

Part IV: Network Optimisation — Case study

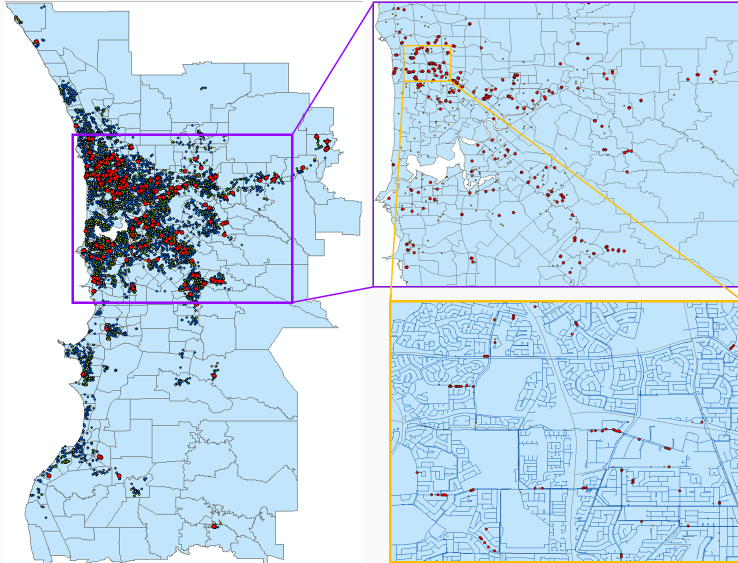
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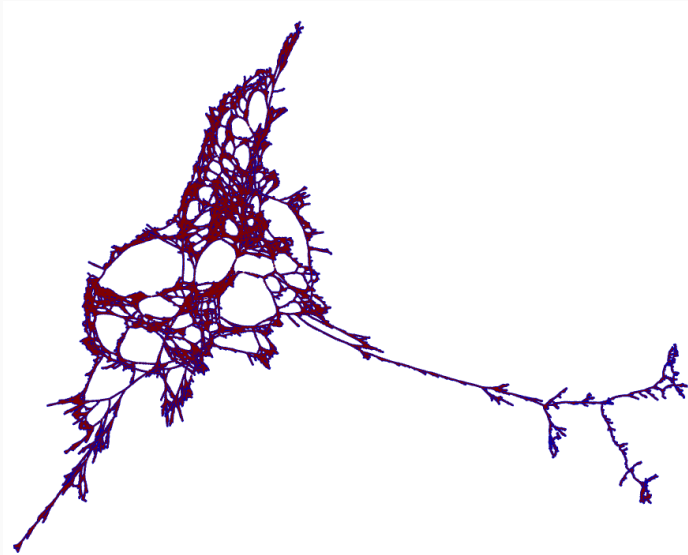
Mineral Resources
Commonwealth Scientific and Industrial Research Organisation
Australia

Water

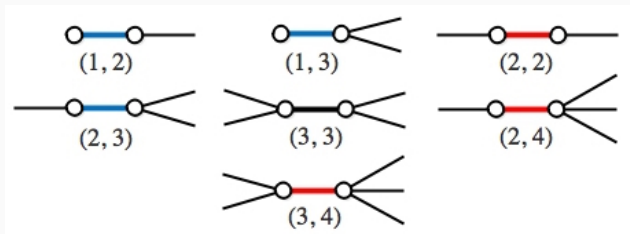
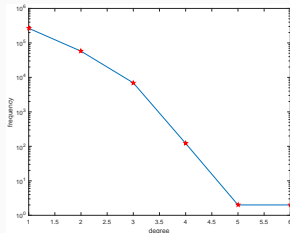
Scaling in the city



Water distribution network



Power law and order

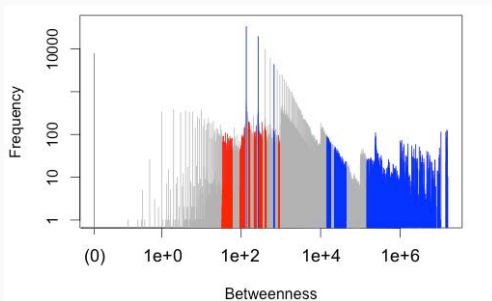


Left: Average degree is low, network is largely tree-like, only the most optimistic complex network person would even say “power-law”.

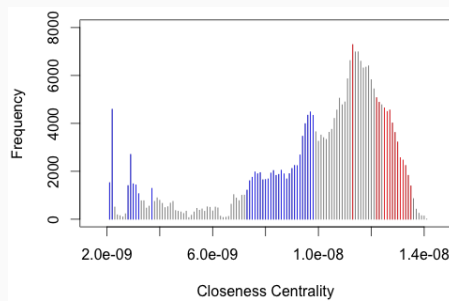
Right: Maintenance records and failure data from January 2010 – January 2017. Some local topologies fail more often (red) than chance ($p < 0.01$), some less often (blue).

A tail of two centralities

Betweenness



Closeness



Leaks occur most often in the core of the network, and least often in the periphery. Higher or lower than expected ($p < 0.01$) rates of leakage are shown in red and blue.

Distance in a (not so) small world

Previous contract work by Water Corp has studied statistical predictors of failure (age, material, soil, etc.) but not the topology of the network (above) or network distance.

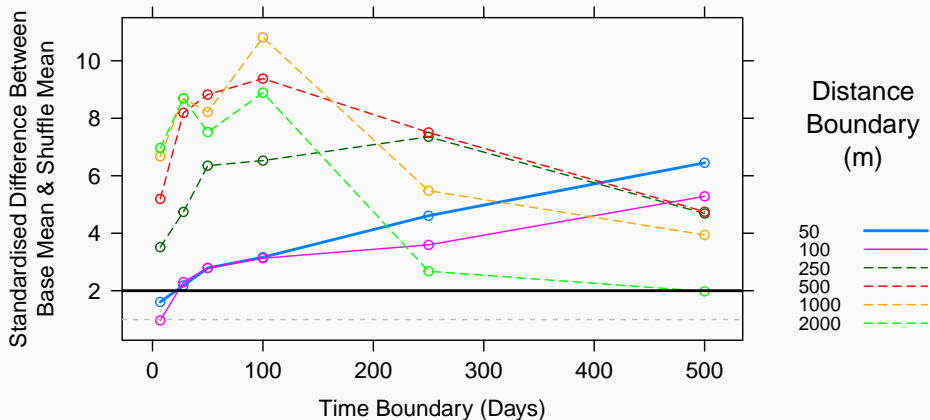
Here we ask whether two pipes which are “close” on the network are likely to fail at the “same” time — given a pipe failure, are its network neighbours now more likely to fail?

We need to construct a more complex null hypothesis — the distribution of distances between pipes is complex and spatially dependent.

Spatial pipe distribution as a predictor of failure (SPeDAPOF) surrogate: null hypothesis is that there is no spatial correlation and this is achieved by shuffling (sampling without replacement) the pipe failure times.

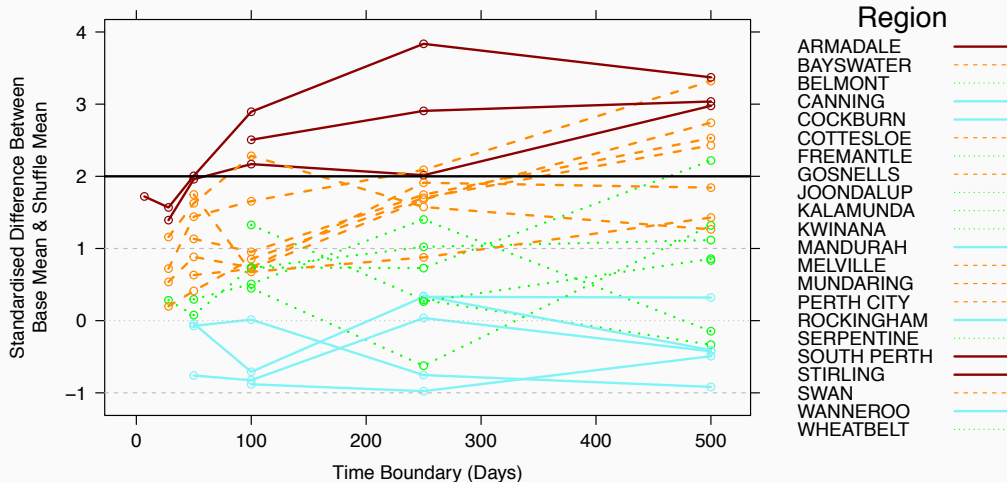
Time and relative distance in space

Plot of Standardised Differences between Baseline Mean and Shuffle Mean Distance to the Closest Subsequent Failure across Joins where Pipe Materials Change and over Differing Distance Boundaries



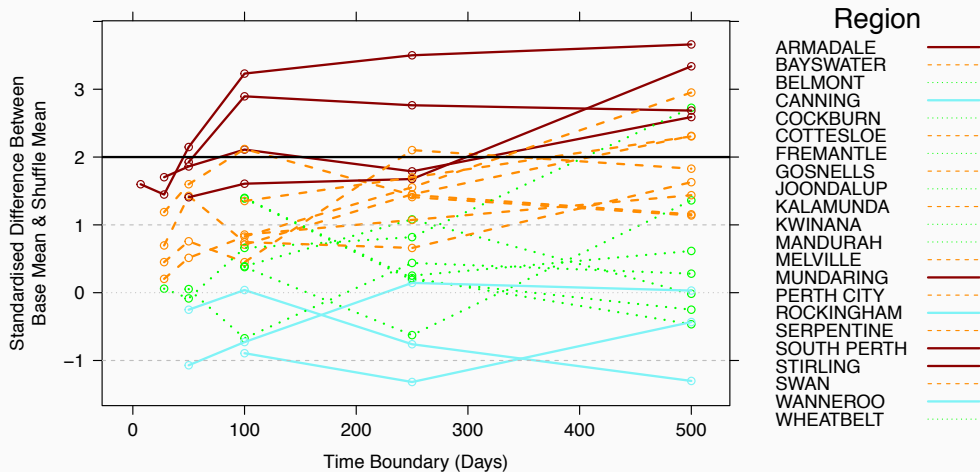
Time and relative distance in space

Plot of Standardised Differences between Baseline Mean and Shuffle Mean
for Differing Time Boundaries by Region in Concrete and Cement Pipes



Time and relative distance in space

Plot of Standardised Differences between Baseline Mean and Shuffle Mean
for Differing Time Boundaries by Region in Metal Pipes



Football

Network measures as predictors in football

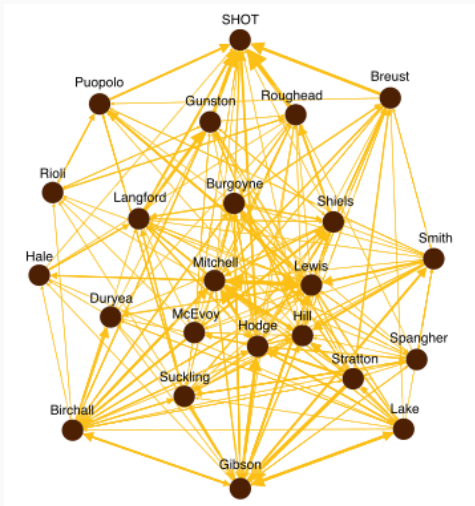


TABLE VI. Winners predicted using the means of network measures from all previous matches in the season. Measures where a net profit is made are shown in bold. Prediction using the mean betweenness over one or four previous matches is shown below. Unless otherwise stated, $n = 197$. (Significance codes: $p < 0.05^*$, $p < 0.01^{**}$, $p < 0.001^{***}$.)

	Winners predicted (%)	p-value	Net profit
Favourite	72.6	$<10^{-4}***$	-7.65
Mean betweenness	67.5	$<10^{-4}***$	10.01
Players with non-zero betweenness	65.8 ($n = 193$)	$<10^{-4}***$	3.31
Mean out-strength	65.0	$<10^{-4}***$	5.99
Mean closeness	64.0	$<10^{-4}***$	7.73
Mean in-strength	63.5	$<10^{-4}***$	1.94
Disposals	63.3 ($n = 196$)	0.00012***	0.18
Mean out-degree	62.9	0.00017***	-0.55
Mean in-degree	61.4	0.00050***	-4.40
Passing rate (no shots)	60.4	0.0021**	12.22
Team entropy	59.9	0.0033**	-6.05
Disposal efficiency	56.3	0.044*	-1.09
Eigenvector std. dev.	55.8	0.058	-23.67
Mean chain length	52.3	0.28	-9.30
Global clustering	50.8	0.44	-16.47
Passing rate	48.7	0.67	-35.45
Shot efficiency	46.7	0.84	-24.65
Mean betweenness (1 match)	66.0	$<10^{-4}***$	26.46
Mean betweenness (4 matches)	65.3 ($n = 170$)	$<10^{-4}***$	12.01

References

- C. Braham and M. Small. “Complex networks untangle competitive advantage in Australian football” *Chaos* 28 (2018) 053105.
- A. Ballantyne, N. Lawrance, M. Small, M. Hodkiewicz and D. Burton “Fault prediction and modelling in transport networks” *IEEE International Symposium on Circuits and Systems Proceedings* (2018)

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