RV-DSS: Towards a resilience and vulnerability- informed decision support system framework for interdependent infrastructure systems[1]

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1. Abstract

The common challenge currently faced by critical infrastructure (CI) asset owners and operators is the lack of an integrated and robust resilience-informed business planning and management approach in response to interdependent assets' failures in particular due to low-probability/high-impact environmental hazards.

Interdependencies among CI can cause cascading failures and hence, amplify impacts due to these failures. This can also affect CI's service restoration rate and consequently, reducing their resilience in coping with these hazardous events. As infrastructures are becoming more interdependent in some sectors, there is an increasing need for better management of the interactions and interdependencies.

To reduce these impacts, an integrated resilience and vulnerability- informed Decision Support System (DSS) is required to identify interdependent network vulnerable components and introduce adaptive capacities accordingly. This is of particular importance as CI operators due to their growing investments in asset management to improve the resilience of the networks in response to extreme environmental hazards.

This study presents a novel framework for building a resilience and vulnerability-informed decision support system (RV-DSS). This framework provides potential means of communicating challenges induced due to interdependencies and quantifies benefits of considering interdependencies in streamlining strategies for interdependent systems. It also proposes a measure of network resilience in response to hazardous events, in addition to the commonly used measures of vulnerability for assessment of the network performance. The framework can be used in initiating the interdependency-based communications among different CI network owners and managers, leading to shared knowledge and common understanding of their connected assets, hidden failure propagation mechanisms and collective recovery process. The application of the framework is then demonstrated using a case study in North Argyll, Scotland. It is quantitatively demonstrated that although infrastructures with a higher level of interdependency, can impose the network to higher vulnerability, it provides a greater opportunity for an integrated recovery process.

Keywords

Systems interdependency management, Systems -of-systems, System resilience, Resilience, Systems decision analysis

2. Introduction

The failure of the water drain and sewer system due to 2002 Glasgow flooding affected many homes and closed many main roads and stations such as the A82 and A8 roads, Buchanan Street subway station and Dalmarnock through to Exhibition Centre stations on the Argyle Line. Storms in March 2013 brought down power lines and left thousands of homes on Arran and the mainland without power. Reinforcing the electricity network has cost £197m and taken just under three years to complete. In another example, flooding during the winter of late 2015 and early 2016 washed away three bridges in Cumbria and left thousands of people in Lancaster

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without power. These events highlight that infrastructure networks do not exist in isolation; rather they are interconnected to other infrastructures. Interdependencies among Critical Infrastructures (CI)s can cause cascading failures and hence, amplify consequences due to these failures. This can also affect CI's service restoration rate and consequently reducing their resilience in coping with these hazardous environmental events. As infrastructures are becoming more interdependent, there is an increasing need for better management of these interactions and interdependencies. With growing investments on infrastructure resilience by CI owners and operators, understanding and coordinating these connections become considerably important across all these sectors.

Currently, the available decision support systems (DSS) rely on risk/vulnerability measures while interdependencies and their resilience in response to extreme environmental hazards are overlooked. Conventional CI management techniques aim to provide a high degree of reliability in the design process and risk analysis is the commonly used technique in assessing the response to disastrous threats. However, there are limitations to risk assessment in which not all risks can be quantified due to the existence of emerging and unobserved threats and highly improbable events with a high degree of uncertainty are dealt with poorly (Sweetapple et al., 2018). Furthermore, risk analysis techniques are not capable of assessing infrastructure failure consequences due to low-probability/high-impact crises.

These shortcomings highlight that CI interdependencies management, requires the integration of resilience-informed approach in addition to the conventional holistic risk/vulnerability mitigation approaches. This will enable stakeholders to identify the key components of existing CI networks and will assess the sensitivity of these components to disastrous events and their capacity in coping with such events.

In this study, the authors have developed a novel decision-making framework, titled RV-DSS (resilience and vulnerability-based decision support system). This framework provides a measure of network resilience in response to hazardous events, in addition to the measure of vulnerability and can be used as a means of coordinating the complex connections between different infrastructure systems. The proposed resilience and vulnerability-informed decision making, in general, can provide greater scope than risk analysis and can account for a wider range of threats (e.g., low probability/high impact hazards).

This study presents an overview of the technical details of the RV-DSS framework and its application on the North Argyll case study. The following section provides a brief overview of the state-of-the-art studies in the field of infrastructure interdependencies, resilience and vulnerability quantification. Section 4 presents the RV-DSS framework and section 5 demonstrates the application of the framework on the case study, followed by reflection on results in section 6 and conclusion in section 7.

3. Critical infrastructure interdependencies: state-of-the-art review

3.1. Infrastructure interdependencies

A fundamental characteristic of interdependent networks is that the failure of a node/component in one network may lead to failure of the nodes in another network. The literature on interdependent infrastructure networks covers a diverse set of networks including transport networks, communication networks, financial transition networks, energy networks, water supply networks, food supply networks and fuel networks.

Given the importance of infrastructure interdependencies, considerable attempts have been made in capturing these connections. For example, (Zimmerman, 2004) collected the empirical data available on web sites of construction accidents, reports of the National Transportation Safety Board, and news media searches and verified the application of theories developed on civil infrastructure interdependencies. Similarly Luiijf et al. (2009) have studied the frequency of cascading events by analysing the major events leading to cascading failures affecting more than 10,000 critical infrastructure users (referred as cascading outages). Collectively, these studies have concluded that the energy network is one of the main networks that initiates cascading failure although it is less recipient of such cascaded failures.

In another study, Macaulay (2009) has shown that water systems need steady supply of electric energy to maintain their normal operations; while electric power systems require the provision of water and various telecommunication services for power generation and delivery. This is also confirmed by Cimellaro et al. (2014)'s study where it is shown that restoration of the water network can be highly dependent on power network. Literature is in agreement that generally energy network represents high level of independency while water and transport network (rail network in particular) represent steady dependency on energy. This level of dependency is a function of time, implying that the impacts of interdependency-induced failures increase by time.

To categorize CIs interdependencies, different scholars have provided different classifications. Ouyang (2014) has conducted an extensive review of infrastructure interdependency classification and modelling approaches. Ouyang's study concludes that that among all different interdependency classification, the Rinaldi et al. (2001)'s definition provides a self-contained and more inclusive classification which can cover a wide range of interdependency scenarios.

There are many references classifying the modelling approaches as well as the evaluation criteria (Bloomfield et al., 2009; Bloomfield et al., 2008; Casalicchio et al., 2004; Ghorbani & Bagheri, 2008; Glass et al., 2003; Peerenboom & Fisher, 2008; Pye & Warren, 2006; Rigole & Deconinck, 2006; Schmitz et al., 2007; Solano, 2010; Xiao et al., 2008) . Specifically, Griot (2010) has conducted a meta-review of 12 studies on infrastructure interdependency assessment and suggested a list of 11 criteria and 25 sub-criteria for characterizing each type of models. Similarly, Pederson et al. (2006) have conducted a comprehensive overview of methods and models using six criteria: infrastructures, modelling and simulation techniques, integrated vs. coupled models, hardware/software requirements, intended user and maturity level.

Ouyang (2014) categorises the infrastructure interaction modelling approaches into six broad types: empirical approaches, agent-based approaches, system dynamics-based approaches, economic theory-based approaches, network-based approaches, and other approaches and definitions. A similar categorisation was adopted in the most recent review conducted by Saidi et al. (2018) where the infrastructure system modelling approaches and techniques are classified into five broad categories: 1. System dynamic based approaches, 2. Agent-based simulation and modelling, 3. Input-output models (economic flows), 4. network-based approaches, and 5. Empirical approaches. Ouyang (2014) shows that most of the modelling and simulation approaches are only capable of supporting part of resilience improvement strategies. The High-Level Architecture-based (HLA) method can support all strategies, given its hybrid approach which is capable of integrating all other approaches. Apart from HLA method, the agent-based and network flow-based methods can support most improvement strategies, but they require the largest quantity of input data.

While each method has its own strengths and weaknesses (full description provided by Ouyang, 2014), the focus of most literature on the infrastructure interdependency modelling is on extreme events examining a short-run operational behaviour of the system as opposed to the long-term planning purposes (Saidi et al., 2018). Jeziah et al. (2016) have conducted a study, contextualising the role of the CI interdependency simulations as part of a complete disaster and emergency management program. Pederson et al. (2006) and Eusgeld et al. (2008) have conducted an overview of the 33 different modelling and simulation tools aiming to model infrastructure interdependencies. While there are many well-defined models and simulations exist for different infrastructure sectors, the actual implementation of these interdependencies in high-level command and control is yet to be well-explored (Dudenhoeffer et al., 2006). According to the review conducted by Saidi et al. (2018), many existing works and tools are not well suited for examining long-term impacts and facilitating the infrastructure investment decisions which has derived few studies in this area (Almoghathawi et al., 2019; Ouyang & Wang, 2015).

One of the main barriers in infrastructure interdependency assessment in practice is the lack of structured and systematic data required to conduct these assessments. In the cases where this information exists, there is a significant concern with security and commercial sensitivity of the information. With the benefits of such assessments hidden in qualitative descriptions, there is no sufficient incentive among stakeholders for sharing such information. This study focuses on communicating and quantifying the importance of infrastructure interdependencies and highlighting the potential challenges and benefits of considering infrastructure interdependencies in practice. By providing means of highlighting the importance of infrastructure interdependencies, the proposed framework aims to provide opportunities for avoiding ineffective responses and poor coordination for rescue, recovery, restoration and, mitigation. This can also provide support in coordinating such responses during normal operation rather than solely exceptional circumstances. The consideration of integrated modelling, with the aim of incentivising shared intervention measures, is the main ethos of RV-DSS project.

3.2. Quantification of resilience and vulnerability

The review of resilience definitions in the literature indicates that there is not a consensus in the definition, however, there are several common and shared concepts in all the resilience definitions, notably the capability of a system to "absorb" and "adapt" to disruptive events, and "recovery" from it, ability to stave off disruption, returning to steady-state performance level. Collectively, literature is in agreement that resilience is a collection of related ideas, which explains many faces of resilience and the difficulty in defining it in one single term (Westrum, 2017; Zolli & Healy, 2012). This becomes an even greater challenge when the definition is further elaborated in a conceptual framework with limited means of quantification.

In addition to resilience definition, its assessment and means of quantification have received considerable attention in engineering community in the recent years, as shown in a review study by (Hosseini et al., 2016). In their study, the authors have reviewed several metrics and techniques under the overarching term of resilience. For example, Haimes et al. (2008) introduced resilience as the trajectory of recovery time, following a disruptive event. Inspired by Reed et al. (2009)'s scoring system, based on input-output model, Vugrin et al. (2011) use deviation from a business-as-usual operation, in two dimensions of magnitude and duration, as a measure of resilience. Omer et al. (2014) use graph theory to relate resilience to closeness centrality of the network, before and after a disruption event. Youn et al. (2011) assess resilience as a degree of passive survival rate plus proactive survival rate. Inspired by Henry and Emmanuel Ramirez-Marquez (2012) metric as a ratio of recovery to loss, Hosseini and Barker (2016) assess resilience using Bayesian network, as a function of absorptive, adaptive and restorative capacities. Hosseini et al. (2016) used this Bayesian network in assessing a supply chain system resilience of sulfuric acid manufacturer.

With the complexity of the resilience concept, it has often been confused with the vulnerability of a system. Within the context of disasters, vulnerability is interpreted as the consequences of exposure to a disastrous event (Dalziell & Mcmanus, 2004). McEntire (2001) describes vulnerability as the relative degree of 'risk, susceptibility, resistance and resilience in an occurrence of a disruptive event. Pant et al. (2014) define vulnerability as lack of ability to maintain performance and Pant et al. (2014) assess vulnerability by quantifying the disruptive impacts on passenger travel due to the removal of affected assets. The concept also has often associated with risk analysis concept (Aven, 2011; Haimes, 2006). In several studies vulnerability assessment leads to a measure of risk, interpreting vulnerability as a form of negative consequences (Douglas, 2007; Hall et al., 2005).

Proag (2014) suggest that vulnerability implies a measure of risk, associated with the physical, social and economic aspects. Park et al. (2013) argue that risk analysis needs to be complemented by resilience analysis for appropriate protection of critical infrastructure. As resilience may imply preparation for unexpected, the risk analysis relies on the premise that hazards have been occurred before and are identifiable (Holling, 1973). The risk analysis technique particularly falls short in events with low-probability/high-consequence or high-frequency/low recovery period. This becomes more problematic in considering the probability of joint events.

The debate about the existence and typology of a possible correlation that links resilience and vulnerability has been reviewed by several studies (Folke et al., 2002; Klein et al., 2003; Manyena, 2006). Manyena (2006) has summarised these views in two main standpoints: the first one considers resilience and vulnerability as separate entities, whereas the other one sees them as related. Cutter et al. (2008) investigate the relationship between vulnerability and resilience.

According to Cutter's study, this relationship essentially depends on whether resilience is considered as an *outcome* or a *process* in the system and this is an important step toward application to disaster reduction. According to Miller et al. (2010) study, vulnerability research generally seeks to understand the underlying causes of vulnerability, the scale at which it occurs, and the main actors involved, to identify opportunities for risk reduction, coping, and adaptation.

Generally, the literature suggests that vulnerability studies often neglect the long-term behaviours of the systems. On the other hand, resilience-based approaches cannot be fully realised without a deep understanding of the processes and linkages that underpin the foundations of vulnerability. Miller et al. (2010) conclude that integrated assessments that consider both aspects (i.e. resilience and vulnerability) are required, underpinning more sustainable livelihood strategies and more adaptive governance. It is also evident from the literature that both resilience and vulnerability are multi-disciplinary, cross-sectoral and complex contexts, therefore their definition or quantification in one dimension may limit their application. However, for decision-making purposes, it is crucial to establish a common understanding of the definition amongst all stakeholders (Cerè et al., 2017). In the authors' opinion, this definition also needs to be relatable, meaningful and transferable from one system to another in the context of interdependent networks.

Reflecting on Woods (2015)'s four concepts, the RV-DSS framework has adopted the first definition. In this definition, resilience is the post-event rebound capability of a system to an (original) equilibrium condition. Also, the duration of system rebound is considered, as well as capabilities and resources present before and after the rebound period. In this study, the system behaviour is defined as a function of the key performance indicators (KPI) that are of the utmost importance for asset owners and operators. This is a common practice by literature as shown by Alderson et al. (2015). This seeks to provide a tangible and meaningful metric for resilience using parameters, KPI, that can be monitored and compared with the assumed objective or the desired level.

The implemented resilience quantification technique aims to highlight the importance of interdependency connections and offer means of communicating the impact of these connections on the resilience of the system itself and the integrated infrastructure networks. These communications can lead to introducing buffering capacity and flexibility in restructuring connected systems and altering typically individualistic responsive system management. This would also allow for consideration of cross-scale interactions and cross-sectoral dynamics.

To highlight the importance of multi-dimensionality, the vulnerability definition used in this study is close to the opposite definition of robustness provided by Woods (2015). This definition reflects on worst-case performance of a system to a variety of disturbances and perturbations and reports performance envelope in negative consequences due to a set of perturbations. This could also be considered as a close metric to brittleness which reflects on how system stretches to handle surprise (Woods, 2015).

For vulnerability measure, the magnitude of the loss in functionality is used as a metric representing the vulnerability of the system in response to a failure event. With the conventional definitions of risk as a function of probability and consequences, as a function of vulnerability, this metric can be used as an indication of consequence dimension of the risk. Consideration of the probability and likelihood of the hazardous event occurring is beyond the scope of the current study.

With these definitions, this framework aims to support decision-making for CI resilience planning by addressing the following questions (so called decision-making objective - DO):

DO. 1. What are the potential means of communicating complex concepts of resilience and vulnerability for operation purposes?

DO. 2. How interdependency assessment can be used in resilience engineering of a system?

DO. 3. What is the relevance of the interdependencies in asset management of a single system?

DO. 4. How and why interdependency assessment can be beneficial for each system?

DO. 5. Means of anticipating interdependency-induced failures, perceiving and addressing them when and where they occur?

4. RV-DSS framework

4.1. General network description

RV-DSS framework uses resilience measures, as well as vulnerability, in developing operation and management scenarios. To provide means of communicating complex concepts of resilience, vulnerability and infrastructure interdependency, RV-DSS simplifies the interconnected infrastructure systems into a series of nodes (e.g., power plans, transformers), links (e.g., distribution lines, information exchange, roads) and flows (e.g. energy, information or people). In RV-DSS framework, simulation of the actions and interactions of each infrastructure element (nodes and links) is modelled to assess their effects on the network performance as a whole.

The following section illustrates the details of the mathematical and numerical modelling of a single system network along with failure propagation mechanism in a system due to a failure scenario and corresponding recovery process. Then details of numerical representation of the interdependent multi-system network are provided to demonstrate the process of building an interdependent multi-layered system of systems utilised in this study.

4.2. Single system network

4.2.1. System configuration

In general, for a single infrastructure network, network properties can be represented by $\Gamma = \{\mathrm{N}, \mathrm{E}, \mathrm{M}\}$. In this representation, N, denotes the node sets, E, denotes the link sets, and M is a $N \times N$ matrix representing *links* to pair-wise *nodes*. Table 1 and Figure 1 outline the utilised asset inventory attributes in the numerical modelling in this study. For a network consisting of ν number of nodes and ω number of links, Γ is given as Eq. 1.

$$\Gamma\colon \begin{Bmatrix} N = \{n_1, \dots, n_\nu\}, E_{\Gamma_k} = \{e_1, \dots, \{ \quad e_\omega\} \\ M = \{e_{\mathrm{j}} \to (n_i, n_z), \forall\, j \epsilon [1, \omega], i, z \epsilon [1, \nu]\} \end{Bmatrix} \quad \text{Eq.1}$$

Table 1 - Asset inventory attributes in the RV-DSS framework

XY	Node coordinates (illustrating the geographical location of each asset)
PI^0	Status-quo performance indicator of the asset
Rc^0	Recovery initiation time
FS^t	Asset functionality state over time, varying from 0 (i.e. no functionality) to 1 (i.e. full functionality)
fFa	Failure absorption function given FS^t
fRc	Recovery process function as a function of FS^t
PI^t	Asset performance indicator in time as a function of PI^0, FS^t, fFp, $Rc^0$and fRc
fC	Cost function associated with the fluctuations in level of service and recovery process, fRc

The members of the node vector, N, represent three types of assets, namely source node(s) (providing service), sink node(s) (receiving service) or both (transition asset). The members of the link matrix, M, represent the connection between source nodes and sink nodes. In other words, the link matrix defines the dependency functions, where the functionality of a sink node is defined as a function of the functionality state (FS^t) of the node itself and the functionality state of source nodes, providing service directly or indirectly to that node. The state of each asset, represented by FS^t, is used as an agent that is communicated (via matrix M) to the connected nodes.

As can be seen from Figure 1, both failure absorption and recovery process functions can be represented by five possible options, varying from most conservative behaviour in option 1 to worst case scenario in option 5.

4.2.2. System performance

As the continuity of (business-as-usual) service is of utmost importance for asset owners and managers, the overall service delivered by the system, at any given time, is used to define the '***performance indicator' (PI)*** of the system, in this study. Noteworthy that the performance indicator for any system is defined by the decision-making criteria but ultimately for utility services, this is tied to 'continuity of service' provision to end-users.

An ideal system is responsible for service provision to 100% of its users, at any given point in time. In this system, each asset is directly responsible for a proportion of the 'total number of users'. In this study, this metric is used to define the PI of each asset. In a business-as-usual scenario, the PI of an asset, shown by PI^0, can be idealised and represented as a uniform value with time. At any given time, the performance indicator of the asset is evaluated as a function of asset functionality state (FS^t) (e.g. FS^t of 1 at time t implies $PI^t = PI^0$).

In an event of a failure, the PI will be reduced depending on the impact of failure on asset functionality state FS^t and the failure absorption pattern (fFa) given the event. Once the failure is absorbed by the asset, the recovery process will be initiated at time $t + Rc^0$ and depending on the recovery pattern, fRc, the PI bounces back to a recovered state.

Figure 1, schematically, demonstrates the variation of PI of an asset with time, in response to a failure scenario and as a function of parameters outlined in Table 1. The PI variation with time is represented by the Eq. 2.

$$PI^t = \begin{cases} PI^0 & t < t_{z1} \\ PI^0 - fFa(t) & t_{z1} \le t < t_{z2} \\ FS^t \times PI^0 & t_{z2} \le t \le t_{z3} \\ PI^0 - fFa(t) + fRc(t) & t_{z3} < t \le t_{z4} \\ PI^0 & t_{z4} < t \end{cases} \quad \text{Eq.2}$$

Where, $t_{z1} = t_h$, $t_{z2} = t_h + t_{Fa}$, $t_{z3} = t_h + t_{Fa} + Rc^0$ and $t_{z4} = t_h + t_{Fa} + Rc^0 + t_{Rc}$. In these definitions, t_h is time of failure occurrence, t_{Fa} is duration of failure absorption, and t_{Rc} is duration of recovery.

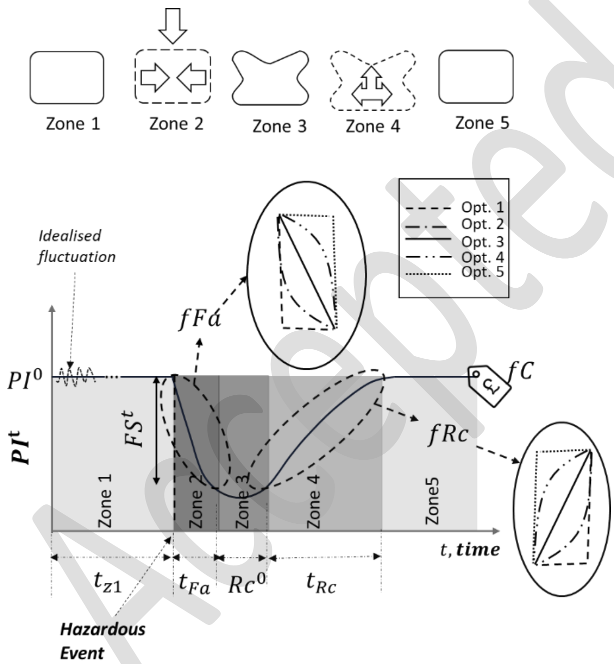

Figure 1 – Nodal asset profile

As can be seen from this figure, the entire journey from pre-failure to post-recovery can be divided into 5 zones:

- Zone 1: The status-quo equilibrium zone
- Zone 2: Failure absorption zone
- Zone3: Initiation of recovery
- Zone 4: Recovery zone
- Zone5: post-recovery equilibrium zone

Having defined PI in asset level in Eq. 2, the functionality of the entire interdependent network can be defined as the sum of the total number of users receiving service from the system in this study, given as:

$$PI^t_{network} = \sum_{r=1}^{v} PI^t_r \quad \text{Eq. 3}$$

where PI^t_r represents PI for asset r at time t.

In line with the above definition, the 'impact' of any failure scenario is reported in the 'total number of users remaining in service', in any given time.

To generalise the analysis, the failure scenarios can be defined regardless of the origin, type and severity of the initiating hazardous event (e.g. extreme rainfall, earthquake, etc.), so-called 'failure state'. Failure state represents the condition (operational condition and/or physical condition) of a network (or any asset), causing negative impacts on network performance (partially or fully), regardless of the initiating source.

In an event of a single failure scenario, the failure of an asset will be propagated to its connected assets, as a function of failure absorption pattern for each asset. Once the recovery of the failed asset is initiated, the service will be restored in the failed asset and this will be communicated to all affected assets. The example in Figure 2 demonstrates a single failure scenario propagation in a conceptual network. The conceptual network comprises of 6 nodes and 5 dependency links.

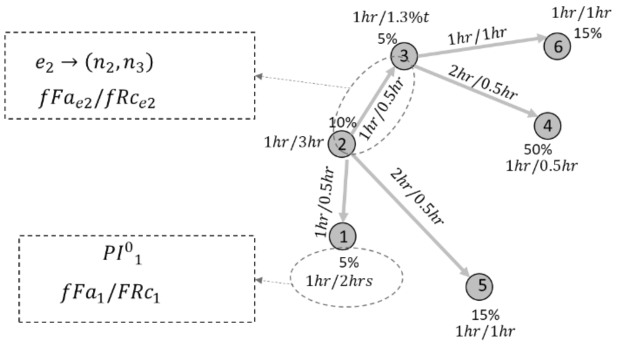

Figure 2 - Conceptual network with assumed failure and recovery patterns for nodes and links

For illustration purposes, Figure 3 demonstrates the change in PI of all 6 nodal assets in response to a failure scenario where node 3 has experienced 80% loss on its functionality state at time=1hr (i.e., $FS^1_3 = 20\%$). As can be expected, the PI of nodes 1, 2 and 5 remain intact as there is no failure propagation path from node 3 to these nodes.

The profile of the PI for the entire conceptual network is calculated as the sum of the PI for all 6 node (see Eq. 3). Given the contribution of asset 4 in the number of users, it is not surprising that the profile of the PI for the entire system is dominated by asset 4's performance.

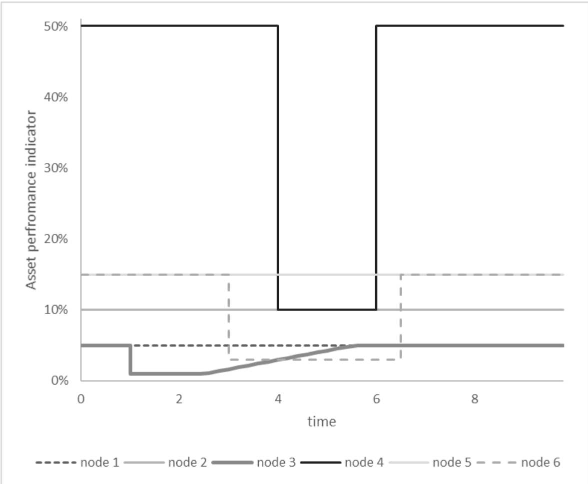

Figure 3 - Impact of 80% failure on the functionality of asset 3 in the conceptual network for each individual node

4.3. Multi-system configuration

To expand the single system modelling configuration to multi-layered interdependent systems, in addition to dependency mapping of each system, the interdependency mapping is required to establish the connections between individual assets from a different network. Similar to dependency connection, any link in interdependency mapping represents any form of service flow from one asset to another.

Eq.4 shows a representation of interdependency mapping for a multi-layer interdependent system with u individual networks. In this equation, M_i represents dependency matrix for network i and $O_{ij}, i \neq j$ represents interdependency links from source node in network i to sink nodes in network j.

$$\boldsymbol{M} = \begin{bmatrix} M_1 & \cdots & O_{1,\mathrm{j}} & \cdots & O_{1,\mathrm{u}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ O_{\mathrm{j},1} & \cdots & M_{\mathrm{j}} & \cdots & O_{\mathrm{j,u}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ O_{\mathrm{u},1} & \cdots & O_{\mathrm{u,j}} & \cdots & M_{\mathrm{u}} \end{bmatrix} \qquad \text{Eq.4}$$

4.4. Resilience and vulnerability metrics

As discussed in the review section, the resilience and vulnerability of any engineering system need to be linked to decision-makers' defined KPIs. Often the performance of an engineering system can be expressed in terms of its demand (load) and capacity (resistance). In the transport system context, the load can be the traffic demand and the capacity is dictated by the available infrastructure, in this case, roads.

In light of the conventional network performance measures, this study uses the status-quo 'total number of users in service', as the commonly used network performance metric for all the infrastructure networks considered. The main advantage of this PI is the possibility of its direct translation to corresponding economic implications. In addition to heavy compensations, frequent failure in service provision can also have reputational damage which is of particular importance for private utility service providers.

With the definitions provided in section 3.2, in this study, the **vulnerability** is measured as the worst performance of the system subjected to a failure scenario represented in Eq. 5. For the **resilience**, the area under PI vs time is used to capture the rebounding journey of a system following a disruptive event, shown in Eq. 6.

Eq.5.

$$network\ vulnerability_{\Gamma_j} = max\,(\sum_{r=1}^{v} PI_r^0 - \sum_{r=1}^{v} PI_r^t)$$

Eq.6.

$$network\ resilience_{\Gamma_j} = \int_t \left(\sum_{r=1}^{v} PI_r^t\right).dt$$

One of the limitations of the considered resilience metric may seem to be its lack of capability in acknowledging the importance of the number of users over time. In other words, the resilience of a system losing 100 users for an hour prior to recovery could be similar to the resilience of a system losing 10 users for 10 hours. This highlights the importance of consideration of resilience and vulnerability as complementary metrics.

The following section provides details on how this framework is applied to a multi-layered integrated system developed for the North Argyll case study.

5. North Argyll case study

To demonstrate the application of the developed framework in initiating interdependency-based decision making, a case study in Scotland is selected and presented here. The case study was selected given the recent widespread interdependency-induced failures due to increased frequency and magnitude of environmental hazards in Scotland. The selected critical infrastructure networks in this area include drinking water distribution system, electricity distribution network (utility networks) and three modes of transport: road, rail and ferry networks.

As mentioned previously, the major problem in modelling and validating infrastructure interdependencies is posed by the fact that detailed information about CI dependencies can be highly sensitive and is usually not publicly available in the UK. As it is evident from the previous section, network modelling approaches have a wide range of data requirements. Collecting this information is generally difficult due to several concerns, including the high cost of monitoring the real-time performance of infrastructures, assembling and maintaining databases, privacy, commercial sensitivity, security, and proprietary issues (Rinaldi et al. 2001). Furthermore, infrastructure owned and operated privately often have a restricted policy to collect and share data. Moreover, the commercial sensitivity of this information aggravates the security concerns in sharing infrastructure asset inventory information. In cases where sensitivity is not of concern, the information required is not readily available due to the complexity of many failure scenarios and recovery measures in many different types of assets which in practice, are seldom recorded in detail. The case study presented here is used to demonstrate the application of the framework to an interdependent infrastructure system and offers a systematic mechanism for collecting interdependency data for connected systems.

5.1. Data collection

Given the challenges with availability and sensitivity of data and associated security concerns, in this study, open access data are used to build the case study. The aim of the case study is to illustrate the capabilities and application of the RV-DSS framework in providing means of understanding how integrated infrastructure design can deliver local and regional economic resilience. Furthermore, it highlights the extra value for money where shared interdependencies can be co-managed between sectors. To overcome the challenge with data, in a recent study by Oughton et al. (2019), the authors have employed a stochastic counterfactual risk analysis using expert elicitations.

5.1.1. Three modes of transport

In this study, the sources of data are: Ordinance Survey data , Department for Transport, Office of Rail and Road Data, Argyll and Bute Council and Transport Connectivity and Economy Research studies. By crosslinking the database from these sources, a comprehensive map of the transport network in the case study area was prepared. In addition to the transport network assets, Argyll and Bute Council database was used in obtaining the coordinates for water reservoirs and power stations. Figure 4 presents the geographical locations of all transport assets (road, rail and ferry ports), reservoirs and power stations based on open access data.

This physical network is then used to generate the simplified node and links representation network. In this study, every junction in the road network considered to be a node and every connection between the junctions are simplified by bidirectional links. A similar method is used for rail and ferry networks.

To generate the expected performance indicator (status-quo) for each asset in the road network, the annual average daily traffic (AADF) dataset published by the Department for Transport is used. The dataset provides AADF for a-road and b-road links for each direction.

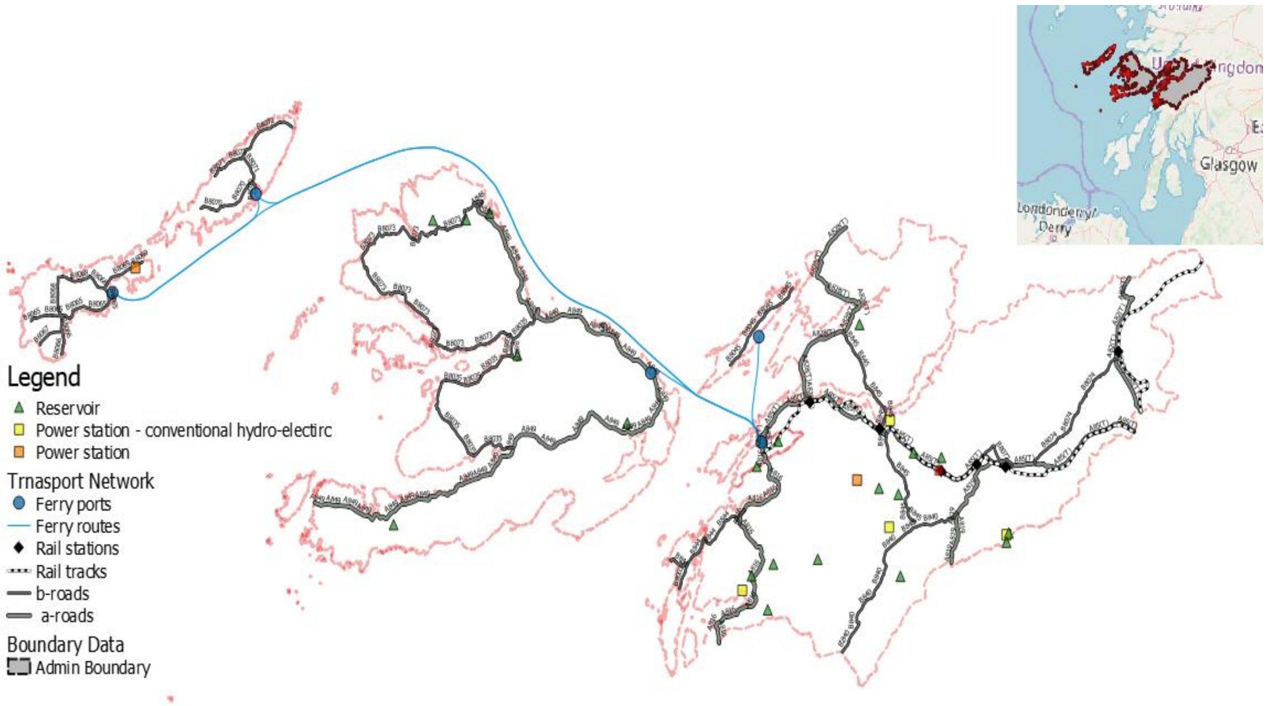

Figure 4- Collected data for the North Argyll Case Study

The collection points for the b-roads in North Argyll area is limited, therefore, an interpolation technique was used to estimate the number of users for the b-road links. Given the limitation of the available data, the minor roads are not considered in the case study.

For the rail network, the total number of exits/entries from the Office of Rail and Road Data were used to estimate the number of users for each station (i.e. node) and each rail (i.e. link).

It should be noted that the case study area only covers 8 rail stations. Three dummy stations are considered at the boundary of the case study (Rannoch Station, Tyndrum Lower Station and Upper Tyndrum) to represent the impact of these connected stations on the case study area.

The data from Argyll and Bute Council on ferry routes provide the number of passengers per each route, which is then used as the number of users per link (i.e. ferry route) and consequently used in calculating the number of users per each node (i.e. ferry port) in a similar approach to the road network. To compare the performance of different networks, the total number of users in each network is normalised to 100%.

5.1.2. Utilities and independency connections

Using population distribution and the collected open access data on transport, reservoirs and power stations in the case study area, a hypothetical drinking water network and electricity distribution network are designed. The approximate location of storage tanks and energy distribution substations and population concentration points are used to divide the case study area into serving zones, using Voronoi partitioning. The approximate population in each zone is calculated to estimate the number of users per storage tank and substation.

To explore the impact of interdependency on the network's vulnerability and resilience, in this study, different level of interdependency is introduced. As shown in the literature review, the energy is generally assumed to be an independent network, except for its dependency on the road network for maintenance purposes. For demonstration purposes, in this study, the energy network is considered to be an entirely independent network. This is to investigate the impacts of zero interdependency level. A higher level of interdependency is considered for the road and ferry networks, where, interdependencies are introduced in bi-directional connections between ferry terminals and road assets due to geometrical and physical dependencies.

For the rail network, in addition to assets connection to nearby road assets, it is assumed that all assets in the rail network are recipients of water and energy services. For the drinking water network, it is assumed all assets in the water network requires energy for the service continuity.

Furthermore, it is assumed that assets in water network are dependent on road network for maintenance purposes. To accommodate this, a nominal network, so-called *maintenance network*, is introduced, where, the maintenance routes on the road network are represented by a node in the network.

5.1.3. Case study summary

Table 2 provides a summary of the number of nodes and links in each network. It can be seen that the road network, expectedly has the largest cohort of nodes and links. The connectivity quality of the entire network is summarised as the ratio of the number of links to the number of nodes. The summary of links excludes the number of interdependency links.

Table 2 - Summary of network representation with nodes and links –North Argyll case study

Network	No. Nodes	No. Links	Link/Node Ratio
Road	242	490	2.02
Maintenance	12	0	0.00
Water	43	32	3.20
Energy	29	20	4.00
Rail	10	18	1.8
Ferry	5	10	2

Table 3, provides a summary of non-zero elements of master dependency and interdependency matrice, $\boldsymbol{M}$.

Given the connections between road assets and notional maintenance routes, the latter represents a high level of interdependency. Water network ranks second as it receives service from both maintenance and energy networks. The latter connections are those directly provided by the electricity main distribution network and excludes the electricity provided independently.

Table 3 - Distribution of all links in the integrated North Argyll case study network

		Sink					
		Road	**Maintenance**	**Rail**	**Ferry**	**Water**	**Energy**
Source	**Road**	490	153	10	5	0	0
	Maintenance	0	0	0	0	13	0
	Water	0	0	0	8	32	0
	Energy	0	0	8	0	43	20
	Rail	0	0	18	0	0	0
	Ferry	0	0	0	10	0	0

Despite the notional nature of the case study data for water and energy networks, the exercise of identifying potential connections between these two networks and other three transport modes proved to be of great value. This information is not readily available for infrastructure system owners/operators and this exercise initiated the interdependency discussions among case study stakeholders. The purpose of the co-created dataset was not only to close the gap in the information required for the framework but also to provide means of demonstrating how integrated infrastructure design can have potential in delivering extra value for money where shared interdependencies can be co-managed between sectors.

6. RV-DSS analysis and results

To analyse the impacts of failure propagations due to inherent interdependencies, this study considers all "what-if" scenarios where the failure scenarios are defined regardless of the origin, type and severity of the initiating hazardous event (e.g. extreme rainfall, earthquake, etc.), the so-called 'failure state' concept. The impacts of these failure scenarios are reflected on the number of remaining users in service for each asset and the entire interdependent network.

6.1. Single failure scenarios and interdependency-induced propagation

For the first experiment, the impact of all possible single failure scenarios is considered. For each scenario, an asset is failed with 100% failure in functionality state. For consistency, the failure propagation profile is considered uniform and abrupt for all assets. Figure 5 demonstrates the result of this experiment in the form of alluvial flow diagram with five shades of grey allocated to five infrastructure networks. This diagram visualises the criticality of different failure scenarios in each network In addition, it directly supports the developed framework's response to the DO.3 and DO.4 to support the decision-making process.

In this diagram, the impact of single asset failure on the number of remaining users in service is demonstrated in weighted flows. Each strand on this diagram demonstrates the impact of an asset failure, on PI of the entire interdependent network.

For example, for the road network with 242 nodes, Figure 5 shows 242 strands (also 242 single failure scenarios) on left-hand-side with the impact represented by the thickness of each strand and the endpoint demonstrating the affected network, in this example, road, rail, ferry and water. It is shown that not surprisingly, as the interdependency increases, the network vulnerability increases. For example, the rail network with interdependency on energy, water and road demonstrates four shades of strands (including assets in the system itself). These strands illustrate the number of scenarios that can have a negative impact on rail network PI, in this case, the number of users. On the other hand, energy network, notional independent network with 29 assets and shown in the lightest grey, has no strands feeding from other networks (i.e., the system is not vulnerable to failure scenarios in other networks). Noteworthy that individual assets can have an impact on more than one network, which is shown by strand split on left-hand-side of the figure.

Figure 5 shows that in the networks with the highest level of interdependency (i.e., rail and water in this case study), interdependency-induced failure scenarios are governing. The cluster of different shades of grey on right-hand-side for each system is an illustration of potential *hidden vulnerabilities* and *hidden failure scenarios* that may have been overlooked by a system operator. This highlights the criticality of considering interdependency links in asset management decisions and also short-term and long-term investment strategies (DO.3 and Do.4).

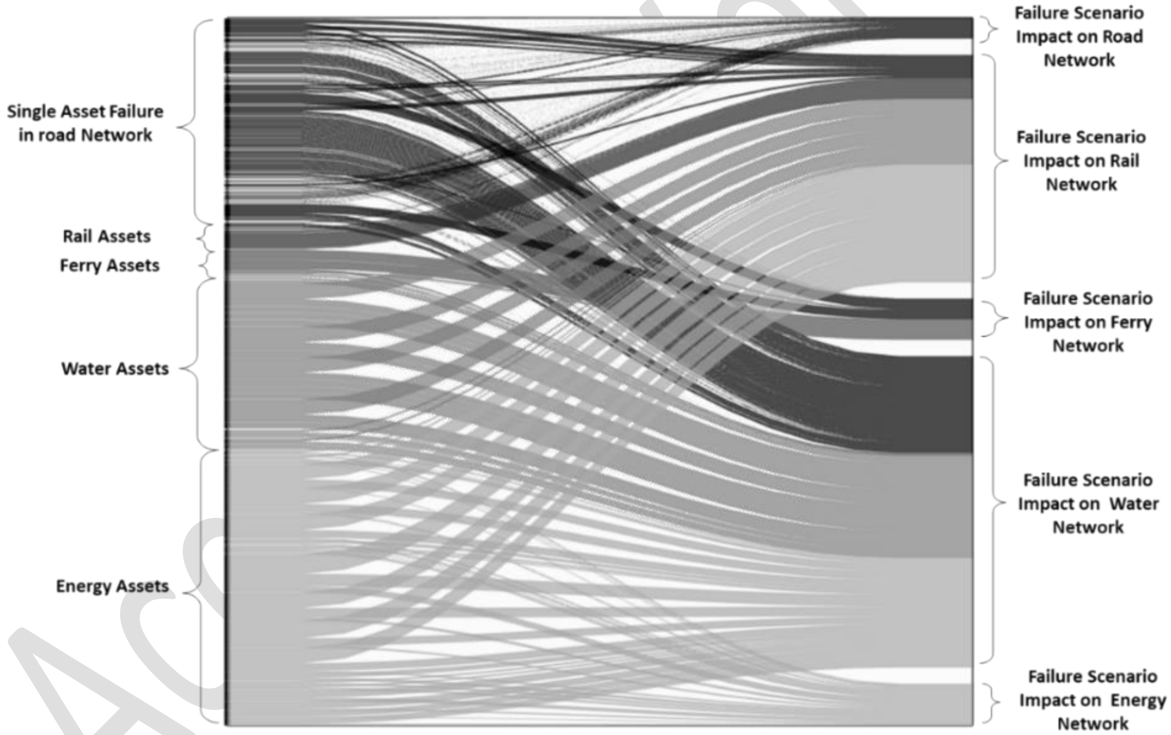

Figure 5 - *Alluvial Flow Diagram for all single failure scenarios – the left-hand side demonstrates all assets in all networks, shown with different shades of grey for each network and the right-hand-side demonstrated the collective scenarios for each individual network.*

6.2. Resilience versus vulnerability in RV-DSS framework

In order to study the impact of interdependency on resilience, a similar experiment with single failure scenarios are conducted. To assess the resilience of the network, in addition to the failure propagation process, the recovery process is also considered. In a similar attempt to the previous scenario and for consistency purposes, the recovery initiation, Rc^0, and recovery duration, fRc, are assumed constant for all assets (nodes and links). This assumption helps to focus the study on the impact of interdependency level on vulnerability. Variation in failure absorption, recovery profile and initiation time, add another level of variability which is beyond the scope of the current study.

For the purpose of the analyses, the recovery initiation and recovery duration are considered to be 1hr and 4hrs, respectively. Figure 6.a. demonstrates the resilience and vulnerability of all single failure scenarios for the water distribution network. The area in this graph is divided into four zones: i. high resilience-low vulnerability, shown in white; ii. Low resilience-low vulnerability, shown in light grey; iii. High resilience-high vulnerability shown in dark grey; iv. Low resilience- high vulnerability shown in black. The intensity of the shade of grey demonstrates the importance of the scenarios for decision-makers from resilience and vulnerability point of view (DO.1 and DO.2).

In Figure 6.a., every single grey point demonstrates a single failure scenario in a network, which means all figures contain 341 points (total number of nodes). Scenarios with no impact on resilience and vulnerability are shown on the far-left side of the figure, demonstrating a resilience of 2000 and failure of 0. The magnitude of resilience is calculated for PI of 100% for 20 hours.

Repeating the experiment for all networks, it is found that in networks with a low level of interdependency, such as road and energy networks, the correlation between resilience and vulnerability, as defined in this study, is linear. As the interdependency level increases, for example in water and rail networks, single failure scenarios show a more scattered pattern in resilience versus vulnerability graphs. This highlights the importance of considering these two metrics as complementary measures and not in isolation.

In practice, critical failure scenarios are those with concurrent failures. Figure 6 compares the impact of all single failure scenarios in Figure 6.a, to double failure scenarios in Figure 6.b. For double failure scenario, all possible combination of two-asset failures, in total 115,940 scenarios, are considered. For consistency, it is assumed that both assets fail at the same time with functionality state of 0% upon failure. It can be seen that as the number of concurrent failed assets increases the scattered pattern in resilience-vulnerability diagrams becomes more pronounced. This complements the behaviour observed for networks with a higher level of interdependency. As expected in double failure scenarios, the number of points in black and dark grey zones grow.

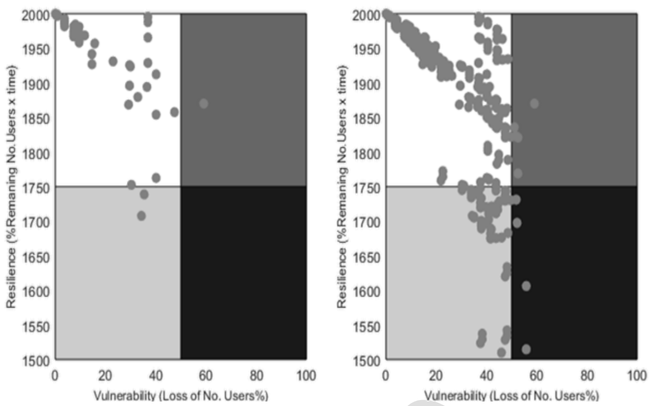

Figure 6 - Resilience vs vulnerability for water network a. Single Failure Scenarios b. Double failure scenarios

As part of this experiment, the correlations between resilience and vulnerability with graph theory metrics such as betweenness, degree and cluster coefficient are also assessed. The results show that ferry network with the highest ratio of nodes to links, results in the highest correlation between these variables. This is not a consistent trend among all other four infrastructure networks and there is no obvious correlation between graph topology and resilience/vulnerability of an interdependent network.

6.3. Concept of shared intervention

This framework can also be used in a higher resolution analysis by introducing "shared intervention" concept to address the DO.2, DO.4 and DO.5. Figure 7 demonstrates the impact of individual asset failures in the water distribution network on vulnerability of the water network itself and the interdependent rail network. For this purpose, all single failure scenarios for nodal assets in the water network is assessed and the impact on the network itself and the independent network is calculated and shown by bar size in Figure 7.

The figure shows that several assets in the water network can result in considerable failure in the interdependent network. Generally, these assets are of high importance in the water network itself, shown by the size of the bars, therefore, in an event of failure, recovery initiation would be expected to be rapid. In the scenarios where the asset may not be immediately considered important for the network itself, but it could result in significant loss of service in the interdependent network (e.g. 28W in this case), asset owners can discuss the possibility of sharing intervention measures. This can help speeding up the recovery initiation and hence, leading to speedy service restoration in the interdependent network. This decision can be considered in conjunction with recovery cost associated with each asset and savings for both networks in the form of rapidity in recovery and hence, improved resilience.

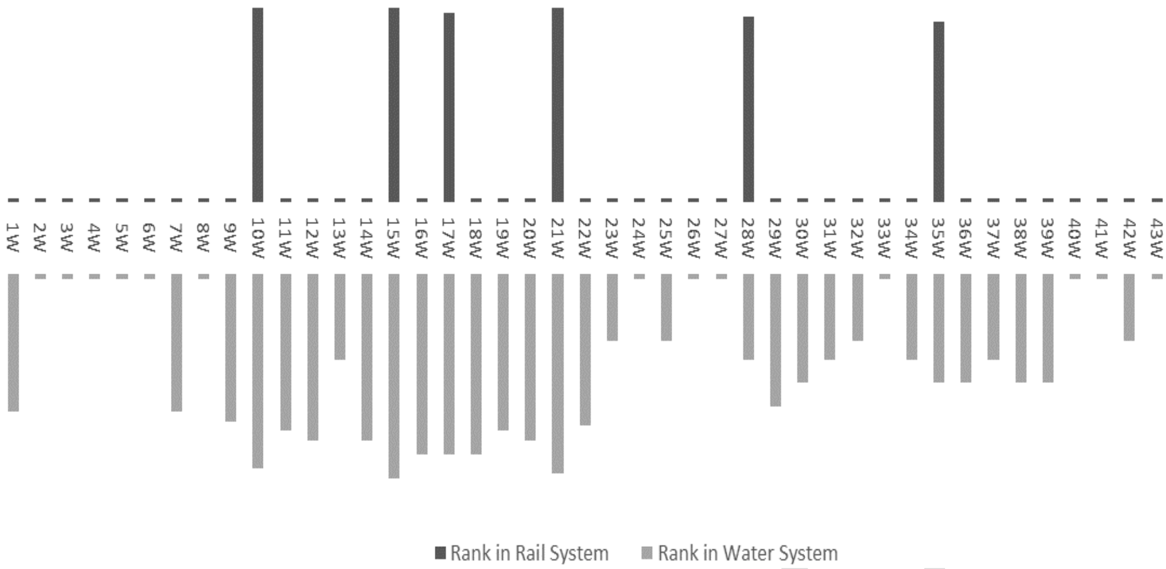

Figure 7 - Water network asset ranking for dependent and interdependent network based on their impact on key performance indicator of each network.

The results of this analysis can also be used in identifying the ideal location for maintenance depot or instigating redundancy options for networks with a high level of interdependency. For example, Figure 8 demonstrates the overlap of "interdependency clusters" for all interdependency-induced single failure scenarios. Interdependency cluster demonstrates the area affected by the source asset. The dark grey areas in this figure demonstrate the overlap in areas affected by different scenarios. This area also shows the spatial extent of the failure in the case study area. The shaded area covers the initiating failed asset and propagated failure. As the shaded area becomes darker, it means that the area is affected by a larger number of failure scenarios.

This can be used as means of identifying the most vulnerable areas and hence, can provide guidance in improving resources or redundancy level required. It can also support optimising decisions concerning emergency systems. This is particularly useful in addressing and responding to DO.5. This element of the framework was well received by stakeholders for the selected case study as a means of spatial visualisation of low resilient areas.

To demonstrate the potential of RV-DSS framework in operational decision-making and considering interdependencies, Figure 9 illustrates an example of the contribution of all networks in improving the resilience of the rail network. For this purpose, all single failure scenarios that can have an impact on the overall KPI of the rail network is assessed. In this exercise, the recovery initiation and profile are considered constant for all scenarios. These scenarios are shown in a cluster of strands for the rail network in Figure 5. In the next stage, the same experiment is repeated with 1 hr change in recovery duration for all scenarios. This change in recovery can be in the form of improving the rapidity or increasing the resources available for the recovery process.

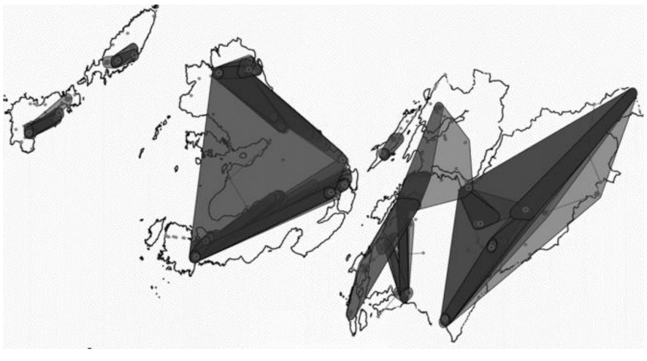

Figure 8 - Interdependency Cluster for all interdependency induced failure scenarios – failure propagation zones for all interdependency-induced scenarios

The difference between the resilience values from these two experiments is recorded as a percentage of change in resilience and is categorised by each network. Figure 9 demonstrates the cumulative impact of 1hour reduction in recovery duration of all single failure scenarios on the rail network.

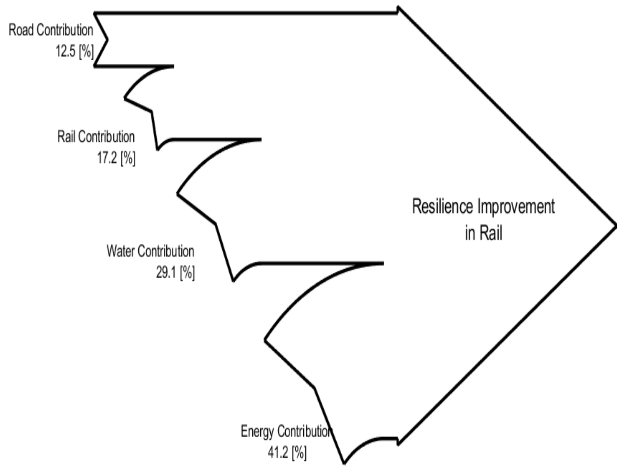

Figure 9 – The Impact of 1hr change in recovery duration in all single failure scenarios on the resilience of the rail network

It can be seen that although a change in recovery duration in the network itself has a considerable contribution to resilience improvement, change of recovery duration on source interdependent networks can have a significant impact too. This further reinforces the previous results on the importance of the shared intervention strategies in improving the resilience of interdependent networks. This assessment can be used in the cost-benefit assessment of CI networks, where, the cost associated with recovery measures is compared to the savings in resilience.

7. Conclusion

This study presents the outcomes of a feasibility study on producing a framework for a resilience and vulnerability-based decision support system (RV-DSS) and its application on a case study in North Argyll, Scotland, UK.

Infrastructure systems are heavily connected and lack of/ineffective consideration of these primary and 'n-ary' connections and the implication of the interdependency-induced failures, presents a great challenge in understanding system behaviour. For this purpose, a network-based framework is developed to simulate failure propagation and recovery process for a multi-layered interdependent network consisting of five infrastructure systems. The impacts of the interdependency-induced failure scenarios are then quantified and assessed to establish and map the resilience and vulnerability of the integrated system accordingly.

Different levels of interdependency and their impacts on system resilience and vulnerability are investigated to demonstrate why interdependency assessment is important in infrastructure asset management and how this can be used in resilience engineering of a system. It is also shown how a higher level of interdependency highlights the importance of consideration of resilience as a complementary metric to vulnerability, as it provides a broader picture of system behaviour in response to failure scenarios. The vulnerability and resilience measures in this study can provide common means of communication and frame of reference for different critical infrastructure systems' performance assessment. Nonetheless, further research is required in investigating the applicability and effectiveness of other measures, introduced in the literature, for each infrastructure system. This also includes consideration of multi-dimensional performance indicators.

In this study, the complex structure of a multi-layered interconnected systems is simplified into a system of nodes and links and the failure is interpreted as form of discontinuity in service. While there are many well-defined models and simulations exist for individual systems, integration of these systems for interdependency assessment is rather limited to qualitative and conceptual frameworks. This study is an attempt in quantifying the benefits and the importance of considering infrastructure interdependencies in decision-making. The developed methodology is then applied to a case study. The notional nature of the co-created data limits the validation capabilities; however, despite its limitation, the case study serves the purpose in demonstrating means of communicating interdependency-induced vulnerabilities and resilience capacities. The validation process also requires an in-depth investigation of failure absorption and recovery patterns for individual assets

To realise the potential benefits of inherent interdependencies in infrastructure systems, a concept of *'shared intervention'* is introduced. This concept can be used in anticipating interdependency-induced failure scenarios, perceiving and addressing them in a collaborative manner with other infrastructure networks. This is the very first time that such concept is exercised in collaboration with stakeholders concerned, in a practical form in Scotland.

It is highlighted that infrastructure interdependency assessment requires a large and reliable set of structured data concerning the failure mechanisms and recovery strategies in place and in response to different failure scenarios. This emphasises the importance of incorporating an appropriate *'shared data management system'* to record and reflect on failure scenarios that are induced by interdependent assets. Failure and recovery mechanism of individual assets and connections and their impact on the overall multi-layered interdependent system requires further investigation.

It is shown that although infrastructures with a higher level of interdependency, can impose the network to higher vulnerability, however, this provides an opportunity in shared recovery strategies. Since majority of the decisions in each infrastructure sector relies on the network itself (so-called 'dependency') rather than its interconnectedness to other infrastructure (interdependency), it can bias the decision-making process and result in neglecting the cascading failures.

This study shows how understanding the dynamics underlying the infrastructures' design and operation is of particular importance not only for asset owners and operators, but also for emergency responses. This understanding can also create opportunities for infrastructure decision-makers to optimise their intervention strategies. Ultimately, this can lead to effective response and coordination among decision makers responsible for rescue, recovery, and restoration services.

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