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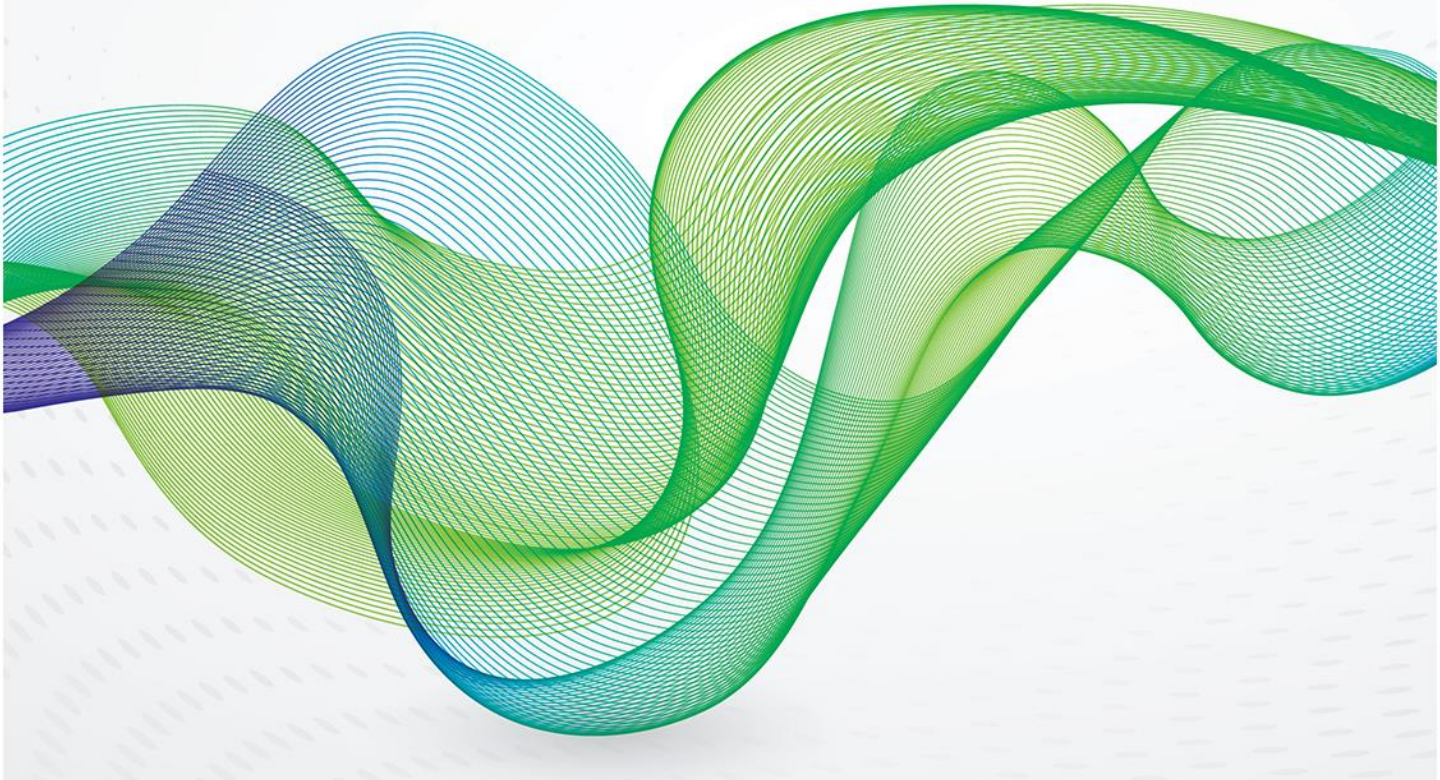
Electricity Supply Interruptions:

Sectoral Interdependencies and the Cost of Energy Not Served for the Scottish Economy



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Electricity supply interruptions: Sectoral interdependencies and the cost of energy not served for the Scottish economy

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Abstract

The power sector has a central role in modern economies and other interdependent infrastructures rely heavily upon secure electricity supplies. Due to interdependencies, major electricity supply interruptions result in cascading effects in other sectors of the economy. This paper investigates the economic effects of large power supply disruptions taking such interdependencies into account. We apply a dynamic inoperability input–output model (DIIM) to 101 sectors (including households) of the Scottish economy in 2009 in order to explore direct, indirect, and induced effects of electricity supply interruptions. We then estimate the societal cost of energy not supplied (SCENS) due to interruption, in the presence of interdependency among the sectors. The results show that the most economically affected industries, following an outage, can be different from the most inoperable ones. The results also indicate that SCENS varies with duration of a power cut, ranging from around £4300/MWh for a one-minute outage to around £8100/MWh for a three hour (and higher) interruption. The economic impact of estimates can be used to design policies for contingencies such as roll-out priorities as well as preventive investments in the sector.

Keywords: Power blackout, inoperability input–output model, interdependent economic systems, cost of energy not supplied

JEL classifications: C67, L52, Q40

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1. Introduction

Modern economies are crucially and increasingly dependent on the services of a reliable power sector. This dependence, to a large extent, stems from the reliance of other critical infrastructure (CI) sectors such as natural gas, water supplies, petroleum, telecommunications, and transportation, on power supplies. Meanwhile, critical infrastructures are also interdependent and interact with each other in numerous and sometimes complex ways.

The interdependencies among CIs are the main factor behind the unforeseen chains of events, or the ‘cascade effect’, in the event that at least one CI fails. This is particularly important in the case of failure in the power supply system, as this tends to propagate the ripple rapidly to other infrastructure sectors. Furthermore, the ripples of electricity supply shocks often reach beyond their first-order effects. This implies that the socio-economic cost of power outages can be considerably larger when the cascading effects and interdependencies among infrastructures are taken into account (Kjølle et al., 2012).

Previous experience from exceptional events in the power sector has raised concern about the economic consequences of such failures.[2] An important part of these costs is due to the indirect and induced effects resulting from interdependency and the spilling over of power failures to other infrastructures.[3] This highlights the importance of understanding the interdependency of the power system and other CIs, and the impact of power failure on interdependent economic systems. Despite its importance, insufficient information is available about the economic impact of large electricity supply interruptions (Linares and Rey, 2013). This is mainly because such interruptions are rare events and the data about them is thus scarce. An optimal response to these events entails having information about their (economic) impact at sector and economy level. Such information would help to protect the critical infrastructures better in the event of major service disruptions and to minimize the consequences of cascading effects resulting from power failure.

Moreover, risk-informed decisions will help the development of investment strategies and the adoption of measures to reduce the overall risk (Conard et al., 2006). Also, questions such as how to design contingency plans to minimize the economic impact of power outages can be explored when the most vulnerable sectors to interruptions are identified. Additionally, a related query from a policy perspective is the level of investment required to prevent major incidences in the power sector. The estimated societal cost of major service interruptions can be a useful figure when calculating the amount that a society might be willing to invest in order to avoid catastrophic events (Pindyck and Wang, 2013).

This paper contributes to the literature as follows. First, we investigate the interdependency effects and economic impact of power supply disturbance through a Dynamic Inoperability Input–output Model (DIIM) applied to 101 sectors of the Scottish economy in 2009. Second, using the DIIM model we estimate the societal cost of energy not supplied (SCENS), [4] taking into account the interdependencies among infrastructures.

The following section describes sectoral interdependencies and discusses some previous approaches to estimating the cost of power outages. Section 3 puts forward the methodology adopted to assess

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[2] For example, on 17 December 1978, almost the entire French electricity system failed (except in regions which were supplied by Germany) for around 2 hours and 15 minutes in the morning and resulted in a cost of more than US$1 billion in terms of lost production (Sanghvi, 1982).

[3] An example is the major US blackout in August 2003. This triggered several cascading effects, for example: traffic lights went off, computer systems went out, trains and subways were disrupted, the banking and financial sectors were severely affected, health care was only able to work on emergency power (if available) or had to close, all sporting events cancelled, and schools closed (Min et al., 2007).

[4] This is called ‘societal’ because SCENS includes the cost to both the power sector and to the rest of the economy resulting from interruption.

the impact of electricity supply disruption on interdependent economic systems and to compute the value of energy not served. Section 4 presents the results of applying this method to the Scottish economy, together with policy implications. Section 5 gives the concluding remarks.

2. Sectoral interdependency and power interruptions

Knowledge of the economic impact of electricity supply disruptions is important for regulators and policy makers, given the extensive interdependencies between the power sector and other infrastructure industries. These interdependencies generally fall into four categories: geographical, logical (also called procedural), cyber, and physical (Rinaldi et al., 2001; Dudenhoeffer et al., 2006). Geographical interdependency is related to locational proximity. Procedural interdependency is due to protocols for example halt in operation following a security threat. Cyber and physical interdependency reflects engineering reliance to inputs (in the form of data or physical materials) from other infrastructures.

The physical and cyber interdependencies prevailing between the electricity sector and the rest of economy are highly susceptible to shock transmission. This stems from the central position of electricity in modern economies. For instance, all sectors of the economy use electricity directly as an input in the production process, or indirectly to support a production process. In turn, the power sector itself relies on inputs from other sectors for its output. This implies that the system of interdependent infrastructures is capable of transmitting power failures shocks that can create unforeseen repercussions throughout the economy. Furthermore, with the increased use of information and communication technologies in the power industry, there is a strong element of informational reliance between the electricity system and other infrastructures, thus increasing the intricacy of the interdependency even further.

The other forms of interdependencies can also be relevant in the context of the power sector. For example, there is often some geographic proximity between power grid infrastructure and telecommunication networks (such as telephone lines) or transport infrastructures (such as railways). Such proximity can influence the functionality of these infrastructures when an event damages one of them. This suggests that reliable operation of the interdependent infrastructures is fundamental to preventing costly consequences resulting from cascading effects in the event of failure. Also, it underlines the role of regulation and policy in incentivizing resiliency enhancement in critical infrastructures.

The cost of energy not supplied is an important measure for the sector regulator to use in incentivizing power quality and resiliency improvements. An accurate estimation of the societal cost of interruption allows policy makers and managers to make a better case for investments in resiliency enhancement and contingencies. However, the complexity of modern economies makes this objective a challenging task. Moreover, there are significant differences in the estimated value of lost load among the current studies (see Table 1). This is partly related to the differences in approaches taken and to the structures of economies investigated.

The previous studies often revolve around two main approaches to estimating the cost of energy not supplied (although there are more approaches in practice). Some studies use surveys to elicit consumers' preferences based on the willingness to pay (WTP) for reliable services or willingness to accept (WTA) interruptions. The second approach is based on production functions which relate electricity consumption with the value of output of firms, or the time spent on non-paid work in the case of households (Leahy and Tol, 2011). In this approach, the gross value added (GVA) of a sector is divided by the electricity used in the sector in order to estimate the output value of each unit of electricity supply. This figure is then used as an estimation of production lost for each unit of electricity not supplied. Table 1 summarizes selected previous studies on the cost of electricity interruptions using these two approaches. A detailed presentation of interruption cost studies and corresponding approaches can be found in Toba (2007).

There are, however, several issues with the aforementioned two approaches. Firstly, the implementation of comprehensive surveys that accurately reflect the preferences of all consumer categories is time consuming and expensive. Secondly, there are issues with surveys, such as the possibility of poor measurement, omission of relevant cases, and non-response. The production function approach has its own drawbacks. For example, the ratio of gross value added (GVA) to electricity consumption, in a given sector, only reveals the average productivity of electricity in that sector. The relationship of this with the true value of the interruption cost is slight because it only shows the value added from electricity under the normal production process; during the interruption this does not hold, due to disequilibrium, interdependency, and associated effects.

Furthermore, many of the earlier studies estimate the cost of power outage as a constant function in terms of $/KW or $/KWh without taking into account the time dependency of outage cost (Lo et al., 1994). Additionally, perhaps the most serious shortcoming of the aforementioned approaches to estimating the societal cost of interruption, is that they do not allow for interdependency effects among infrastructures. Interdependency can become more significant with increased duration of the interruption, because the higher order and induced effects cause additional costs. Therefore, given the issues with the traditional approaches used in previous literature on interruption costs, we use a dynamic inoperability input–output model. The method adopted in this study not only accounts for the interdependencies but also captures time dependencies of interruption costs.

Table 1: Summary of selected power interruption cost studies

Study	**Country**	**Year**	**Method**	**Estimated costs**	**Adjusted based on 2009 prices**
Leahy and Tol (2011)	Ireland	2007	Production function	Total €12.9/kWh	€13.63 /kWh
Balducci et al. (2002)	USA	1996	Surveys	Total $8.76/kW (1 h)	€8.55/kW (1 h)
Nooij et al. (2007)	Netherlands	2001	Production function	Total €8.56/kWh	€10.27/kWh
Diboma and Tatietse (2013)	Cameroon	2009	Survey	€3.62 to 5.42/kWh for a 1-h interruption and €1.96 to 2.46/kWh for a 4-h outage.	€3.62 to 5.42/kWh for a 1-h interruption and €1.96 to 2.46/kWh for a 4-h outage.
Reichl et al. (2013)	Austria	2011	Production function and survey	€17.1/ kWh	€16.80/ kWh

Another important point, which is often overlooked, is the class of outages for which a specific type of method is suitable. Weather-related incidences – such as wind, lightning, snow, rain, ice, and dust events – are among the most important causes of power outages. Other factors also can affect network operational conditions – such as when animals, trees, vehicles, or flying objects come into contact with power lines, fuses, and other equipment – resulting in power faults and consequent blackouts. Equipment failure and surplus or insufficient demand can also cause outages; the need for planned outages must also be taken into account. In recent years, with an increase in the share of renewable resources, the risk of power outage has increased due to both under and oversupply of energy from resources with stochastic outputs, such as wind and solar. This is because such variability can lead to grid instability as it affects frequency.

However, none of the existing methods covers all types of power cut. The approach adopted in this study (DIIM model) is mainly suitable for the class of outages which is related to the network, it thus covers a wide range of outage types. This is reasonable given that more than 90 per cent of power outage incidences are related to the grid (Hammond and Waldron, 2008). Furthermore, electricity distribution networks are often composed of hundreds of thousands of kilometres of overhead lines and underground cables which can be easily exposed to extreme weather conditions.

3. Methodology

We use a dynamic inoperability input–output model (DIIM) to assess the direct, indirect, and induced impacts of power supply interruptions on different sectors of the economy. Input–output models are effective tools for investigating the spread of failure and recovery in a system of interdependent infrastructures (Ward, 2010).

DIIM has several interesting features which makes it the method of choice for our analysis. First, unlike traditional approaches, DIIM views the economy in a holistic way by taking the interdependency between different sectors of the economy into account. Second, DIIM allows for intertemporal analysis; this has proved to be useful given that the cost of outage changes with duration of interruption (most traditional methods do not have the capacity to capture the dynamic nature of power cuts). Finally, DIIM enables us to distinguish inoperability from the economic loss effect of a power outage.

The inoperability input–output model (IIM), as a derivative of the Leontief model, was first introduced by Haimes and Jiang (2001) to model interdependent infrastructure sectors. It was later developed further by Santos and Haimes (2004) to quantify the impact of terrorism on critical infrastructures. Some of the studies using the IIM approach and its variations to address the behaviour of interdependent infrastructures are: Haimes et al. (2005a; 2005b), Setola et al. (2009), Crowther and Haimes (2010), and Oliva et al. (2011).

The simple form of a Leontief input–output model (see Leontief, 1936; Santos, 2006) can be written as in (1).

$$X = AX + C \qquad (1)$$

where C denotes the demand vector, which is the amount of product that consumers consume. X represents the total production which is required to satisfy the demand vector C. The technology coefficient matrix A describes the relations among sectors of the economy. The matrix is such that each column vector represents a specific industry, while each corresponding row vector represents the amounts that each industry contributes as an input into the industry represented in each column.

In a similar manner the general form of the IIM model can be presented as in (2) (Santos and Haimes, 2004; Santos, 2006):[5]

$$q = A^{*}q + C^{*} \qquad (2)$$

where q is an inoperability vector which is defined as the ratio of unrealized production to normal production. A^{*} is the interdependency matrix which presents the degree of correlation among different industry sectors. C^{*} is the demand disturbance vector which is the ratio of demand reduction over the normal production level.

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[5] See Haimes et al. (2005a) for detailed description of the derivation of the IIM model from the Leontief equation.

Equation (3) thus represents the demand side perturbation where $\hat{c}$ and $\tilde{c}$ are, respectively, normal demand and reduced demand, and $\hat{x}$ is planned production. The assumption of non-zero production values for each industry guarantees the existence of $diag(\hat{x})$ inverse, which is also a diagonal matrix.

$$C^* = [diag(\hat{x})]^{-1}[\hat{c} - \tilde{c}] \qquad (3)$$

$$\begin{bmatrix} c_1^* \\ \vdots \\ \vdots \\ c_i^* \\ \vdots \\ \vdots \\ c_n^* \end{bmatrix} = \begin{bmatrix} \frac{1}{\hat{x}_1} & 0 & \dots & \dots & 0 \\ 0 & \ddots & \ddots & 0 & \vdots \\ \vdots & \ddots & \frac{1}{\hat{x}_i} & \ddots & \vdots \\ \vdots & 0 & \ddots & \ddots & 0 \\ 0 & \dots & \dots & 0 & \frac{1}{\hat{x}_n} \end{bmatrix} \begin{bmatrix} \hat{c}_1 - \tilde{c}_1 \\ \vdots \\ \hat{c}_i - \tilde{c}_i \\ \vdots \\ \hat{c}_n - \tilde{c}_n \end{bmatrix}$$

It is evident that it is always the case that: $0 \leq C_i^* \leq \frac{\hat{c}_i}{\hat{x}_i}$ where $i \in \{1,..,n\}$. The lower limit corresponds to the case that reduced demand is the same as normal demand, so there is no deviation from the steady state. However, when reduced demand is zero, the deviation is maximized, equalling the upper limit of the aforementioned inequality.

The interdependency matrix, A^*, is related to the Leontief technical coefficient matrix A, and vector of normal production of industries as in (4).

$$A^* = [diag(\hat{x})]^{-1}[A]\,[diag(\hat{x})] \qquad (4)$$

If we substitute (4) and (3) into (2) we obtain (5):

$$q = [diag(\hat{x})]^{-1}[A]\,[diag(\hat{x})]q + [diag(\hat{x})]^{-1}[\hat{c} - \tilde{c}] \qquad (5)$$

which presents inoperability vector q in terms of planned production, the Leontief technical coefficient matrix, normal demand, and disturbed demand. It can be shown that inoperability vector q is between zero and one (see Santos and Haimes, 2004). When q is equal to zero, there is no disruption and the production is ongoing ('business-as-usual'). In the extreme case where q equals one, the production process is completely disrupted.

The IIM model can be extended to represent a dynamic inoperability input–output model (DIIM), by introducing the dynamic aspect of interdependent economic systems and resiliency of the sectors, as in (6) and (7) (see, for example, Haimes et al., 2005a; Orsi and Santos, 2010).

$$q(t+1) = q(t) + K[A^*q(t) + c^*(t) - q(t)] \qquad (6)$$

where K is a resiliency matrix and its elements show how the system responds to disequilibrium and t is time period. The relation in (6) can be approximated with a differential equation as in (7).

$$\dot{q}(t) = K[A^*q(t) + c^*(t) - q(t)] \qquad (7)$$

As seen from equations (6) and (7), the inoperability in each period is equal to the inoperability in the previous period plus the partial adjustment of inoperability due to resiliency. The value of the resiliency matrix can be either negative or zero. Under the condition that resiliency is zero, the inoperability does not change over time and these equations will be the equivalent of the static IIM formula in (2). However, when the resiliency matrix is negative, it can be seen from (6) and (7) that inoperability will eventually decrease over time. The coefficients of the resiliency matrix depend on the characteristics of the industry and on the risk mitigation policies implemented. In other words, the resiliency of the sector can be controlled through risk mitigation measures such as redundancy, which consequently reduces the recovery time and financial losses following a disturbance.

The general solution to the differential equation in (7) will be as in (8) (Haimes et al., 2005a).

$$q(t) = e^{-K(I-A^*)t}q(0) + \int_0^t Ke^{-K(I-A^*)(t-\xi)}\,C^*(\,\xi)d\xi \qquad (8)$$

The assumption of stationarity of final demand, c^*, allows us to simplify (8) further as follows:

$$q(t) = (I - A^*)^{-1}c^* + e^{-K(I-A^*)t}[q(0) - (I - A^*)^{-1}c^*] \qquad (9)$$

$$q(t) = q_\infty + e^{-K(I-A^*)t}[q(0) - q_\infty] \qquad (10)$$

where q_∞ is the steady state (equilibrium) level of inoperability determined by final demand c^*, and $q(0)$ represents the initial inoperability imposed by the shock. As seen from (9) and (10), the term including $e^{-K(I-A^*)t}$ fades off over time and, in an infinite time horizon, these equations will converge to a static IIM.

A key feature of DIIM is the resiliency matrix coefficients, which show the response of individual industries to the imbalance between supply and demand. Under the conditions that $k_i > 0$, $a_{ij}^* = 0$ $\forall\ i \neq j$, and final demand stays constant, the following equation, based on (8), can be written:

$$q_i(t) = q_i(0)e^{-k_i(1-a_{ii}^*)t} \qquad (11)$$

which leads us to obtain elements of the resiliency matrix as in (12).

$$k_i = \frac{\ln[q_i(0)/q_i(T)]}{T_i(1-a_{ii}^*)} \qquad (12)$$

where $q_i(0)$ is the magnitude of initial inoperability of sector i imposed by the shock and T_i is the time taken by the sector to arrive at the inoperability level of $q_i(T_i)$. Naturally, the final level of inoperability must be lower than the initial inoperability level to ensure a positive k_i.[6] Finally, a_{ii}^* is the element of A^* that can be obtained using its relationship with the Leontief coefficient matrix A. The underlying assumption is that the resiliency of the sector solely depends on itself and not on the other sectors. Thus, the resiliency matrix is diagonal.

Under the input–output framework discussed above, the impact of a shock to any sector (such as the power industry) can be measured both in terms of inoperability (q) and economic loss (Q). The cumulative economic loss, over period of recovery, for an individual sector and for the whole economy (n sectors) can be obtained from (13) and (14) respectively.

$$Q_i(t) = \hat{x}_i \int_{t=0}^{t=T} q_i(t)dt \qquad (13)$$

$$Q(T) = \sum_{i=1}^{n}\left(\hat{x}_i \int_{t=0}^{t=T} q_i(t)dt\right) \qquad (14)$$

The concept of inoperability in our model corresponds to the reliability concept in the power sector. In the electricity industry, system reliability is usually defined as $1 - \frac{\text{unsupplied energy}}{\text{energy that would have been supplied without an interruption}}$. Using a similar analogy we can compute the cost of supply disruption using the inoperability metric and societal cost of power sector inoperability as previously presented in (14). Thus, if E represents the total electrical energy that is normally delivered during each period, we can calculate the cost of a major supply disruption using relation (15):

$$SCENS = \frac{Q(T)}{E\int_{t=0}^{t=T} q_i(t)dt} \qquad (15)$$

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[6] Because the resiliency matrix already has a negative sign, as can be seen from Equation (8).

where $SCENS$ is the socio-economic cost of energy not supplied and can be presented in terms of £/MWh or £/KWh. The term $E\int_{t=0}^{t=T} q_i(t)dt$ shows the total electrical energy interrupted during the outage, as a result of inoperability shock $q_i(t)$ to the power sector.

3.1 Household sector

Input–output data does not render information about the value of leisure for the household sector, and electricity is important for leisure activities. Therefore, we extend our analysis to include the effect of outage on this crucial sector as well. Obtaining an accurate estimation of the economic cost of power loss in the household sector is a challenging task. Methods based on a 'stated preference' are costly and sometimes misleading because it is hard to quantify the value of leisure by asking consumers about their willingness-to-pay for reliable service (or willingness-to-accept outage).

Approaches based upon 'revealed preference', where the actual choice of households is observed, can be another proxy for consumer willingness to pay for continuity of supply. (For example, the amount invested by a household in backup generation facilities to compensate for poor electricity reliability.) However, despite the appealing characteristics of this method, the problem of data (collection) is often a major impediment.

An alternative method deals with approximating the monetary value of utility derived from electricity-dependent leisure activities. Becker (1965) was among the first who attempted to estimate the value of lost leisure time. This approach is founded on the basic microeconomic theory that labour supply is the result of utility maximization of a household given the trade-off between leisure and income (or consumption when it is assumed all income is spent). Households are suppliers of labour to other sectors of the economy and the time which is not spent on working or sleeping is referred to as leisure. Several studies in the literature have adopted this approach (see for example, de Nooij et al., 2007; Wolf and Wenzel, 2014). Following this method, we estimate the value of leisure and integrate this in our DIIM model as explained in the previous section.

The value of leisure is estimated indirectly through the opportunity cost of leisure. For an employed person, the marginal benefit of (his/her last unit of) leisure must equate to its opportunity cost in terms of forgone income due to labour (Burkett, 2006). In the case of unemployed persons, we need to consider the fact that there might be involuntary unemployment or unemployment due to low compensation. This implies that the opportunity cost of leisure for unemployed people can be lower than for those who are employed. To account for this, we assume that the value of leisure for an unemployed person is a percentage of that for an employed person. Furthermore, since all leisure activities are not electricity-dependent, we adjust leisure times to reflect better the impact of power cuts.

Therefore, we can calculate the value of leisure to the household (CL_h) as follows:

$$CL_h = [\gamma(T - Wh)W]P_e + [\gamma T(\theta W)]\,(P - P_e) \qquad (16)$$

Where γ is the percentage of electricity-dependent leisure activities, T is the total time available to spend for work or leisure, Wh is total working hours, W is average wage per hour, θ is a factor to adjust the opportunity cost of leisure for an unemployed person, P_e is the population of employed people, and P is the total population.

In the absence of information on either the stated or revealed preference of households, this method approximates the utility gained from consuming electricity. However, as noted in Wolf and Wenzel (2014), the flexibility assumed in allocation of time between work and leisure can be unrealistic given that working hours are specified by contracts, and some people may not work full time. Furthermore, people may adapt if they experience frequent power cuts. These factors are the shortcoming of this approach and cannot be fully accounted for using our adopted approach.

4. A case study of the Scottish economy

4.1 Scottish economy and data

We explore the economic impact and interdependency effects of power supply disturbance through a case study of Scotland. Following the industrial revolution, Scotland became a leader in manufacturing industries and this has left a legacy in the diversity of its goods and services. However, over time as in the rest of the UK, there has been a decline in manufacturing and primary based extractive industries, while the service sector has been on the rise. Scotland has oil and gas resources in the North Sea and a large potential for renewable energy sources such as wind and wave, and is a net exporter of electricity.

The economic activities of Scotland, as for any other modern economy, involve four types of primary activities: (a) production of goods and services by industries; (b) consumption of goods and services by industries and domestic final users (comprising mainly households and government, both local and central); (c) the accumulation of fixed capital and stock changes in the economy; and (d) trade which involves imports and exports to the rest of UK and the rest of the world (Scottish Government, 2011b).

The measurements of these four activities are represented in an input–output framework. The input–output data provides a comprehensive picture of the flow of goods and services in the economy in a given year. The data also describes the interaction between producers and consumers, together with details of interdependencies among industries.

The data used in this study includes the 101 different industries of Scotland in 2009. The dataset contains the output of each industry as well as its reliance on other sectors, based on a Leontief coefficient matrix. The Leontief coefficient matrices are derived from the industry-by-industry matrix which shows how much of each industry's output is needed, in terms of direct and indirect inputs, to produce one unit of a given industry's output. Table A1 (Appendix) presents these industries which can be grouped under the following broad categories:

- Agriculture, forestry, and fishing,
- Mining,
- Manufacturing,
- Energy and water,
- Construction,
- Distribution and catering,
- Transport and communications,
- Finance and business,
- Public domain etc.,
- Education, health, and social work,
- Other services,
- Households.

The population of Scotland is slightly over 5 million; this has remained stable in the past half century although recent immigration from the EU has supported a modest growth. Due to the general shift over the past 30 years from manufacturing to services, the service sector now accounts for around 75 per cent of the Scottish economy's output and 82 per cent of the country's employment, whereas manufacturing contributes 13 per cent to total output with only 7.5 per cent of total employment (Scottish Government, 2011a). According to the 2011 Annual Population Survey, around 73.6 per cent of Scottish people are working full time (73.8 per cent in 2010 and 76.2 per cent in 2008)

(Scottish Government, 2012). Furthermore, around 8.3 per cent of employed people were underemployed – in other words, searching for extra hours in their current job. Table 2 presents a summary of important statistics on the Scottish economy in 2009.

Leisure activities in Scotland are similar to those in the rest of the UK and are not entirely electricity-dependent. In order to evaluate the effect of power cuts on households we need to define the percentage of leisure time which relies on electricity supply (parameter γ in equation 16). It is clear that $0 < \gamma < 1$. Some studies have assumed that only half the leisure activities require electricity (see Growitsch et al. 2013). Other studies assume this figure to be higher (for example, 65 per cent in Wolf and Wenzel, 2014). According to the office for national statistics (ONS) (2011), in 2009/10, adult people aged 16 and above in the UK spent, on average, 3.5 hours a day watching TV, 2.5 hours using a computer, and one hour listening to the radio. If we consider other indoor and outdoor activities – such as holidays and day trips, sporting, social and political participation, shopping, eating out, cinema, and religious activities – we can clearly see that a huge portion of mainstream leisure activities are electricity-dependent. Of course there are always activities that do not require electricity directly – such as reading in daylight or walking – however, these are often a small portion of the total leisure time of most people. Therefore, following Wolf and Wenzel (2014) we assume that γ is 65 per cent. Furthermore, we assume that the opportunity cost of leisure for unemployed people is half that for the employed (de Nooij et al., 2007).

Table 2: Summary statistics – Scottish economy (2009)

Population	5,194,000
GDP (£m)	106,781.5
Electricity sales (public supply) (GWh)	29,955
Total domestic electricity consumption (GWh)	11,434.8270
Commercial and industrial total sales (GWh)	15,631.8888
Average domestic electricity consumption per capita (kWh)	2201.5454
Population in employment	2,529,000
Average hourly earnings (full-time employee)	£11.98/hour

Sources: Scottish Government Input–Output Tables 2009; Scottish Government Energy Statistics Database (2014); Scottish Government Annual Population Survey (2009); Office for National Statistics (2014)

4.2 Scenario generation and framework

The scenario generation process involves specifying the initial inoperability vector (q_0), recovery time (T), and final level of inoperability (q_T). For example, we specify the initial inoperability as a shock to the electricity industry which disrupts q_0 percentage of electricity supply (for example, 5 per cent); this figure diminishes exponentially, with a final level of inoperability of q_T (for example, 0.001) achieved after T period (for example, 12 hours).

The perturbation vector for all sectors can be obtained using the share of its output reliance on electricity as follows:

$$q_i = q_0 \frac{u_i}{\max(u_i)} \qquad (17)$$

where q_i is the perturbation to sector i as a result of q_0 shock to the electricity industry and u_i is the share of electricity in the output of industry i divided by the share of electricity in the output of the maximum consuming sector. As electricity has the highest share in the output of the electricity industry itself, the relation in (17) results in an inoperability of q_0 in the electricity industry and a proportional inoperability for other industries based on their electricity usage.

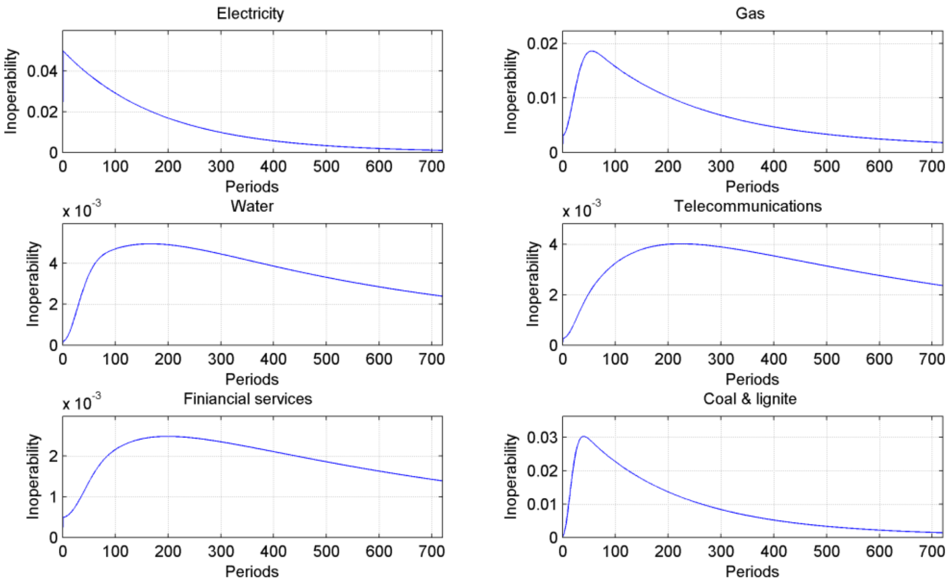
In the absence of data on the recovery process of each individual industry, we assume a similar recovery period, T, for all sectors as for the perturbed sector. This is because, as noted in Santos (2012), if a given sector is dependent on the perturbed sector it will follow the same recovery path as the initially perturbed sector. However, if a given sector does not rely upon the perturbed sector it will not be affected by the initial shock, irrespective of the recovery period chosen. The recovery period T can be as short as few minutes or as long as days or weeks.

A systemic analysis will be carried out by considering various sources of uncertainty – such as the degree of perturbation of the initially affected sector and temporal issues around sector recoveries. We compare inoperability with economic loss and identify the sectors most vulnerable to lack of electricity supply in Scotland. Also, we will analyse the robustness of the ranking of vulnerable sectors to different durations and extents of power supply interruptions. Finally, we compute the cost of 'energy not supplied' in Scotland for various inoperability levels and periods of interruption.

4.3 Results and discussion

A power outage shock propagates rapidly and affects the whole economy through direct and indirect effects. These effects are more apparent in industries with higher levels of interdependency with the power sector. Figure 1 depicts the impact of power sector perturbation in terms of inoperability variation over the period of recovery. The figure presents a scenario where a shock is applied to the power sector with an initial inoperability level of 5 per cent which declines exponentially to 0.001 after 12 hours (720 minutes). In order to trace the effect of this inoperability shock we have selected five critical infrastructure sectors for illustration purpose. These infrastructures are: gas, water, telecommunication, financial service, and the coal industry in Scotland.

Figure 1: Inoperability change over the recovery period in selected sectors



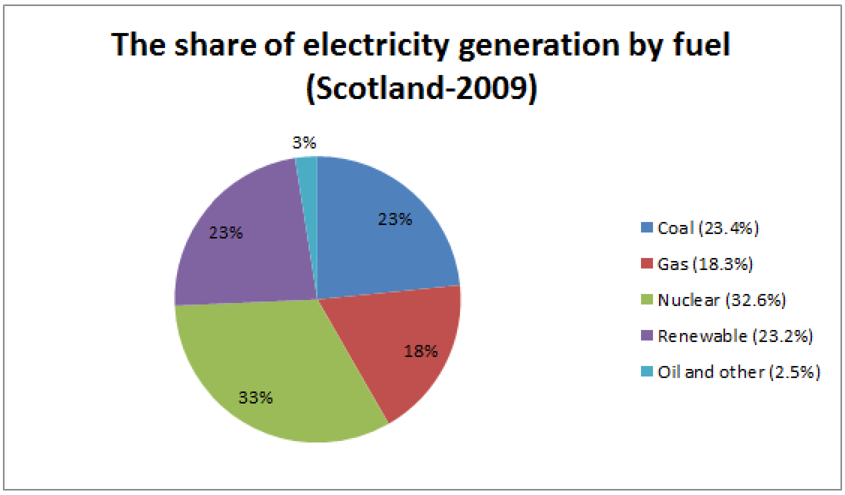
Source: Authors

As shown in Figure 1, the affected sectors follow a similar recovery path but with different level of inoperabilities over time. In all cases, inoperability initially increases until it reaches a maximum and then starts to decline. In the absence of resilience, inoperability will not decline, but instead reach a new steady state. However, in practice inoperability decreases because the perturbed sector (the power sector in this case) and other infrastructures are assumed to follow a recovery process (in other words, they are resilient). The inoperability following the electricity supply disruption can be the result of direct, indirect, and induced effects.

A sector becomes inoperable in a scenario such as that outlined above if electricity is an important input in its production process. The same can happen if an industry supplies the inputs (such as gas or coal) of the electricity industry. This is because interruption in electricity services damages the business of the sectors that supply its inputs. Therefore, inoperability is not limited to the unidirectional effects of interrupted power as an input to other industries; it also embraces the sectors on which the electricity industry relies. For example, as seen from Figure 1, the inoperability of the coal industry progresses rapidly following an electricity disruption until it reaches slightly over 3 per cent (after approximately 40 minutes) and then the recovery starts. This means that the coal industry is highly affected, directly and indirectly, by the initial inoperability shock to the power sector. The main source of the inoperability impact on the coal sector, however, is that the Scottish electricity industry is highly dependent on coal. Thus, when an event interrupts the electricity industry it will also disrupt the coal sector. A similar situation holds for the gas distribution network, though with a lower peak inoperability.

The marked reliance of electricity on coal and gas can also be seen from Figure 2, which shows the share of electricity generation by fuel in Scotland in 2009. At the same time, both of these sectors consume electricity for their production process- an example of interdependencies among the industries within the energy sector.

Figure 2: The share of electricity generation by fuel in Scotland

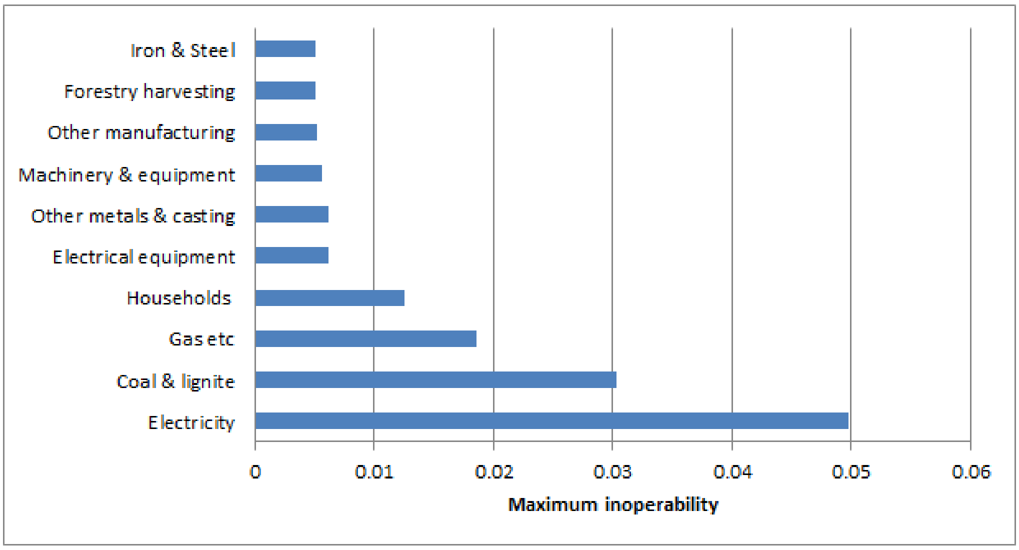


Source of data: Scottish Government Energy Statistics Database (2014)

Although all the sectors follow a similar recovery process, the graphs in Figure 1 show a weaker inoperability for water, financial services, and telecommunication industries. Also, their recovery process takes slightly longer than that of the gas and coal industries. The lower inoperability in these sectors can be the result of the lower level of interdependency between these industries and the power sector, as opposed to the case of coal and gas infrastructures. In other words, the greater the interdependency between the affected infrastructures and the initially perturbed sector, the higher will be their inoperability over the period of recovery.

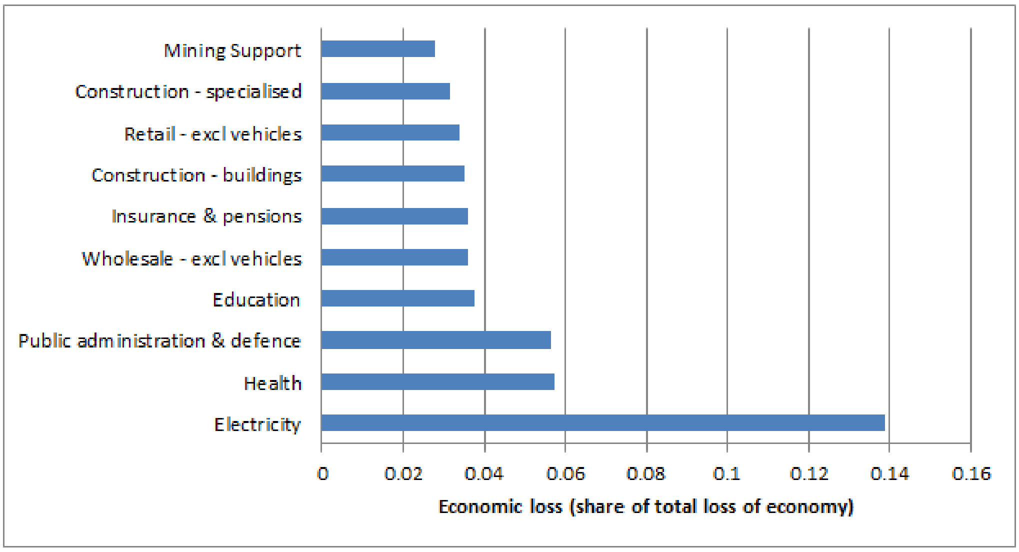
Figure 3 illustrates the top 10 sectors with the highest levels of inoperability during the recovery time. Figure 4 depicts the sectors incurring maximum economic loss over the aforementioned period. As can be seen from both figures, with the exception of the power sector (the initially perturbed industry) which has the highest rank in terms of both inoperability and economic loss, the remaining sectors do not hold the same ranking orders. For instance, the coal and lignite sector is ranked second for inoperability (Figure 3), while it does not appear among the 10 most highly affected sectors in terms of economic loss (Figure 4). Conversely, the health sector appears to be highly affected financially (Figure 4) whereas it is not among the top 10 in terms of inoperability (Figure 3). A similar situation holds for other sectors.

Figure 3: Top 10 sectors with highest inoperability over the period of recovery



Source: Authors

Figure 4: Top 10 sectors with highest economic loss over the period of recovery



Source: Authors

These results suggest that inoperability does not directly translate to a corresponding level of economic loss. In effect, the sensitivity of revenue and operational status to a particular input (for example, electricity) varies across and within each industry. This is due to the fact that operational responsiveness depends on the occurrence of indirect effects, the importance of power as an input in production, and the flexibility of the production processes. On the other hand, economic responsiveness depends on the value of produced goods or services which have been disrupted as a result of inoperability shock.

These findings lead us to make a distinction between the operational responsiveness of a sector and its economic sensitivity to an input shock from the initially perturbed industry. The implication of this for critical assets is that prioritizing for the preservation of a sector during an extreme event should be based on some weighted average index that contains information about its operational status and economic loss, as well as its importance for the welfare and well-being of the population.

The results in Figures 1, 3, and 4 are based on an arbitrary recovery period of 12 hours and an arbitrary shock with initial inoperability level of q_0=0.05 for the electricity sector; and proportional for other sectors depending on their electricity usage. A valid query is whether the ranking of sectors based on inoperability and economic loss is sensitive to the level of initial shock or recovery period chosen for the analysis. In order to investigate this, we analyse two different cases with several underlying scenarios. In the first case, we assume different inoperability levels of 20, 40, and 80 per cent for the power sector, with a common level of recovery period of 12 hours. In the second situation, we investigate a common inoperability level of 15 per cent but different recovery periods of 1, 3, and 6 hours. In all these cases, the power sector is assumed to become 99.999 per cent operable after the recovery period. The results of the above sensitivity analysis for inoperability and economic loss are presented in Tables 3 and 4 respectively.

As Table 3 shows, there is no change in the ranking of the top ten sectors in terms of inoperability when different levels of shocks are assumed for the power sector (Case 1). This is also largely the case when different recovery periods are considered (Case 2), where some sectors shift one place up or down at some duration of recovery. Indeed, for three and six hours outage duration (second and third columns of Case 2) the ranking of sectors matches that in Case 1 except that the eighth sector is now ‘mining support’ rather than ‘other manufacturing’. For one hour of outage duration, the ranking of sectors is somewhat different, although it contains broadly the same sectors identified previously, except for ‘repair and maintenance’. Therefore, the top ten sectors, in terms of inoperability, are almost invariant with changes in the extent and duration of interruptions.

A similar result can be seen in Table 4 for the top ten sectors in terms of economic loss. Again some sectors shifted one place up or down at some inoperability levels or recovery periods. However, these are the same previously identified top ten sectors in terms of financial loss (see Figure 4). The result of the above sensitivity analysis is a reassurance that the ranking of the sectors in terms of inoperability and economic loss is almost independent of the initial shock and recovery period assumed for analysis.

Table 3: Sensitivity analysis of inoperability ($q_T = 0.001$)

	Case 1				Case 2		
Top ten sectors	q_0=0.20 T=12 h	q_0=0.40 T=12 h	q_0=0.80 T=12 h		q_0=0.15 T=1 h	q_0=0.15 T=3 h	q_0=0.15 T=6h
1	SE45	SE45	SE45		SE45	SE45	SE45
2	SE6	SE6	SE6		SE6	SE6	SE6
3	SE46	SE46	SE46		SE101	SE46	SE46
4	SE101	SE101	SE101		SE46	SE101	SE101
5	SE38	SE38	SE38		SE8	SE38	SE38
6	SE35	SE35	SE35		SE35	SE35	SE35
7	SE39	SE39	SE39		SE38	SE39	SE39
8	SE43	SE43	SE43		SE39	SE8	SE8
9	SE3	SE3	SE3		SE3	SE3	SE3
10	SE34	SE34	SE34		SE44	SE34	SE34

SE45=Electricity,

SE6=Coal & lignite,

SE46=Gas etc.,

SE35=Other metals & casting,

SE38=Electrical equipment

SE44=Repair & maintenance

SE39=Machinery & equipment,

SE3=Forestry harvesting,

SE43= Other manufacturing,

SE34=Iron & Steel,

SE101=Households

SE8= Mining Support

Table 4: Sensitivity analysis of economic loss ($q_T = 0.001$)

	Case 1				Case 2		
Top ten sectors	q_0=0.20 T=12 h	q_0=0.40 T=12 h	q_0=0.80 T=12 h		q_0=0.15 T=1 h	q_0=0.15 T=3 h	q_0=0.15 T=6 h
1	SE45	SE45	SE45		SE45	SE45	SE45
2	SE91	SE91	SE91		SE91	SE91	SE91
3	SE89	SE89	SE89		SE89	SE89	SE89
4	SE90	SE90	SE55		SE55	SE90	SE90
5	SE55	SE55	SE90		SE8	SE54	SE54
6	SE71	SE71	SE71		SE54	SE55	SE71
7	SE50	SE50	SE50		SE90	SE50	SE50
8	SE54	SE54	SE54		SE50	SE71	SE55
9	SE52	SE52	SE52		SE71	SE52	SE52
10	SE8	SE8	SE8		SE52	SE8	SE8

SE45=Electricity,

SE89=Public administration & defence,

SE91=Health,

SE55=Retail – excl. vehicles,

SE54=Wholesale – excl. vehicles,

SE8= Mining Support

SE50=Construction – buildings,

SE90=Education,

SE52=Construction– specialized,

SE71=Insurance & pensions,

The inoperability and economic loss metrics provide a picture of the vulnerability of infrastructures following electricity supply disruption, based on an *ex ante* analysis. This information is important in policy making, to enable risk management and investment to protect critical assets against extreme events. As the inoperability ranking order does not necessarily coincide with economic loss, an integrated form of these metrics is required to make a better reflection of the situation following a power cut. This analysis has been presented in Figure 5.

Figure 5 provides the matrix of inoperability and economic loss impact for the top 10, 20, and 30 sectors (horizontal axis – economic loss; vertical axis – inoperability). Any sector on the diagonal of this matrix is equally important from inoperability and economic loss perspectives. Those that are above the diagonal are affected more financially while those that lie below the diagonal are affected more operationally. As can be seen from Figure 5, in each zone there are a few sectors that are vulnerable both from the operational and economic metric perspectives (although the top 10 zone only contains the electricity sector, implying that inoperability and economic loss follow a different ranking order in this zone). Other sectors such as: gas, wholesale, the coke, petroleum and petrochemical products industry, mining support, and fabricated metals are located in the top 20 zone. Overall, the matrix identifies 14 sectors as vulnerable, when considering the integrated metrics of inoperability and economic loss based on an *ex ante* analysis.

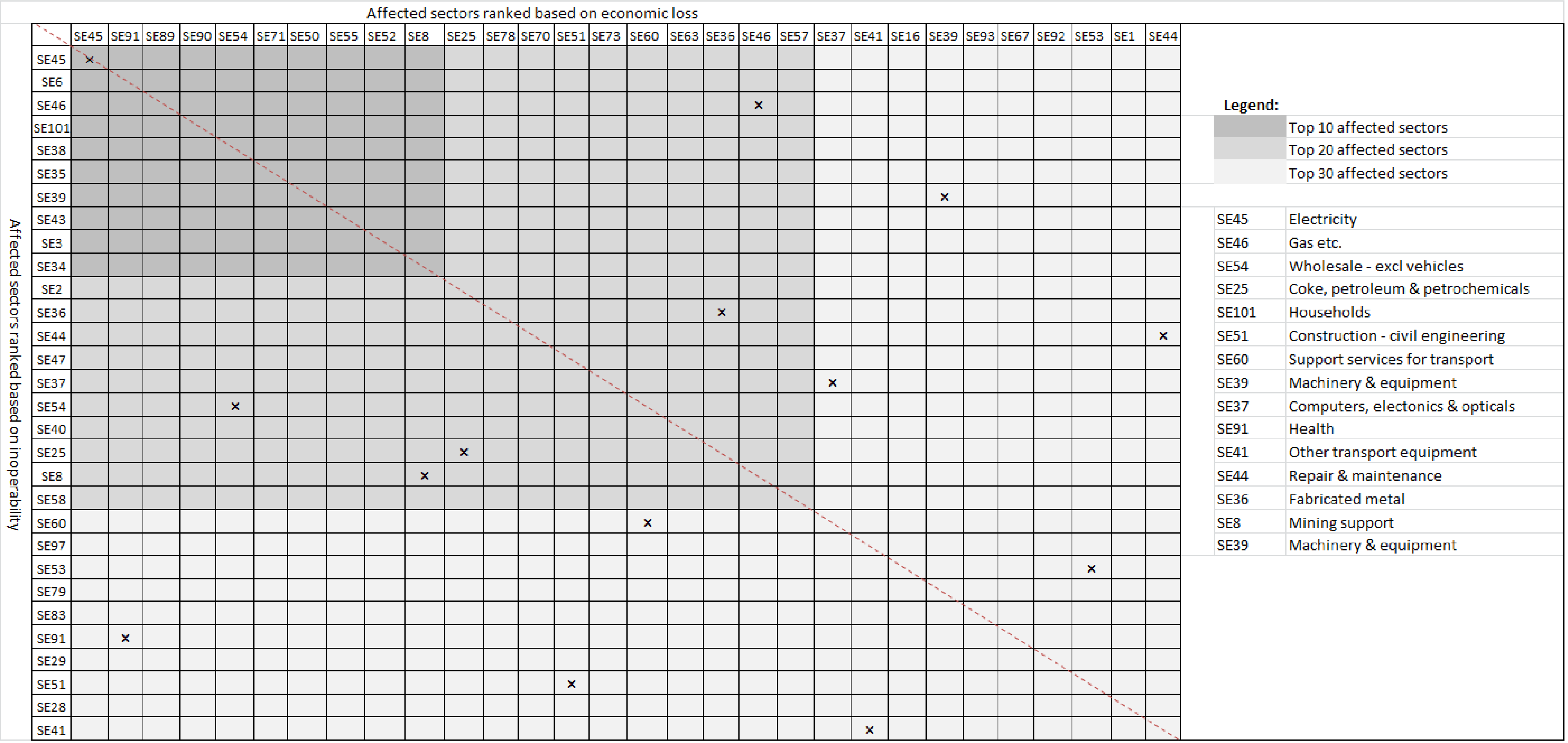
The *ex ante* analysis of infrastructure vulnerability to power loss is important for policy making; however, it does not do away with the need for an *ex post* evaluation of vulnerable sectors. This is because there are sectors which may not appear in the ranking order presented in Figure 5, although their functioning is critical during a major power cut. For instance, backup generators to support telecommunication systems during a major blackout are not normally deployed, and there is little economic incentive to deploy these costly arrangements (O'Reiley and Chu, 2008). However, for the purposes of crisis management, the perceived good of society, and in order to provide access to emergency services during a blackout, it may be desirable to supply such cross-infrastructure backup. A similar situation holds for emergency services, water, and industry, among others.

The above analysis shows the importance of a reliable power supply given the interdependency among sectors and the consequent effects on the cost to society of energy not supplied. The societal cost of energy not supplied (SCENS) is among the important motives underlying investment in resiliency and reliability. The regulatory framework of electric utilities is designed in such a way that SCENS affects their revenues directly or indirectly. Therefore, the utility companies have an incentive to minimize this cost by reducing the duration and frequency of interruptions, as well as the number of affected customers.

Figure 6 presents the societal cost of energy not supplied (SCENS); estimation of this is based on a range of different inoperability levels for the power sector and on a duration of interruption of up to 360 minutes (6 hours). The inoperability levels assumed are 5, 20, 40, 80, and 100 per cent (blackout), and they decrease exponentially as explained and presented previously. The SCENS is estimated in terms of £/MWh of electrical energy interrupted, using total inoperability of the power sector over the period of recovery and the assumption of uniform electricity supply in each period if there was no interruption. Figure 6 shows that SCENS changes by only a trivial amount with the extent of interruption (different inoperability levels). For example, the graph shifts very slightly upward when the level of inoperability increases from 5 per cent towards 100 per cent. Thus, it can be concluded that SCENS is almost independent of the extent of interruption. This also coincides with intuition, because one would expect to see SCENS varying only with duration of outages.

As seen from Figure 6, in all scenarios SCENS starts from around £4300/MWh for a 1 minute interruption and increases with the increased duration of the power cut. The SCENS rises rapidly to more than £7000/MWh for a duration of around an hour, after which time its rate of increase slows. Additionally, the graphs show that regardless of initial inoperability level, all scenarios converge to around £8000/MWh after two and a half hours. That is to say, for service interruptions lasting for three hours and over, SCENS ranges from £7865/MWh at 0.05 inoperability level to £8100/MWh for a total blackout.

Figure 5: The matrix of inoperability and economic loss impacts



Affected sectors ranked based on economic loss

Affected sectors ranked based on inoperability

	SE45	SE91	SE89	SE90	SE54	SE71	SE50	SE55	SE52	SE8	SE25	SE78	SE70	SE51	SE73	SE60	SE63	SE36	SE46	SE57	SE37	SE41	SE16	SE39	SE93	SE67	SE92	SE53	SE1	SE44
SE45	×																													
SE6																														
SE46																			×											
SE101																														
SE38																														
SE35																														
SE39																								×						
SE43																														
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SE34																														
SE2																														
SE36																		×												
SE44																														×
SE47																														
SE37																					×									
SE54					×																									
SE40																														
SE25											×																			
SE8										×																				
SE58																														
SE60																×														
SE97																														
SE53																												×		
SE79																														
SE83																														
SE91		×																												
SE29																														
SE51														×																
SE28																														
SE41																						×								

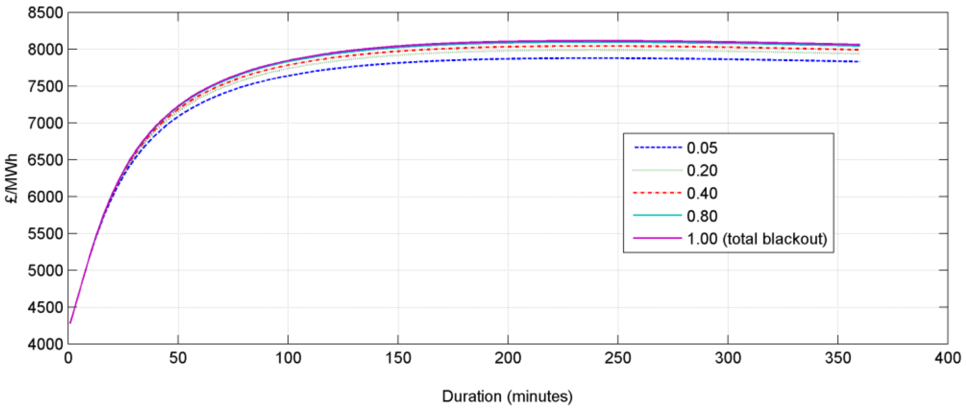
Legend:

▓	Top 10 affected sectors
▒	Top 20 affected sectors
░	Top 30 affected sectors

SE45	Electricity
SE46	Gas etc.
SE54	Wholesale - excl vehicles
SE25	Coke, petroleum & petrochemicals
SE101	Households
SE51	Construction - civil engineering
SE60	Support services for transport
SE39	Machinery & equipment
SE37	Computers, electonics & opticals
SE91	Health
SE41	Other transport equipment
SE44	Repair & maintenance
SE36	Fabricated metal
SE8	Mining support
SE39	Machinery & equipment

Source: Authors

Figure 6: Societal cost of energy not supplied (SCENS) for Scotland – 2009 prices



Source: Authors

Additionally, these results show that figures obtained using SCENS are significantly higher than those derived using traditional measures of societal cost of interruption (which can be obtained by dividing GDP by the total electricity sales in an economy). Using the information in Table 2, we calculate this figure as £3564.73/MWh. This is the average productivity of electricity for the Scottish economy and shows how much each megawatt-hour of electricity contributes towards GDP. With increased duration of interruption, this figure underestimates the societal cost of interruption to a greater extent. Furthermore, although the cost of energy not supplied depends on the structure of economies, and cross country comparisons may not be very accurate, our estimation of SCENS in Figure 6 is comparable with previous studies presented in Table 1.

In summary, we have investigated the interdependency effects and the economic impact of electricity supply interruptions. The most vulnerable sectors to power outage, in terms of inoperability and economic loss, were identified. The results of the study showed that inoperability does not necessarily correspond to a similar level of economic loss and these two metrics can differ in the case of power supply shocks. The results also showed that the ranking of sectors in terms of vulnerability to power supply disruption is robust in relation to the extent and duration of interruptions. We also computed the societal cost of energy not supplied (SCENS) given the interdependency among the infrastructure sectors and showed that SCENS strictly depends on the duration of interruption. The results also indicated that SCENS starts from moderate values for very short duration of interruptions before increasing rapidly. Beyond a certain duration of interruptions, the SCENS converges to a specific range irrespective of initial inoperability level.

The results of this study provide some useful insights for policymakers and planners in their pursuit of improved electricity supply reliability and reductions in the economic impact of possible power outages. First, at sector level the regulatory incentives to reduce power interruptions need to be able to justify investment in resiliency enhancement and quality of supply improvement. An estimation of the societal cost of power outage, which also takes into account the interdependency effects, can be used to calculate societal ‘willingness to invest’ in power quality, given the probability of outage. Overestimation or underestimation of the societal cost of power outage could lead to overinvestment or underinvestment, respectively, in power quality and security of electricity supply.

Second, at economy level, measures to protect critical assets need to be based on cost–benefit and risk analysis. There is always a trade-off between improving the resiliency of the power sector versus that of vulnerable infrastructures. An accurate analysis which compares the costs and benefits of resiliency improvements to the power sector with those of vulnerable sectors leads us towards an economically optimum level of reliability. Also, such analysis sheds light on the effectiveness of available risk management measures such as reducing interdependency among critical infrastructures, increasing preparedness, and enabling a smart response to major power cut incidences.

Third, the results highlight the need for an integrated security indicator which reflects several aspects of industry and business under extreme events. Such aspects would include: inoperability, economic loss, and the degree of importance of the sector for the welfare and well-being of the population. There is also a need for the development of relevant indices which measure the risk of different sources of failure, in addition to sector resilience and reliability. Theses indices could support managers and operators of critical infrastructures with tools enabling them to analyse and manage the risk holistically.

Finally, the results of this study provide valuable insights for the management of outages and optimal operation of the power system. The ranking of vulnerable sectors based upon the *ex ante* analysis presented in this study, can help decision-makers address the issue of forced outage under extreme events in an economically informed way. This can be accomplished by avoiding random outage in favour of commencing power rationing in the sectors at lower economic cost and inoperability level.

Despite the appealing characteristics of the DIIM model used in this paper, it also has some limitations. First and foremost, the most important assumption of the model is that the level of economic interdependency remains the same as the level of physical interdependency, and thus two sectors with high economic interdependency also have high physical interdependency (Haimes et al., 2005a). To the extent that economic interdependencies are obtained from a multiplication of real physical interdependency and ‘undistorted producers’ prices’ this can be reasonable. This means that having an undistorted electricity price across an economy is crucial for this model, as this is a basic assumption of input–output tables. In the absence of real physical data (given that collecting such information is extremely costly) on the interaction of sectors, the use of economic interdependency can be the second-best option for evaluating physical interdependency effects (Haimes et al., 2005a).

However, there are situations which may lead to underestimation or overestimation of the economic costs of power outage using the DIIM approach. If the price of electricity is subsidized, or taxed differently in some sectors than others, this may lead to a distortion of outage costs, because it directly affects the strength of interdependency among them. Furthermore, there are some forms of losses which normally are not valued by DIIM and should be included separately, as in this paper. For example, the cost of lost leisure resulting from a power cut is not normally accounted for in input–output models; such costs should thus be evaluated separately. Additionally, DIIM may not calculate the restart cost of industries following interruption of production lines. Another form of loss which is not captured by this model is that caused by stock damage – for instance to items such as perishable goods and ticket sales (Théron and Bologna, 2013).

The second limitation is that the DIIM model strictly relies on the assumption of a Leontief coefficient matrix (A), hence all the limitations and assumptions in construction of this matrix apply to DIIM as well. Finally, the inoperability input–output model assumes an equilibrium condition in its static form (Haimes et al., 2005a). This implies that the industries’ inputs and outputs are in equilibrium with the final consumption. This assumption is true for the long-run analysis but can be violated after an inoperability shock and during the recovery period, if the initial inoperability level is assumed to be very high. In this situation, the recovery process does not reflect the actual behaviour of an economy under extreme events. However, if the initial inoperability shock is a fraction of total output (in other words, less than 100 per cent) then the results of the DIIM model are more reliable. This is because a partial inoperability within a large economy can be dealt with by redirection of resources from other parts of the economy during the recovery period.

5. Conclusions

The power sector is an industry on which many other infrastructures rely heavily. Hence, security of electricity supply has always been high on the agenda of policy makers and sector regulators. At the same time, many of these infrastructures are interdependent and a failure in electricity supply will result in cascading effects, with consequences for the societal cost of energy not supplied (SCENS).

Therefore, it is imperative to understand the intricate interdependencies between the power sector and other infrastructures, together with the impact on other interdependent sectors when the power supply is perturbed. This study analysed the interdependency effects and economic impact of electricity supply disruption using a DIIM model. We applied the model to a case study of 101 sectors of the Scottish economy in 2009.

Our analysis demonstrated that inoperability can be different from economic loss and that highly inoperable industries in the short run (after shock) are not necessarily the same as those most affected economically. This is because the sensitivity of revenue and operational status to a particular input (for example, power) might vary for a given sector and across different sectors. The results also indicated that ranking of the affected sectors in terms of inoperability and economic loss metrics are robust with respect to extent and duration of interruptions. This *ex ante* analysis helps decision makers to prioritize vulnerable sectors for resource allocation and resiliency enhancement against major power outage incidences. It also helps to manage forced outages in an economically informed way by avoiding random outages.

We also estimated SCENS taking interdependencies among sectors of the economy into consideration. The results show that SCENS ranges from about £4300/MWh for 1 minute of interruption to a maximum figure of around £8100/MWh for an outage of three hours and more. Additionally, SCENS increases very marginally with the extent of power blackout (inoperability). The social cost of interruptions based on direct, indirect, and induced effects due to interdependency can be used to calculate ‘societal willing to invest’ in resiliency enhancement.

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Table A1: Industries of Scottish Economy used in Analysis (2009)

ID	Sector name	ID	Sector name	ID	Sector name
SE1	Agriculture	SE35	Other metals & casting	SE69	Information services
SE2	Forestry planting	SE36	Fabricated metal	SE70	Financial services
SE3	Forestry harvesting	SE37	Computers, electronics & opticals	SE71	Insurance & pensions
SE4	Fishing	SE38	Electrical equipment	SE72	Auxiliary financial services
SE5	Aquaculture	SE39	Machinery & equipment	SE73	Real estate – own
SE6	Coal & lignite	SE40	Motor Vehicles	SE74	Real estate – fee or contract
SE7	Other mining	SE41	Other transport equipment	SE75	Legal activities
SE8	Mining Support	SE42	Furniture	SE76	Accounting & tax services
SE9	Meat processing	SE43	Other manufacturing	SE77	Head office & consulting services
SE10	Fish & fruit processing	SE44	Repair & maintenance	SE78	Architectural services etc.
SE11	Dairy products, oils & fats processing	SE45	Electricity	SE79	Research & development
SE12	Grain milling & starch	SE46	Gas etc.	SE80	Advertising & market research
SE13	Bakery & farinaceous	SE47	Water and sewerage	SE81	Other professional services
SE14	Other food	SE48	Waste	SE82	Veterinary services
SE15	Animal feeds	SE49	Remediation & waste management	SE83	Rental and leasing services
SE16	Spirits & wines	SE50	Construction – buildings	SE84	Employment services
SE17	Beer & malt	SE51	Construction – civil engineering	SE85	Travel & related services
SE18	Soft Drinks	SE52	Construction – specialized	SE86	Security & investigation
SE19	Textiles	SE53	Wholesale & Retail – vehicles	SE87	Building & landscape services
SE20	Wearing apparel	SE54	Wholesale – excl. vehicles	SE88	Business support services
SE21	Leather goods	SE55	Retail – excl. vehicles	SE89	Public administration & defence
SE22	Wood and wood products	SE56	Rail transport	SE90	Education
SE23	Paper & paper products	SE57	Other land transport	SE91	Health
SE24	Printing and recording	SE58	Water transport	SE92	Residential care
SE25	Coke, petroleum & petrochemicals	SE59	Air transport	SE93	Social work
SE26	Paints, varnishes and inks etc.	SE60	Support services for transport	SE94	Creative services
SE27	Cleaning & toilet preparations	SE61	Post & courier	SE95	Cultural services
SE28	Other chemicals	SE62	Accommodation	SE96	Gambling
SE29	Inorganic chemicals, dyestuffs & agrochemicals	SE63	Food & beverage services	SE97	Sports & recreation
SE30	Pharmaceuticals	SE64	Publishing services	SE98	Membership organizations
SE31	Rubber & Plastic	SE65	Film video & TV etc.	SE99	Repairs – personal and household
SE32	Cement lime & plaster	SE66	Broadcasting	SE100	Other personal services
SE33	Glass, clay & stone etc.	SE67	Telecommunications	SE101	Households
SE34	Iron & Steel	SE68	Computer services		