Quantifying system-level dependencies between connected electricity and transport infrastructure networks incorporating expert judgement

ARTICLE HISTORY
Compiled June 3, 2019

ABSTRACT
New Zealand's critical infrastructures are typically managed as isolated systems. Past events have demonstrated that disruptions to electricity supply, for example, can cause major social and economic impacts across electricity dependent infrastructures. This paper investigates and contributes and furthers understanding of the role electricity has on the functioning of the wider New Zealand passenger-transportation sector, namely; airports, ferries, rail, and the petroleum distribution network via state highways. Previous studies have defined system-level dependency relationships of transportation networks on electricity supply through expert-elicitation. Although these are already widely applied in practice, the contribution of this paper lies in the comparison and integration of expert defined relationships with a technical national scale network-of-networks simulation approach – a methodology with the advantage of capturing a far greater range of possible dependency relationships compared to a single expert-elicited curve. In doing so, we examine the geographic and functional dependencies on different levels of the electricity transmission and distribution networks, identify the critical electricity assets for the wider transportation sector functionality, and through further exhaustive disruption, derive a synthesised set of curves integrating the qualitative and quantitative approaches to characterising infrastructure dependencies. The methodological approach and insights developed here are relevant to similar contexts globally.

1. Introduction

Infrastructure networks are becoming increasingly interconnected for normal operation. As a result of such increased inter-connectivity, outages can propagate across networks spanning multiple scales due to losses in physical connectivity, the failure of a co-located infrastructure, or a disruption to information flow and logical processes (Rinaldi, Peerenboom, and Kelly 2001). Such disruptions can lead to cascading failures with significant societal or economic impacts – notably when initiated from the electricity sector (van Eeten et al. 2011; Kjølle, Utne, and Gjerde 2012; Zeng et al. 2015). In particular, analyses of past events have highlighted the vulnerability of transportation networks (e.g. road, rail, and air) to disruptions following the disconnection from electricity supplies (Zimmerman 2004; Luiijf et al. 2009; van Eeten et al. 2011). Further recent examples include, among others, the 2003 North-East blackout (USA-Canada) which led to widespread train cancellations, airport closures, and the suspension of oil refinery production and retailing (Andersson et al. 2005; Chai et al. 2011), the 2013 London-Gatwick Airport substation flooding (McMillan 2014), and the 2017 British Airways IT system power supply disruption impacting 75,000 travellers (BBC 2017). With the increasing reliance on electricity for transportation network signalling, traction, control systems, and ticketing processes (amongst others), there is a risk that such events will become more prevalent.

While numerous methodologies exist for investigating the propagation of outages and related consequences between infrastructure systems (Ouyang 2014), many have adopted network modelling and simulation based approaches for the coupled electricity/transportation sectors, such as: electricity–rail (Johansson and Hassel 2010), electricity–airports (Thacker, Pant, and Hall 2017), and electricty–roads (Fotouhi, Moryadee, and Miller-Hooks 2017). In such examples, physical assets are depicted as spatial networks or graphs comprising nodes and edges with further links between networks to represent physical dependencies. These have the advantage of being largely intuitive while capturing both topological network properties and simplified flow patterns to identify critical network components – without excessive data and computational requirements (Ouyang 2014). Despite typically requiring significant data inputs for model formulation and calibration, such simulation based approaches have the advantage of rapidly simulating different outage scenarios to capture a wider range of failure pathways compared to those observed following real-world events.

Where modelling and simulation approaches may not be feasible, another body of literature focuses on capturing electricity-transportation sector dependencies though expert-elicitation (Setola, De Porcellinis, and Sforna 2009; Prezelj and Žiberna 2013; Buxton et al. 2016). Such dependencies are defined by aggregating multiple domain experts viewpoints to suggest an infrastructure networks functionality for a given reduction in service from another. This generally results in a single defined relationship for each infrastructure-network coupling. While the cited examples tend to focus on capturing system-wide dependencies, spatial variations in network topologies and the possibility of cascading effects are not necessarily considered or represented. However, experts can better advise on specific operational aspects of an transportation system that may be difficult or otherwise not captured in many simulation based frameworks – such as the capacity within a network to absorb any minor reductions in electricity supply before user disruptions are evident, or the level of network functionality that may be reached before a voluntary network shutdown is enforced.

To capture a wider range of relevant aspects in quantifying infrastructure interdependencies, others have suggested an integration of approaches is required (Wang et al. 2011; Zio 2016). In this study we contribute to the existing literature on vulnerability assessments through the comparison and integration of two notably different methodologies for quantifying electricity-transportation infrastructure dependencies at a system level: network simulation and expert elicitation. We demonstrate this comparison and integration with application to New Zealand and the most common transportation related sectors (petroleum, passenger air, rail, road, ferry) and their dependencies on electricity and on each other, where appropriate.

Motivation for a case study of New Zealand lies in the frequency of electricity disruptions due to both single component failures (Stern and Svedin 2003; Rotherham 2014; Helm 2007) and mutiple systems failure due to natural hazards (Small and Clarke 2008; Kwasinski et al. 2014; Liu et al. 2017) ultimately impacting local, regional, and national transportation networks. This exposure and therefore importance of building resilient infrastructure networks to protect against network outages is highlighted in the country's 2015 Thirty Year Infrastructure Plan (National Infrastructure Unit 2015), evinced through the annual national or regional scale preparedness exercises (Ministry of Civil Defence and Emergency Management 2016), and further modelled in the recent efforts into measuring the economic impacts of infrastructure failures on the New Zealand economy across both single (Kim, Smith, and McDonald 2016; Smith, McDonald, and Kim 2016) and multiple concurrent network component failures (Kim et al. 2017; McDonald et al. 2018).

Each of these New Zealand centric studies have used expert-elicited dependency relationships between infrastructure sectors based on experiences over a range of disruption scales – from minor day-to-day network impacts to wide reaching complete connectivity losses following the 2010-2011 Christchurch Earthquake Sequence (Buxton et al. 2016). These quantify experts predictions on the reduction in transportation sector functionality for a range of losses (0%-100%) in electricity supply. With these relationships used to help guide risk reduction investment decisions, it is the comparison and integration of these with national scale electricity and transportation network models which will allow for the validation of the current dependency assumptions used in practice. Through the comparison of approaches, we can expect a more robust quantification of infrastructure dependencies that can be readily applied and overwrite infrastructure dependency relationships currently used in practice. This is the first interdependent network modelling that has been applied across New Zealand at the national scale, and integrated with expert elicitation to make it policy relevant.

The rest of this paper is organised as following. Section 2 begins by outlining our adopted network modelling framework outlining the disruption metrics, topological network representations, and simulation of dependencies. Section 3 then presents the results of various failure scenarios to firstly identify critical assets and then simulate national-level dependency relationships. This is followed by a comparison with those existing relationships used in practice with Section 4 providing an integration of approaches adopting the known redundancies and operational strategies defined by the expert-elicitation process. We conclude the paper with a discussion regarding future applications of these results and where further research and development of this model can be directed.

2. Vulnerability Assessment

Infrastructure network vulnerability is defined as the measure of the degree of negative consequences of disruptions due to external shock events (Pant, Hall, and Blainey 2016). In general every network is understood to be a collection of assets, where an asset facilitates the provision of the specific network service. For example electricity networks are comprised of electricity substation assets that facility the supply of electricity as a service, road segments are assets in the road networks that facilitate mobility as a service, and so on. Following the reduction of service at an asset, disruptions are assumed to propagate instantaneously to any connected assets or other infrastructures through functional dependencies regardless of the initiating source of disruption. Ultimately, an infrastructure asset in one network dependent on the provision of service from another asset in another network is readily identified as more vulnerable to a disruption compared to if the affected network was modelled in isolation without external reliances.

To measure the disruptive impacts across different networks the importance of assets in providing services are measured in terms of the numbers of users in the population demanding those services, which subsequently leads to quantifying vulnerabilities in terms of numbers of users in the population disrupted. Similar understanding of user disruptions has been applied in recent studies (Thacker, Pant, and Hall 2017; Thacker et al. 2017). Some examples could include the cancellation or re-routing of passenger journeys in transport due to asset damages, disconnection of users from the electricity supply grid, or user affected indirectly though damage to an infrastructure such as road bridges required for the delivery of petroleum to retail outlets.

In the first instance the user demands across transportation and electricity infrastructures are mapped both spatially and temporally meaning not all assets carry the same disruptive potential. The number of users, u_j^i, of an asset j in an infrastructure i signify a user dependence metric u_j^i, which equates to the number of users or customers directly dependent on the asset retaining a normal state of functionality (given as $s_j^i = 1$) over a given time period. Due to a disruptive event this asset might lose its functionality (i.e. $s_j^i = 0$) allowing the propagation of disruptions towards other assets through recognised functional dependencies, leading to several other assets potentially losing their functionality and hence creating further user disruptions. Hence the total disruption to an infrastructure network of J assets for a given scenario becomes $\sum_{j=1}^{J}(1 - s_j^i)u_j^i$ across those assets where $s_j^i = 0$. The vulnerability due to such a disruption is then expressed as an inoperability fraction of infrastructure i given by:

$$q^i = 1 - \frac{\sum\limits_{j=1}^{J}(1 - s_j^i)u_j^i}{\sum\limits_{j=1}^{J} u_j^i} \tag{1}$$

where q^i is in the range [0,1] such that $q^i = 0$ where all assets across the network are disrupted and $q^i = 1$ implies a fully functional network. This formulation applies to an general scenario of disruption of assets in an infrastructure network. We note here, that we have assumed the functional states as binary 0 or 1, but the formulation also applies to reduced functionality between 0 and 1.

Further to measure dependent disruptions propagating from electricity to transport infrastructure different measures of q^i can be combined. For example, through single electricity substation disruptions, the most critical assets for the transportation sector are identified from the maximum $\sum_{i=1}^{I} q^i$. The cumulative effects of multiple substation outages are obtained by tracking $\sum_{i=1}^{I} q^i$ as a function of the fraction of the electricity assets outages. Through random ordered disruptions to the complete electricity network component set, a system-level dependency relationship can be represented as a curve and directly compared to the expert elicited system-level relationships used in New Zealand practice (Buxton et al. 2016). Multiple simulations of complete exhaustive failure scenarios allow the average national scale system dependencies to be defined.

While this study focuses on targeting electricity assets and their impacts on the transportation sector, we also recognise how co-location of transportation infrastructure assets can increase an asset's vulnerability to outages due to localised disruptive events, whether natural or targeted. Visualising these geographic dependencies however are not straightforward at a national scale given the comparatively small areal extent of asset footprints and therefore exact co-locations of assets becoming hard to identify. In response, we adopt the common approach in the literature where grids of tessellated shapes are overlaid by the geospatial asset data to create a two-dimensional surface with each grid cell take on attributes based on the cumulative presence of intersecting assets (Johansson and Hassel 2010; Patterson and Apostolakis 2007). For readability and to identify statistically significant concentrations of assets that may required more localised analyses, others have suggested applying a Kernel density function (Silverman 1986) to create a visibly smoother surface both at regional (Auckland

Engineering Lifelines Group 2012) and national scales (Thacker et al. 2017). Applying any of these gridded approaches however come a number of caveats such as an assumption that assets are evenly distributed across the grid cell. Specifically for the Kernel smoothing, the appropriate choice of Kernel and the bandwidth or radius of influence a single infrastructure asset has on the surrounding area are critical (Schabenberger and Gotway 2005; Bailey and Gatrell 1995).

In the subsections below we explain and demonstrate the New Zealand specifc network models and data through which the above vulnerability quantification is achieved.

2.1. *Building Network Topology*

First we need to create the network models before the vulnerabilities can be quantified. The I infrastructure networks studied can be represented collectively by a multi-layer network set $M = \{M^1, \ldots, M^I\}$. Within the set M, each infrastructure $M^i \in M$ is a network comprising nodes and edges, which signify the assets defined in the previous section. These are represented as $M^i \equiv (N^i, E^{ii})$, where $N^i = \{n_1^i, \ldots, n_z^i\}$ is the set of nodes and $E^{ii} = \{e_{jk}^{ii} = (n_j^i, n_k^i) \subseteq N^i \times N^i\}$ is the set of edges, defining the existence and connectivity of all assets belonging only to the infrastructure type M^i. The mapping relation $e_{jk}^{ii} = (n_j^i, n_k^i)$ shows that the edge element e_{jk}^{ii} connects adjacent nodes n_j^i and n_k^i. As passenger transportation flows are largely bi-directional, we make the distinction between edges e_{ij} and e_{ji} such that $e_{ij} \neq e_{ji}$. Since adjacent nodes are not necessarily connected to the wider network, $M^i \equiv (N^i, E^{ii})$ is not a complete graph, as is the case where there are discontinuities between islands.

The multi-layered system also contains edges that connect nodes between two different types of infrastructures to represent a functional dependence. These edges are represented by the set $E^{is} = \{e_{jk}^{is} = (n_j^i, n_k^s) \subseteq N^i \times N^s\}$, which also does not form a complete graph. However, combining all node and edge sets together, the multi-layer network set is defined as a network-of-networks $M \equiv (N, E)$, where $N = \{N^1, \ldots, N^I\}$ and $E = \{E^{ij} \forall i, j \in \{1, \ldots, d\}\}$. This allows a disruption in a single network (such as an electricity node) to propagate to those dependent transportation nodes and then throughout the respective networks.

The network user dependency u_j^i is established by mapping customers to nodes n_j^i, based on either available statistics or by assuming the nodes attract their nearest customers in space (Thacker et al. 2017). These user dependency estimates are specific to infrastructures, and as such they are explained in the next sections through the specific context of the infrastructures in New Zealand.

Once the the network models are created and the users dependencies are mapped onto them, the disruption propagations are governed by the creation of the dependency edges between different networks, namely from electricity towards transport in this study. Hence an electricity node n_j^i in disrupted state $s_j^i = 0$, would knock out an airport node n_k^s connected to it via the dependency edge e_{jk}^{is}, making $s_k^s = 0$ for all users u_k^s. Also there are instances of further allocations of users in a network, for example due to travel from one transport node to another. In such cases the disruptions are assumed to propagate along the nodes and edges that are used for such allocations. This allows for further propagation of disruptions towards other nodes and edges creating further functional states equal to zero.

Next we demonstrate the above network model concepts through the data for New Zealand created for this study.

2.2. *Network Data Assembly*

An overview of data used to populate the detailed node and edge sets is provided in Table 1 and spatially represented in Figure 1.

<< Table 1 >>

<< Figure 1 >>

The representation of the electricity network (Figure 1) shows overhead, underground, and sea-floor lines connecting generation, transmission substation, and distribution substation nodes. We assign direct dependencies on each distribution substation according to the geographically closest substation for each census areal unit (Statistics New Zealand 2013). These users are then aggregated to the transmission substation level along with the dependencies assumed from air, ferry, fuel supply, and rail network components (Figure 2).

<< Figure 2 >>

Where exact physical connections between these assets and substations are unknown due to absences in data, we assume a dependency edge takes an overland path to the geographically closest distribution substation. However, ferry terminals and airports located on islands not connected to the national electricity grid are assumed to be autonomous such that the operability of the transport route is solely dependent on the grid connected port-of-call. This is in contrast to other routes where a disruption to electricity supply at either the departure or arrival nodes would correspond to a disruption in normal service for passengers on the route. The number of passengers dependent on each route for a given day is quantified based on operator provided statistics or known service frequencies with assumed load factors.

While rail freight services extend across the country, passenger rail routes are limited to major cities and selected inter-regional routes. This is depicted in Figure 1 with a breakdown of nodes, edges, and user assignment in Table 1. Figure 2 presents the special case where specific rail network edges (in addition to station nodes) are electrified via distribution or transmission substations to power the traction systems. The edge sections reliant on transmission substations for traction are largely limited to the Auckland area where two independent substations act in parallel to provide electricity to the network. This ensures network redundancy such that a disruption in electricity connectivity is required from both substations before users on all dependent routes are affected. Those edge sections reliant on distribution substations are incorporated into the assumption that if a station node loses electricity grid connectivity, then regardless of the traction energy source (i.e. diesel or electricity), the incoming and outgoing routes are both disrupted. This is based on the premise that signalling, communication, and ticketing systems would face disruption and hence disrupting the expected normal level of service of passengers.

The state highway (SH) network is widely distributed with road edges joining nodes at junctions and in-line bridges/tunnels (Figure 1). User dependencies on each asset are assigned using the product of average annual daily traffic counts (New Zealand Transport Agency (NZTA) 2015) and average vehicle occupancies (Ministry of Transport 2015).

Petroleum is distributed from 11 bulk supply nodes to retail petrol stations via the

SH network (Figure 2). To quantify the dependence at each petrol station, populations (Statistics New Zealand 2013) are assigned to their nearest petrol station node. Daily users are then estimated by further considering, average car occupancies (Ministry of Transport 2015), refuelling rates based on average daily travel distances Ministry of Transport (2015), and regional variations in motor vehicle access (Ministry of Transport 2014). Assuming connections to the nearest SH edge segment and a requirement to minimise travel distances, each petrol station is connected to a single bulk supply point via the SH network as determined by Dijkstra's shortest path algorithm. The number of users dependent on each individual petrol station is added to the SH network edges required for delivery such that a given section of road or bridge/tunnel structure will be allocated both a direct dependence from private vehicle travel and indirectly dependent users reliant on a functioning network for petroleum distribution. User dependencies are then aggregated at bulk supply nodes due to directed edges meaning a disrupted bulk supply node is assumed to affect all dependent petrol stations.

3. Results

3.1. *Geographic and Functional Dependencies*

We start by considering the spatial variability of functional and geographic dependencies across our studied networks (Figure 1) in Figure 3. This highlights (a) high densities of co-located transportation assets, (b) high densities of co-located transportation assets weighted by u_j^i, the combined direct and indirect disruptive potential to transportation users, and (c) the most critical distribution substations for wider transportation sector functionality by aggregating user disruptions (u_j^i) at the distribution substation level.

<< Figure 3 >>

As could be expected, there are increased densities of infrastructure in urban areas (as reflected by population densities in Figure 1) and over main transportation routes, where road, rail, and crossings are in close proximity. Considering the disruptive potentials (Figure 3b), the significant dependence on private car use across New Zealand is made apparent with roads radiating from both urban areas and bulk petroleum supply terminals highlighted. In comparison, the dependence on the other passenger air, rail, and ferry transportation modes are not immediately apparent at this spatial extent as they are absorbed into the urban areas. Similarly, the most critical distribution substations for the transportation networks are largely located in urban areas in Figure 3c, where the resulting surface visually compares to population densities at the nationwide scale (Figure 1). These critical substations are further examined in the following section.

3.2. *Critical Electricity Nodes*

The 100 most disruptive substations at both transmission and distribution levels are ranked according to wider transportation sector disruption and presented in Figure 4 with affected residential electricity customers stacked above for comparison.

<< Figure 4 >>

No significant correlations have been calculated or are visible between the disruptions to electricity customers and transportation users resulting from distribution substation outages. However, those substations with the highest transportation sector responsibilities generally show low relative residential electricity user demands – possibly implying these are dedicated or simply located in land use areas with low residential populations, such as near airports or bulk petroleum storage facilities. When aggregated to the transmission substation level, large variability in electricity user disruptions is observed. Those substations most critical to transportation networks still appear to have significant connections to direct electricity users, however, with further investigation and the recognition of additional electricity dependent infrastructure, a more consistent level of potential user disruptions across the substation set may be reached.

To further investigate the effects of substation outages across transportation modes, the ten transmission and distribution substations identified as having the highest disruptive potential are examined in Figure 4. Across the selected substations, the fuel supply network appears particularly vulnerable to disruption where a number of the larger bars represent lost connections to bulk fuel storage assets. This is indicative again of the high rates of private car access and reduced alternative transportation modes in most urban areas. Both of the transmission and distribution substations assumed connected to the Auckland Airport are ranked as having the third greatest disruptive potential – only surpassed by the bulk fuel supply nodes located in Auckland and Wellington. The comparatively low patronage across the ferry and intercity rail services ensures minimal representation in terms of the wider transportation sector. However, substations connected to stations along the commutable rail routes in Auckland and Wellington are significantly more disruptive. The forth-ranked transmission substation corresponds to disruptions to the Auckland CBD transportation hub with dependencies from a combination of fuel supply, rail, and ferry transportation modes. It is noted that due to the redundancy in rail electrification connectivity from transmission substations for areas of Auckland, a loss of connectivity to one of these assets alone has no effect on the wider traction system. The cumulative effects of multiple substation outages are discussed in the following section.

3.3. *Quantifying System Dependencies*

To quantify national system level dependencies on electricity, 1000 separate exhaustive random ordered failure simulations have been performed at both transmission and distribution substation levels. Results given in Figure 5 show the median and range of cumulative disruptions to users as substations are assumed inoperable and cascading failures are accounted for. While 1000 simulations are only a small subset of possible outage scenario combinations, negligible observable differences (<0.01 of the maximum user disruption fraction) were apparent in median curves for the final 500 simulations of each such that iterations were stopped upon reaching 1000. The predetermined sectoral level of service relationships derived through expert-elicitation and experiences from the 2010-2011 Christchurch Earthquake Sequence (Buxton et al. 2016) are also provided for comparison. These curves were obtained through workshops with infrastructure experts to define the expected disruption of an infrastructure network for a given level of electricity supply disruption (Buxton et al.

2016).

<< Figure 5 >>

The cumulative system level disruptions to the passenger air transportation network show similar properties for both transmission and distribution removal scenarios and present the largest range in simulation results across the studied networks. Lost connectivity to any of the three main airport hubs (Auckland, Wellington, and Christchurch) causes significant disruptions across the network. As a result, the sharp changes of gradient in the simulated median curve reflect the disruption sequence of these three airports. While largely contained within the simulated limits, the expert-derived curve follows a more constant slope up to 80% substation removal, where beyond this point, no change in airport functionality is predicted regardless of electricity network state. This suggests that airport infrastructures are expected to have a redundant supply of electricity and can hence operate at 20% of normal capacity without a grid connection. As this is not adopted for each individual airport modelled, this expert suggestion should be Incorporated.

While ferry and air networks are modelled similarly as nodes with direct dependencies on distribution level substations, the greater number of ferry terminals (Figure 2) are dependent on a smaller number of substations. We relate this to ferry terminals and wharves of different commercial operators frequently adjacent to each other in port areas meaning common substation dependencies are shared. In addition, passenger ferries have a greater number of connections to remote islands which are not connected to the represented electricity network. While the probability of randomly selecting a substation with ferry network connections is smaller than airport nodes, the two networks' median curves show similar properties with flatter gradients at either end and similar generalised concavities. As with passenger air, the expert-elicited curve for port infrastructure, assumed equivalent to passenger ferries in this case, suggests 20% of the wider sector is not affected beyond $\geq$ 80% loss in connectivity to the electricity grid. The differences between the expert-elicited and simulated medians likely corresponds to the assumed definition of a disruption where a loss in electricity will not necessarily stop ferry sailings but instead disrupt communication and terminal operations. Similarly to airports, this observation should be adopted in the resulting integrated curves.

The traction system dependence on transmission substations along some Auckland routes is reflected in the range between the shaded limits for each substation type. Similarly, major impacts are evident with the loss of distribution substations in the Wellington City disrupting all inbound and outbound routes. In each case, the median expert-elicited and simulated curves are all predominantly concave-down in shape and show complete network disruptions between 60% and 80% losses in electricity supply. We can assume our modelling assumptions made for the passenger rail network were appropriate.

Losing electrical connectivity to any of the 11 bulk fuel supply nodes has significant effects on the downstream users. This is reflected in the simulated upper limits where trajectories are similar regardless of substation (transmission or distribution) due to each bulk distribution point being reliant on separate substations. The lower limit curves are representative of those simulations where little disruption has occurred at bulk distribution nodes. The comparatively even slope representing the lower limit of the distribution substation removal scenario suggests a relatively even allocation of the private car dependent population to petrol stations. The concave down median curves however, show a steeper gradient up to 50% electricity substation disruption. This indicates the significance of a randomly selected substation supplying a bulk distribution node or densely populated area with a concentration of petrol stations reliant on the same substation node. The expert-elicited system curves for fuel supply indicate no fuel supply network disruptions are expected during both the initial and final 20% of losses in substation connectivity. Of the studied infrastructures, only the fuel supply network is perceived to exhibit this initial robustness to disruptions in electricity. This is likely due to expert assumptions regarding redundant electricity supplies at petrol stations and users having the ability to redistribute their custom to a nearby alternative petrol station in small outages with minimal inconvenience. As such assumptions are not captured in the applied network modelling approach, the expert curve frequently lies outside the simulation results. These two approaches will be combined in the following section (4).

Figure 5 also presents the wider passenger transportation sector dependence on electricity by combining the user disruptions across each of the given networks. While heavily influenced by the petroleum supply curves (given the significantly larger dependent population's), the general s-shape and dominant downwards concavities of the other infrastructure pairings are still evident with noticeable adjustments to the upper and lower simulated limits.

With the transmission and distribution scenarios showing similar median and limit curves properties, we can conclude that transportation users are spread similarly across the substation types. If allocated evenly across the entire substation node sets, a straight line would be expected. Such is shown in the electricity-electricity plot in Figure 5 where a reduced range of simulated curve shapes is depicted. The slightly larger range for the transmission substation scenario implies electricity customers are not allocated as evenly as across distribution substations. This is a result of some higher voltage transmission substations acting predominately as supply or electricity entry points near generation sources with little distribution network demand. Additionally, these could be located in areas with significant industrial and commercial customers with low resident populations but significant electricity demands to require a dedicated higher voltage substation.

4. Integrating Simulation with Expert Opinion

Combining the expert-elicited operability relationships with our simulated network functionalities acts as a validation for each of the methodologies and allows a more robust quantification of system level dependencies . We adopt the expert perceived system level redundancies to define the reduction in electricity supply connectivity before disruptions impact the transportation network and before maximum expected disruptions. The median distribution substation simulated curves define the trajectory between these limits as they capture a wider range of system level dependency relationship outcomes. As a result, the fraction of total network users disrupted u_i for a given removal fraction of substations x is:

$$u_i(x) = \begin{cases} 0 & \text{if } 0 < x \leq X_i \\ \min\left\{q_i(x), \tilde{q}_i\right\} & \text{if } X_i < x \leq 1 \end{cases} \tag{2}$$

where X_i is the initial resilience of the transportation network (i.e. the disruption to the electricity network before the network is affected), $\tilde{q}_i$ is the expert-elicited maximum inoperability of the network, and the function $q_i(x)$ represents the median simulated distribution curve. In the case where $X_i > 0$, Eq. 2 assumes the median simulated curve is simply translated by X_i units. For future applications to allow the computation of $q_i(x)$, the median simulated curves of Figure 5 are fitted to the Kumaraswamy distribution (Cordeiro and de Castro 2011; Kumaraswamy 1980). Given as Eq. 3, this is an approximation to the Beta distribution without any special functions while bounded over the interval [0,1].

$$q_i(x) = 1 - (1 - (x - X_i)^{b_i})^{c_i} \tag{3}$$

Constants b_i and c_i are estimated for each infrastructure through maximising the coefficient of determination using a generalized reduced gradient algorithm. Parameters for Eq. 2 and Eq. 3 with associated fitting statistics are given in Table 2.

<< Table 2 >>

The coefficient of determinations suggest good fits to the observed data along with the predictions all providing mean absolute errors less than 0.02 or 2% of a networks maximum user disruption. The resulting curves combining expert knowledge and the simulation results are presented in Figure 6.

<< Figure 6 >>

Across the air and ferry networks, the maximum disruption to users $\tilde{q}_i$ is 80% of normal functionality. As a result of the adopted definition of a user disruption, this level of network inoperability is reached with fewer substation outages for both air and ferry networks. Given the expected dependence on electricity for airport communications, safety systems, and passenger control/movements, we suggest the proposed curve for the air network is sufficiently representative of reality. Before applying the combined curve for the passenger ferry network, further expert-elicitation is suggested to provide more detail relevant to ferry operations. Similarly, a range of modelling assumptions of the rail network should be clarified before adopting the updated rail curve. The structure of Eq. 2 and Eq. 3 ensure these can be updated without difficulty.

The expert perceived initial redundancies across the petroleum supply network implies no change in operability for a 20% loss in electricity connectivity. With further substation disruptions, similarities in curves are evident (Figure 6). The maximum user disruption $\tilde{q}_i$ is reached after 75% of substations are removed compared to 80% as suggested by the expert derived curve. We see this as a validation of the petroleum distribution model assumptions discussed throughout Section 2 and therefore is a suitable alternative to sole reliance on the expert derived petroleum-electricity relationship.

5. Conclusion

With application to New Zealand, this work has enabled further understanding of the interactions and reliances placed on electricity for the normal operation of the wider passenger transportation sector.

When considering geographic dependencies, the highest concentrations of passenger transportation infrastructure are observed across the main metropolitan areas and major transportation corridors. Similarly, those areas with the greatest disruptive potential are concentrated in urbanised areas when viewed at the national scale. The importance of maintaining a functional petroleum distribution network and state highways within commutable distances is highlighted.

Little correlation is evident between the number of electricity and transportation users assigned to each substation, where the most critical substations for the wider sector have been identified as those supplying bulk petroleum distribution nodes, the Auckland CBD transportation hub, and the major airports of Auckland, Wellington, and Christchurch. With the greatest potential for significant transportation user disruptions, these sites are the recommended targets for ensuring reliable electricity redundancies.

National transportation-electricity network dependency curves were produced through an integration of existing expert-derived relationships and network simulations. This has allowed both a validation of the two methods, and the production of combined curves to provide a more robust quantification of dependence by combining the system level redundancies from experts with the much wider range of possible failure scenarios through simulation. Each of the passenger air, ferry, and petroleum distribution curves can be applied in practice with straightforward adjustments should network operators refine estimates of system level redundancies and maximum disruptive potentials. Passenger rail has been identified as an infrastructure requiring further investigation to refine a number of assumptions made.

As the first application of a national interdependent infrastructure model for New Zealand, future development should consider the addition of further distributed critical infrastructures such as water supply and telecommunications networks. With a more complete representation of networked infrastructure, investigations can identify asset level risks for given high-resolution hazard information. Similarly, disaster specific scenarios with temporal recovery will allow further validation and a deeper understanding of how best to develop increasingly robust and resilient critical infrastructure networks.

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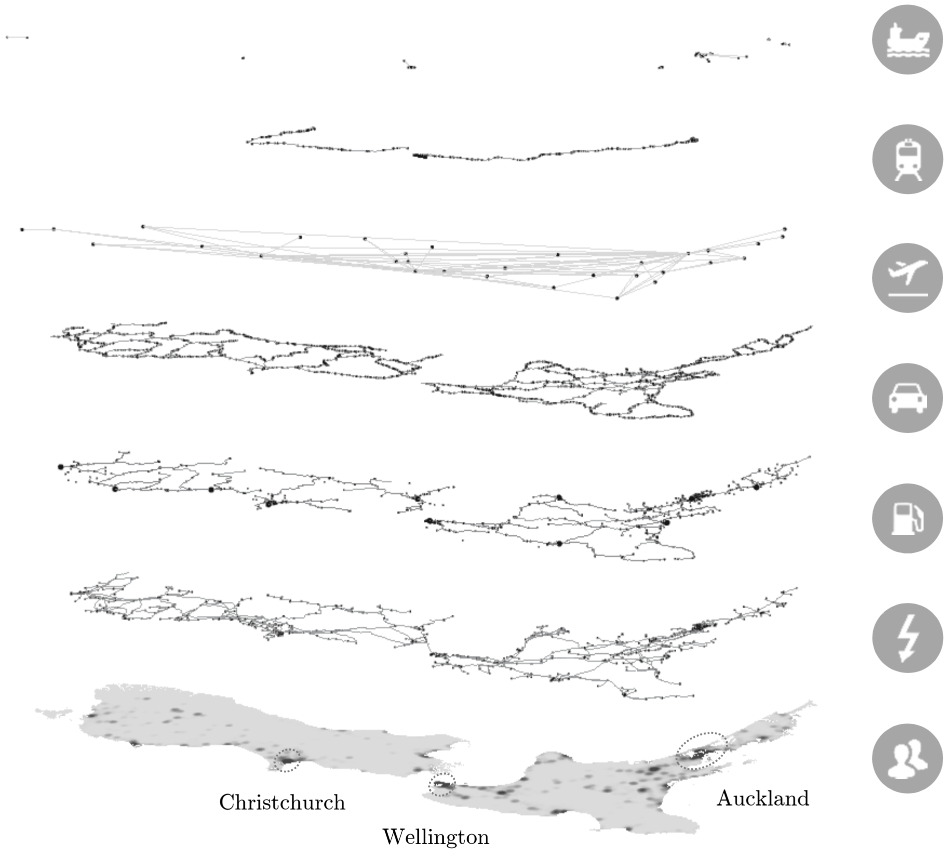

Figure 1. Stacked spatial network representations of studied infrastructures (passenger ferry, rail, air, state highways, petroleum distribution, and electricity supply) compared to the population distribution where darker shades indicate a higher residential density (Statistics New Zealand 2013).

Table 1. Overview of network data

Infrastructure	Nodes	Edges	User Assignment
Ferry	Terminals (45)	Routes (49)	Operator statistics and publicly available service frequencies with assumed loadings.
Rail	Stations (105), Bridges/Tunnels (260)	Rail routes (107)	Operator statistics and publicly available service frequencies with assumed loadings.
Air	Airports (31)	Routes (66)	Operator statistics and publicly available service frequencies with assumed loadings.
State Highways (SH)	Bridges/Tunnels (1914), Junctions (2900)	Road sections (5127)	Average annual daily traffic (New Zealand Transport Agency (NZTA) 2015) with vehicle occupancies (Ministry of Transport 2015).
Fuel Supply	Bulk Storage Point (11), Petrol Stations (1409)	Delivery routes (1409)	Population (Statistics New Zealand 2013) assignment to nearest Petrol Station, regional vehicle access (Ministry of Transport 2014), and refuelling rates based on travel distances (Ministry of Transport 2015). Routes and resulting dependence on SH network sections based on Dijkstra's shortest path connections.
Electricity	Substations: Transmission (137), Distribution (712)	Connections (712)	Population (Statistics New Zealand 2013) assignment to nearest distribution substation.

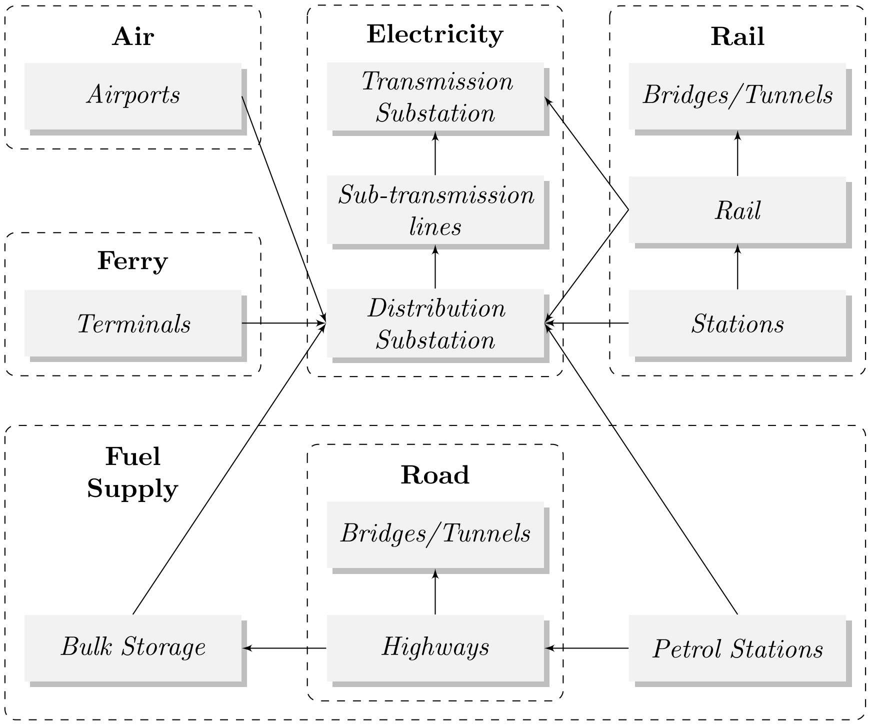

Figure 2. Representations of infrastructures in this study with arrows indicating dependencies for normal operation and dashed lines indicating the groupings of assets within each infrastructure. Regardless of geographic proximity between assets, dependencies are assumed to be realised instantaneously.

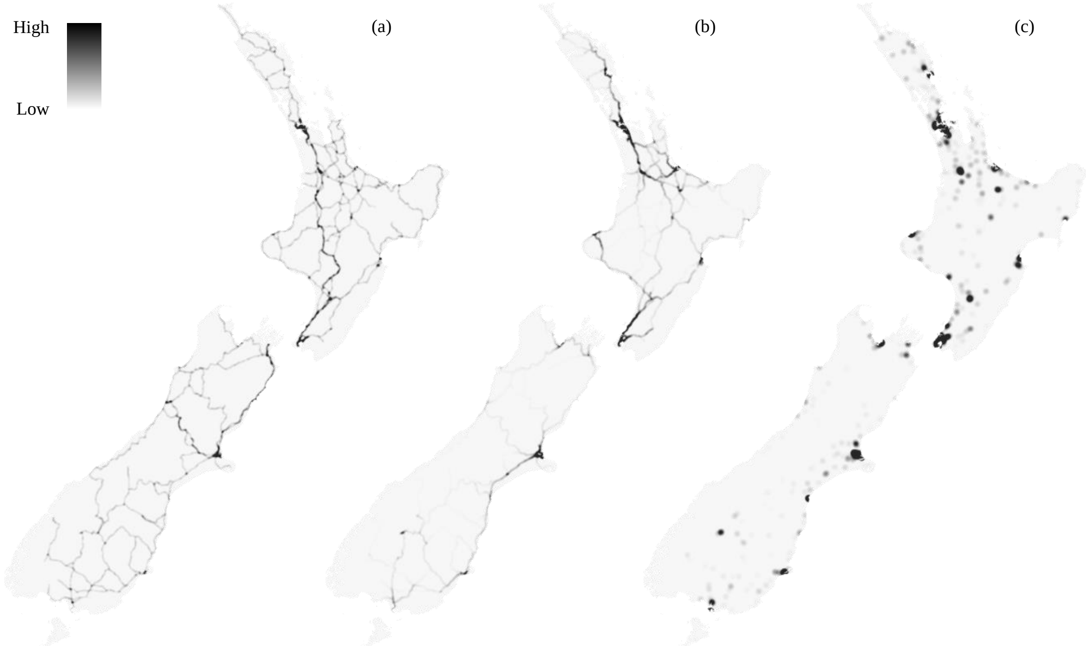

Figure 3. New Zealand's (a) co-located transportation infrastructure, (b) areas with the greatest disruptive potential for transportation passengers, and (c) most critical distribution substations. 5 km grid squares and a Epanechnikov quadratic kernel Silverman (1986) with 10 km bandwidth are assumed for presentation clarity at the national scale. Shading indicates the relative density/user disruptions compared to the maximum measured.

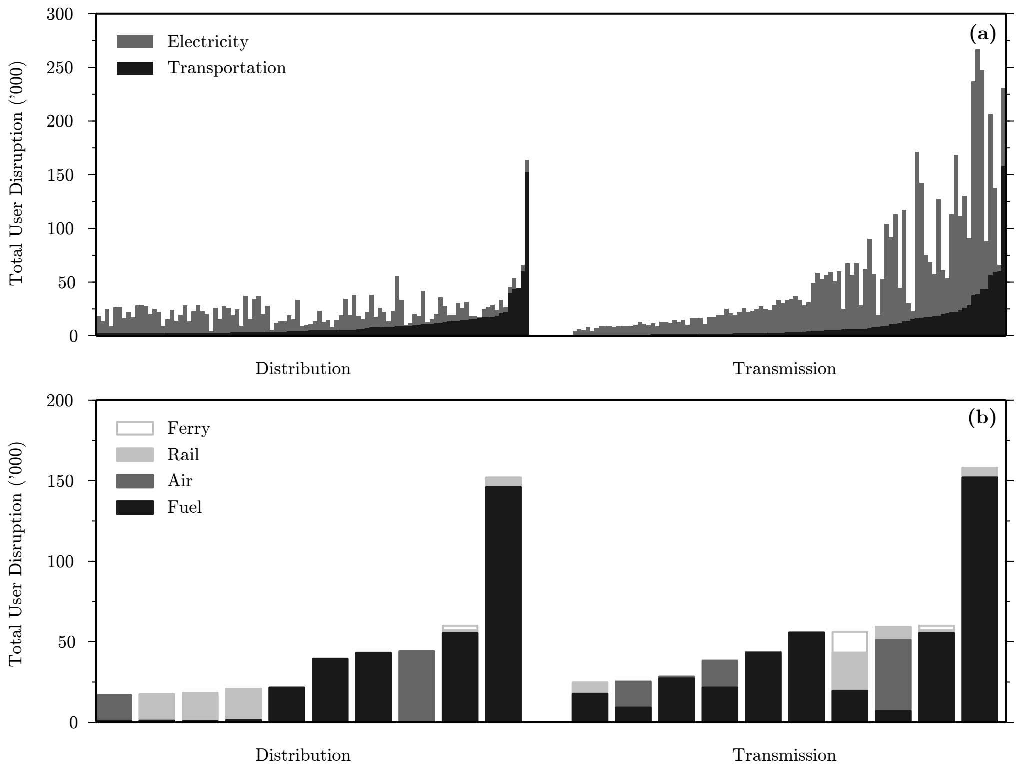

Figure 4. (a) The 100 transmission and distribution substations with the highest disruptive potential to users of the wider passenger transportation sector and (b) the ten most critical substations separated and stacked into the user disruptions arising from each transport network.

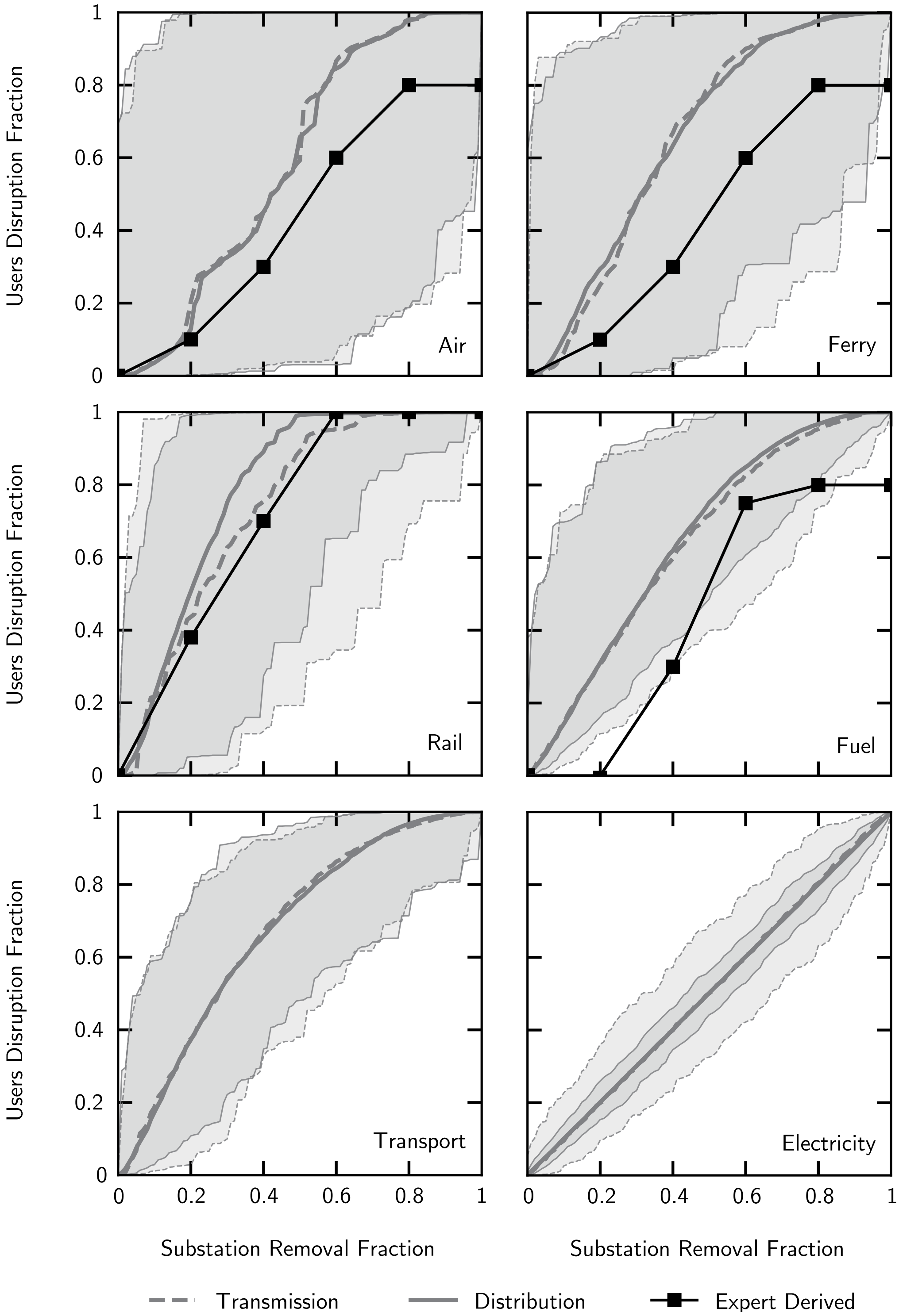

Figure 5. Transportation users disrupted (as a fraction of total) resulting from 1000 exhaustive random removal simulations for both transmission (dashed) and distribution (solid) removals with upper and lower limits with comparisons to local expert derived relationships (Buxton et al. 2016). Shading indicates the limits of transmission (dashed) and distribution (solid) simulations.

Table 2. Fitted curve parameters with the coefficient of determination (R^2) and mean absolute error (MAE) statistics between the fitted and observed median simulations.

Infrastructure	X_i	$\tilde{q}_i$	b_i	c_i	R^2	MAE
Passenger Air	0	0.8	1.952	3.575	0.9949	< 0.02
Passenger Ferry	0	0.8	1.420	3.183	0.9994	< 0.01
Rail	0	1.0	0.984	1.476	0.9995	< 0.01
Fuel Supply	0.2	0.8	1.223	2.454	0.9999	< 0.01

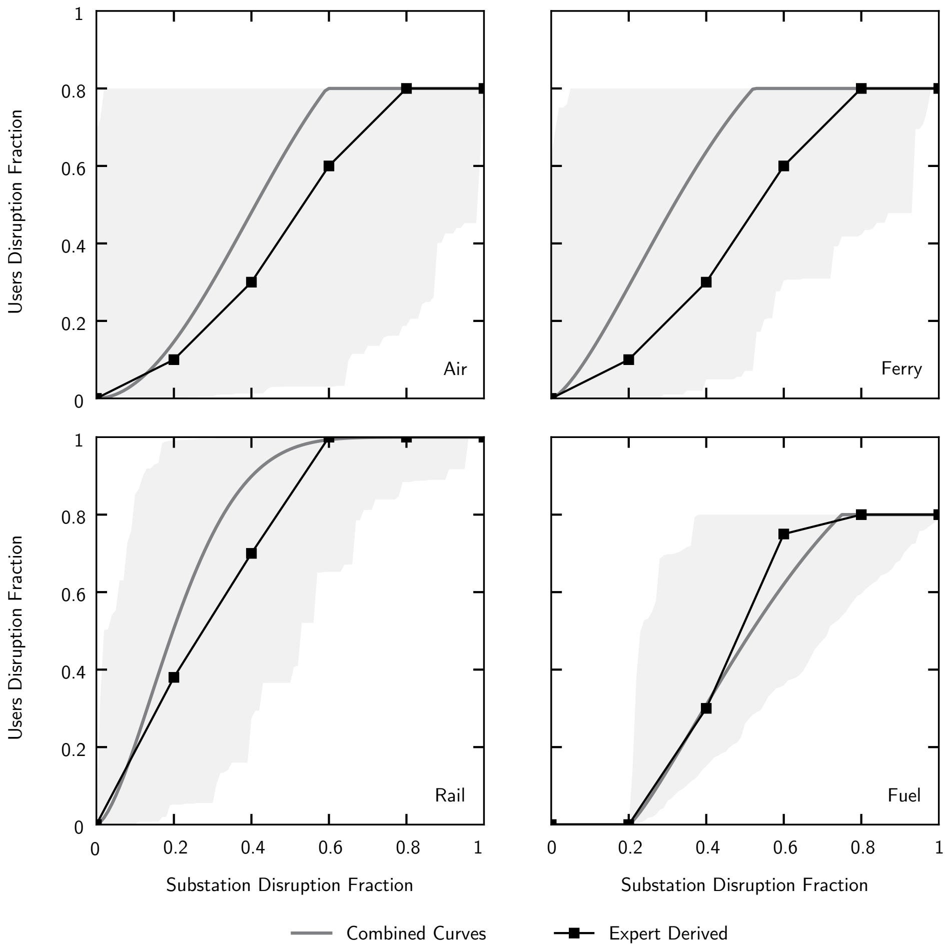

Figure 6. System level dependency curves from combining expert perceived system redundancies with median simulated curves.