  Add valves
  Discard networks with negative pressures
  Save network as Inp file and network statistics as CSV
END
```

1.1 Layout:

We use randomly selected areas from freely available street network data (OpenStreetMap) to generate the layout of the network. Mair et al. (2012)(1) have investigated network similarities between street, urban drainage and water supply networks. Their results showed that there are strong coherences between the three network-types. Moreover, when comparing the layouts and characteristics of the different WDN generation algorithms, R. Sitzenfrei (2016)(2) concluded that this aforementioned approach provides the most realistic layout due to utilizing the correlation with the street network data.
The layout is stored as a Networkx graph G(E,V).

Fig. 1: Layout examples generated from street network data

(a) Area = 36 km^2 (b) Area = 16 km^2



1.2 Elevations:

From the elevation map of the same region (Gmap API), we generate elevation values of the nodes of G.

1.3 Cleaning the graph:

To have a more clean layout we merge the clustered nodes that are within a tolerance value from each other (tol = 15m was taken). We also delete self loops if there are any and parallel edges, keeping just one edge between any two nodes u and v.

1.4 Demands:

The network is divided to communities of 4 nodes each, and each community is randomly assigned a value from the average demand values consumed by different land use types from the table:

Tab. 1: Average demand values consumed by different land use type in gal/day/acre from McGraw Hill (2000)(3)

Land use type	Average demand in gal/day/acre
Low_density_residential	1670
Med_density_residential	2610
High_density_residential	4160
Single_family_residential	2300
Multifamily residential	4160
Office_commercial	2030
Retail_commercial	2040
Light_industrial	1620
Heavy_industrial	2270
Parks	2020
Schools	1700

We consider that each node serves an area of 0.2 acre, the demands are then stored in m^3/s.

For the pipe sizing we use the peak hour demand, which is taken as the average daily demand multiplied by a peaking coefficient, the usual values for this coefficient are presented in table 2. For our algorithm we take a peaking coefficient value of four.

Tab. 2: Typical peaking coefficient from McGraw Hill (2000)3

Ratio of rates	U.S. Range	Common Range
Maximum day : average day	1.5 - 3.5 : 1	1.8 - 2.8 : 1
Peak hour : average day	2.0 - 7.0 : 1	2.5 - 4.0 : 1

1.5 Roughness:

For simplicity a single value of roughness chosen randomly from roughness_values list is assigned to all the pipes.

1.6 Reservoirs:

The number of reservoirs to be added to the network is estimated form the number of pipes and the total area of the network. The network is then divided to 'NUMBER OF RESERVOIRS' random communities either by using FLUIDC ALGORITHM (4) or by using the ZONAGE() function that divides the network to communities each with at most n nodes. Then, for each community a reservoir node is created adjacent to the node in the community with the highest elevation, and is connected to it with a pipe of length 50m. Finally, the reservoir is assigned a random head value from the head_values list.

1.7 Pipe sizing:

First, we create a WNTR WATERNETWORKMODEL object from the Networkx graph we have constructed until now. Then, we start with the same diameter for all the pipes in the network 200 mm except the ones on the main distribution network which start with a diameter of 600 mm. Afterwards,

the diameters are adjusted for each pipe to insure reasonable velocity and pressure values for most edges and nodes, we aim at velocity values <= 2.5 m/s and pressure values between 20 and 100m.
These values are taken from Paez & Filion 6 who surveyed different recommendations for pipe sizing found on different references.
Table 3 presents values and constraints recommended from different expert sources. It includes values for the minimum diameter d_{min} the maximum flow velocity v_{max}, the maximum unit head loss Sf_{max}, the minimum and maximum allowable pressures p_{min} and p_{max}; and sometimes they are defined for different demand conditions where D_{max} is the maximum demand condition (commonly defined as the peak hour demand plus some fire scenario), and D_{ave} is the average demand condition (commonly defined as the mean daily demand).

Tab. 3: Recommendations and constraints for pipe sizing6

Reference	d_{min}	v_{max}	Sf_{max}**(1/100)**	p_{min}	p_{max}
Cesario (1995)	200 mm	$\bar{x} = 2$m/s	$\bar{x} = 6.2$	$\bar{x} = 23$m	$\bar{x} = 77$m
Survey		$x \in [1-6]$m/s	$x \in [1-15]$ $1-2$	$x \in [14-42]$m	$x \in [42-151]$m
Recommended		1.5m/s @$d < 600$ mm	@$d \geq 600$mm $2-5$ @$d < 600$mm	28 - 35 m	63 - 77 m
Trifunovic (2006)		1m/s @large d 1.5m/s @small d	1-2 @large d 2-5 @midrange d 5-10 @small d	20 - 30 m	60 - 70 m @flat zones 100 - 120 m @hilly zones
Kujundzic (1996)				$\bar{x} = 28.5$m $x \in [20-40]$m	$\bar{x} = 93.6$m $x \in [70-160]$m
GLUMR (2012)	75 mm @no fire protection 150 mm @with fire protection			14 m @D_{max} 24.5 m @D_{ave}	70 m
Mississippi Dept. of Health (2001)	100 mm	1.5 m/s		14 m	56 m

Algorithm 2 Simple algorithm for pipe sizing

```
BEGIN
  Start with the 600mm diameter for the main pipes and 200mm for the rest
  While the mean pressure in the network is negative:  assign the next bigger
diameter to all pipes
  Repeat n times (n:  number of diameter types)
    For each pipe
      If the velocity < 0.5 and pressure > 70 make the diameter smaller
      If the velocity > 1.5 and pressure < 40 make the diameter bigger
      If the velocity < 0.01 make the diameter smaller
      If the velocity > 2.5 make the diameter bigger
END
```

1.8 Valves:

We add valves to the main distribution network at the intersections of three or more pipes and at the pipes leading to the reservoirs.

1.9 Saving as INP file:

Finally, we discard networks with negative pressures (are usually around 10% of the networks) and we save the network as an INP file that could be used by the reinforcement learning module for training the agent.

1.10 Conclusion of part1:

The algorithm presented can generate very big numbers of virtual water distribution systems, this is due to the randomization in the generation pipeline, starting with the random selection of the street location from which the layout will be generated and the total area of the network ($1km^2$ to $36km^2$) . Also, the random assignment of demands, the random selection of roughness, the semi-random placement of reservoirs and finally the placement of valves after sectorisation all add to the variability and randomness of the generated networks.

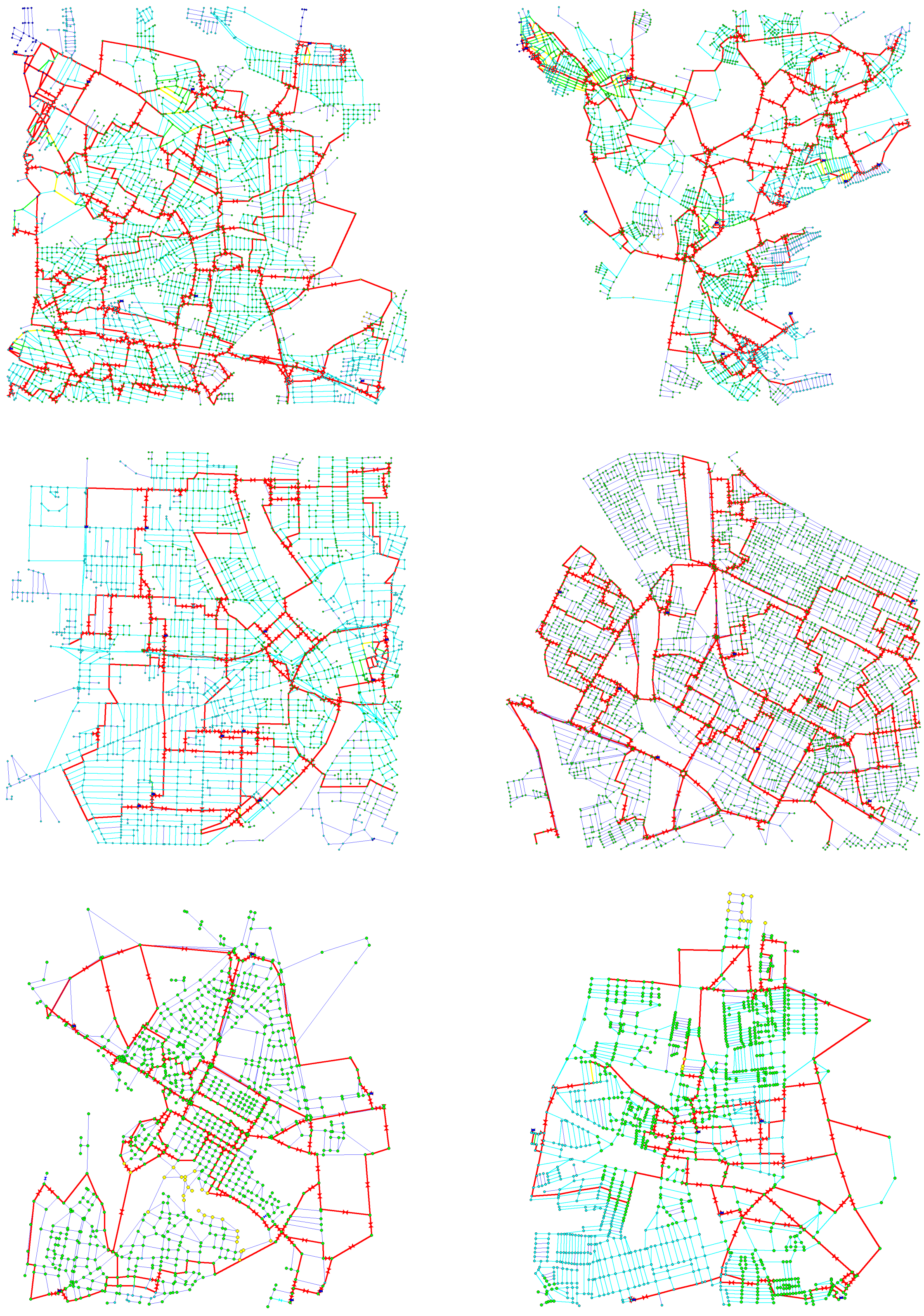


Fig. 2: Examples of INP files created by the algorithm with pressure values and main distribution networks in red

Part II. Comparison with networks from literature using graph theory indexes

In this part we are going to present the results obtained from 100 random networks generated with the algorithm of part 1. First we compare the hydraulic performance of our networks to reference networks from the literature then we compare the two sets using graph theory indexes.

1 About the reference networks:

The set of reference networks are from the Research Database of Water Distribution System Models (7), it is a set of 12 different networks developed from several small and medium actual systems in the state of Kentucky.

2 Hydraulic characteristics:

2.1 Pressure:

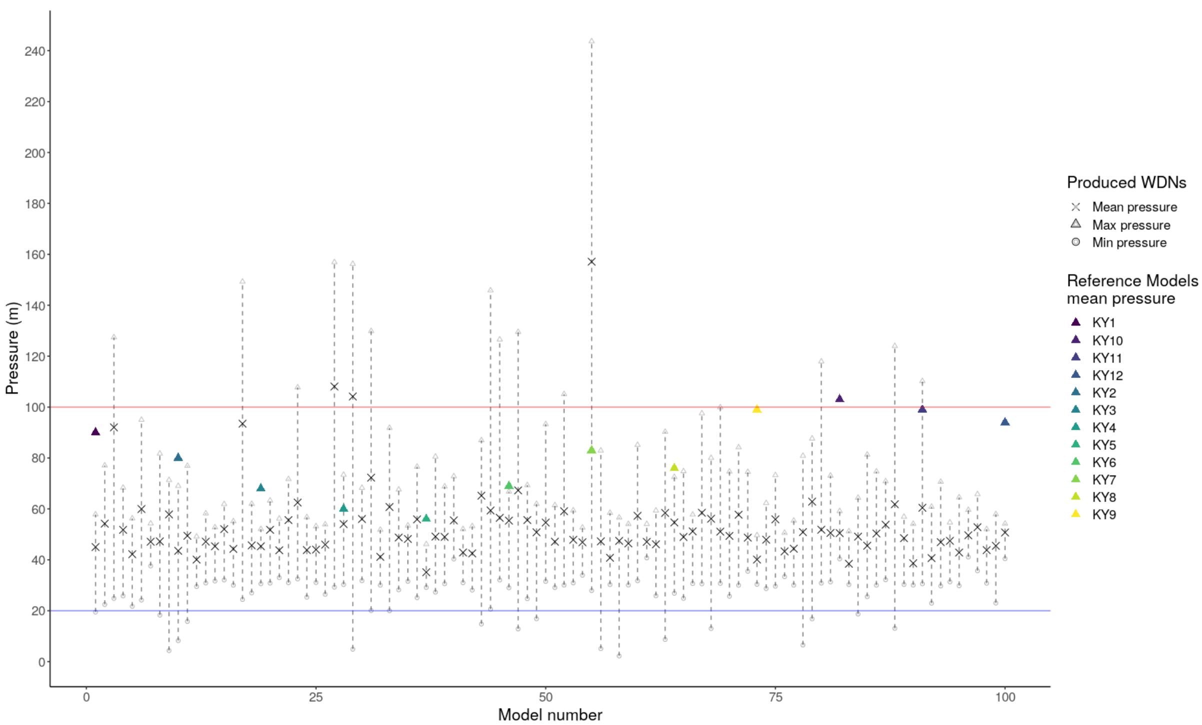
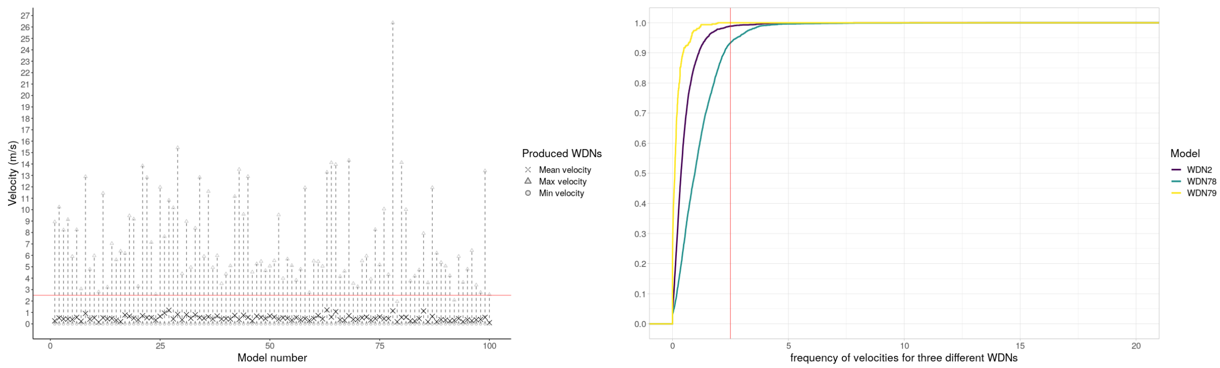


Fig. 3: Pressure variations in 100 networks generated randomly, compared with 12 reference networks

The majority of the generated networks have the pressure values within the interval [20-100]m, with just 3% of mean pressure beyond 100m, and 1% with mean pressure beyond 130m.

2.2 Velocity:



(a) Velocity variations in 100 networks generated randomly

(b) Cumulative frequency of velocities in WDNs number 2, 78 and 79

Fig. 4: Velocity analysis in the generated networks

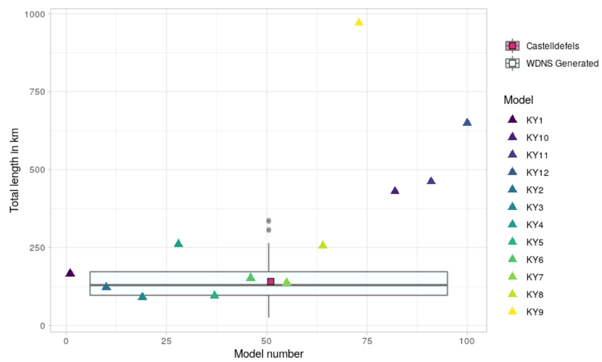
All the maximum velocities are well beyond the 2.5 m/s, although as we can see the mean velocities remain below 1 m/s, this means that those big velocities are exceptions in the network.

In fact when we draw the cumulative frequency plot for some of the networks, for example number 78 which seem to have a very big max velocity of 27m/s, and compare it with 79 that have a max velocity below 2.5m/s and also number 2 which is more representative of the general result. We can see that in all cases more than 90% of the velocities are less than 2.5m/s and 99% are less than 5m/s. The same kind of pattern is noticed when we run the simulations on the reference networks where 90% of values are within the 2.5m/s but the max velocity can also go to around 30m/s (network KY10 for example).

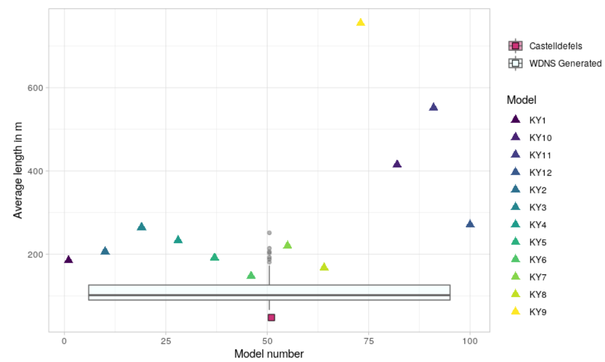
We can conclude that hydraulic characteristic of our networks are acceptable especially considering that they don't contain any regulatory elements such as pressure reducing valves, pressure sustaining valves or pressure relief valves, nor any pumps.

3 Layout characteristics:

3.1 Pipe lengths:



(a) Total length of the network



(b) Average length of the pipes

Fig. 5: Length box-plot for 100 generated networks vs plots of the 12 reference networks vs Castelldefels network

The average length of pipes in our networks is generally smaller than the reference networks, this is probably because most of our networks are generated from streets of high density areas(cities with more than 100k populations). This is moreover confirmed when plotting Castelldefels network characteristics where we find the average length to be even lower than our averages.

3.2 Graph theory indexes:

A WDN can be represented as a graph G = (N, E), containing a set N of n nodes (i.e., water demand and supply nodes) and a set E of m edges (i.e., water distribution pipes). Since the direction of the water flow in the pipes is subject to occasional changes (e.g., pressure changes, pump activation, change of status of shut-off valves, etc.), WDNs are represented as undirected graphs. Moreover, under normal circumstances, there exists at least one path between every pair of nodes and therefore, WDNs are connected graphs. Furthermore, a WDN can be represented as a graph where no edges cut one another (except at their nodes). This planarity could be violated in a WDN due to pipes crossing without intersecting, but this situation is uncommon in reality, therefore, planarity can be considered as a good approximation for WDN.

Given the graph G, the following connectivity indexes can be defined(6):

$$k_{avg} = \frac{1}{n}\sum_{i=1}^{n} k_i = \frac{2m}{n} \qquad k_{max} = max(k_i)$$

$$R_m = \frac{m-n+1}{2n-5} \qquad q = \frac{2m}{n(n-1)}$$

The degree k_i of a node i represents the number of edges incident to this node. The average degree of a graph k_{avg} is defined as the average degree of all the nodes of the graph. It is a measure of connectivity and gives information on the sparseness of the network: treelike network structures have an average degree of approximately 2, whereas an average degree of about 4 indicates a more complete network with grid pattern. As can be derived from the average degree of the observed real networks ($2 < k << 4$), WDNs tend to be rather sparse.

R_m is the meshedness coefficient that represents the fraction between the current number of loops and the maximum number of loops in a planar graph.

q is the link density that represents the fraction between the current number of links and the maximum number of links in a non-multigraph graph (i.e., a graph without edges that share the same adjacent nodes which in WDSs context could be understood as a network without parallel pipes).

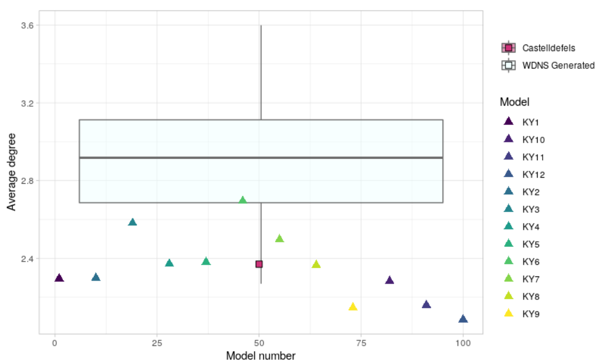
Using our algorithm we generated 100 WDNs covering surfaces from $4km^2$ to $36km^2$, and the following characteristics:

100 Generated WDNs	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Nodes	191	587	909	958.9	1276.2	2912
Edges	271	851	1256	1411	1808.8	4826

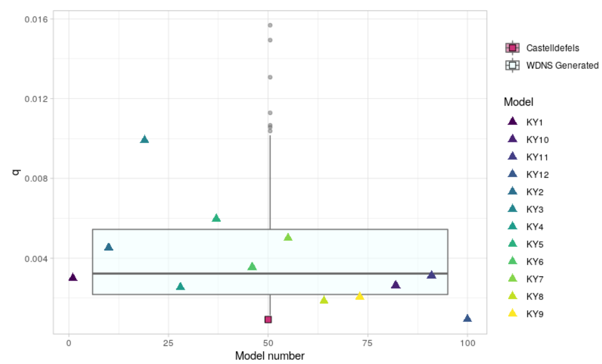
Model	**KY1**	**KY2**	**KY3**	**KY4**	**KY5**	**KY6**	**KY7**	**KY8**	**KY9**	**KY10**	**KY11**	**KY12**
Nodes	777	513	264	939	409	763	500	1283	1118	886	731	2262
Edges	903	595	344	1118	498	1033	624	1523	1284	1036	836	2396

Tab. 4: Summary of the number of nodes and edges of 100 generated WDNs and of the 12 reference networks

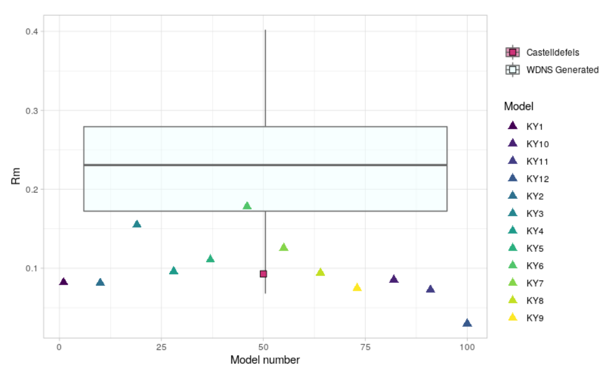
Here we present other graph indexes of our networks against the reference ones:



(a) Average degree k_{avg}



(b) link density q



(c) Meshedness R_m

Fig. 6: Box-plot of 100 generated WDNs vs plot of 12 reference models

We notice that the link density q of the generated networks is within the interval of variation of the reference networks. However, the average degree and meshedness are generally bigger in the generated sets. When we investigate more we can see that generally our networks have less nodes with one degree, about the same number of nodes of two and three degrees, and more nodes with four and 5 degrees, with existing but negligible percentages of nodes with degrees of six and beyond.

Therefore, if it's necessary we can adjust the average degree by deleting some edges to bring the degrees of some nodes from four to one.

Also more real networks have to be investigated to get better data on the true intervals of variations of their characteristics.

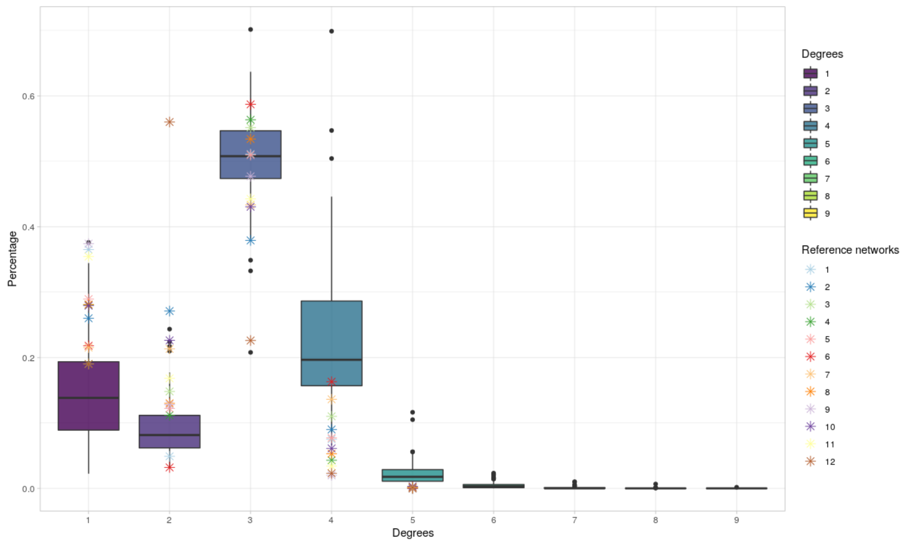


Fig. 7: Degree frequency for 100 generated WDNs vs 12 reference networks

Part III. Conclusion and points of improvement:

In this paper we presented an algorithm for generating virtually infinite numbers of WDNs. These WDNs give good hydraulics performance although they are lacking control elements such as pressure reducing valves, pressure sustaining valves, pressure relief valves, or pumps.

The produced WDNs also compare well to reference networks from literature.

The generation of main distribution circuits was done with a simple algorithm relying on the geographic distribution of the junctions. It would be interesting to use a clustering technique from graph theory instead and compare the two methods.

The average degree of the produced networks is generally 20-25% bigger than the reference set of networks, it could be reduced by deleting some edges from nodes that have a degree of four or more.

More investigation could be carried to check the influence of including less dense areas (now cities with populations more than 100k were used) on the average length of the pipes.

The process would ideally be be taken off-line.

References:

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