

Measuring Community and Multi-industry Impacts of Cascading Failures in Power Systems

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Abstract—Many economic activities strongly depend on critical infrastructure systems, especially the electric power system. Failures in the electric power infrastructure not only cause the disruption of power supply but also result in losses in productivity across other dependent industries. This work aims to develop a framework that uniquely integrates a AC flow-based cascading failure analysis for the electric network with a multi-regional, multi-industry interdependency model to quantify the short-term economic impacts of electric power disruption due to cascading failures. A AC power flow-based cascading failure analysis is developed to enable the accurate reproduction and consequences estimation of a cascading event. We use the economic interdependency model to evaluate the economic impact of a cascading event taking into account spatial explicitness and cross border effects. The economic impacts due to both the direct power supply disruption and the workforce unavailability are estimated. A case study was conducted on the Swiss electric network, accounting for the international impact on other related countries. The results provide guidance for ranking the criticality of the elements in the electric network and for identifying the vulnerable regions and economic sectors that could be strengthened through preparedness planning.

Index Terms—Cascading failure analysis; component criticality; multi-industry impacts; power systems; risk analysis.

I. INTRODUCTION

Cascading outages in power systems are defined as one or more sequential dependent component outages that successively weaken the system [1]. Cascading outages can either terminate before interrupting the electricity service or continue until a blackout occurs. If the cascade process extends to the system level, it can cause massive disruption to electric power service. In August 14, 2003, the blackout event in the Northeastern U.S. and Southeastern Canada led to a disruption in power for 50 million people. The power supply disruption (i.e., 63 GW) accounted for approximately 11% of the total load demand in the affected area. Despite their infrequency, blackout events significantly affect system safety and reduce customer perception of power supply reliability [2, 3]. To maintain the security of the power supply and limit the potential

societal impact of the cascading events, it is important to assess system vulnerabilities and identify critical components that ensure the reliable operations of the power system.

Vulnerability analysis is an emerging approach used in the risk management of critical infrastructures. It assesses the consequence in the system when a set of its elements is removed or when the system is operating in extreme conditions [4]. System vulnerability can be measured from two perspectives: (i) global vulnerability analysis, and (ii) critical component analysis [4], which provide different insights for a system's ability in withstanding disturbances and stress. Global vulnerability analysis is carried out by removing an increasing number of components or changing the loading of the system to increase the stress on the system and uses a model of system response to estimate the resulting consequences. In critical component analysis, a component, or set of components, is identified as critical if, when failed, it gives rise to significant adverse consequences. Criticality measures serve as useful tools to identify weak links that may affect the performance of a system and to prioritize reliability improvement activities, among other uses [5]. Several analytical and empirical component importance measures have been proposed to rank the components according to their criticality in the system [6].

Traditional vulnerability analyses often narrowly focus on the direct consequences of each individual infrastructure. However, the increasing functional and geographical interdependence among critical infrastructures that make them more efficient also make them more complex and vulnerable to the propagation of malfunctions [7]. As such, vulnerability measures should account for larger scale impacts, including across infrastructures and across multiple industries that rely upon them. Adapted from [8], the term *cascading effects* used here refers to the inoperability that occurs internally to a network (e.g., flow redistribution due to capacity exceedances), and *interdependent effects* refers to the inoperability that occurs external to the network as a result of its disruption (e.g., often experienced in communities and different industries that rely on electric power).

In a power system, DC/AC flow-based cascading failure analysis has been proposed to estimate the consequence of a cascading event caused by various scenarios, e.g., ORNL-PSerc-Alaska (OPA) model [9, 10] or Manchester model [11]. These analyses measure the severity of a cascading event based on the direct impact in the power sector such as the power supply disruption. Due to the strong dependency of economic activities on the electric power supply [12], a

The paper was submitted for review on 03.02.2017.

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This work was supported, in part, by the National Science Foundation through award 1635813.

cascading failure in the electric power sector may propagate its impact to interconnected industries. According to [13], the total cost to the US caused by the 2003 Northeast Blackout ranges between \$4 and \$10 billion. Over 10 sectors experienced economic losses of more than \$100 million, with the *business services*, *electric power*, and *depository institutions and brokers* industries among the most affected in terms of three-day economic losses [14]. The extensive societal impact of the cascading events on dependent economic sectors stresses the necessity of a systematic evaluation of the consequence of their disruption. Additionally, the direct infrastructure consequences and the societal effects caused by the component failure may differ to a large extent, which can lead to a different measure of component criticality and incorrect vulnerability reduction decisions [15]. Therefore, it is significant to account for the societal impact when identifying critical components in power systems.

The inoperability input-output model (IIM) is proposed for quantifying the interdependent inoperability and economic losses experienced across multiple industries. The model takes into account both direct and higher-order economic effects caused by a disruptive event (e.g., a regional blackout). The IIM has wide applications in various vulnerability studies. Pant et al. [16, 17] developed an integrated model with the IIM and a simulation model of port operations to assess the interdependent impact caused by disruptions at an inland port terminal and to inland waterways, respectively. In [15], a model of the Swedish power transmission system and a regional IIM are integrated for measuring the long-term societal effects of a power supply reduction.

The use of the IIM for quantifying the interdependency among economic sectors relies on large-scale databases that support the model, and such databases has resulted in the maturity of the field of input-output analysis. The wide application of IIM, especially in the study of the societal impacts of disruptive events [18], validates the application of IIM here. For instance, Anderson et al. [14] applied an IIM analysis to the 2003 US blackout, the results obtained are very similar to other estimations of published empirical studies. As the base IIM only provides an averaged estimation across geography, and model results may be insufficient for preparedness decision making within and across regions [19]. To address such spatial disruptions, Crowther et al. [19] introduced a Multiregional IIM (MRIIM) to extend the IIM for modeling the multiregional interdependencies among the various regions. The MRIIM captures cross border effects by accounting for the spatial explicitness in intraregional and multiregional interdependency matrices.

The contributions of this paper are three-fold. First, a AC power flow-based cascading failure analysis is developed for estimating the consequence of cascading events caused by a set of failure scenarios. Second, the cascading failure analysis is validated against historical blackout data to demonstrate the model's capability in capturing important statistical characteristics of cascading events. Third, the cascading failure analysis for the electric network is uniquely integrated with the MRIIM to quantify the short-term societal impacts of power

supply disruption caused by cascading events. This paper extends prior work by the authors [20] by including the important step of cascading failure analysis validation and taking into account the inter-regional commodity and services exchanged to effectively capture the interdependent effects of economic consequences across the border. In the proposed framework, random failures of physical components are introduced in the power system to trigger a cascading event. The direct power supply disruption in the electric sector and the workforce unavailability in each sector with reliance on power supply are structured as inputs to the MRIIM. The analysis of interdependencies estimates the propagation of the losses among industries at the regional and international level. Both global vulnerability with respect to increasing load factors and critical component analysis are conducted. The case study on the Swiss electric network and affected countries provide an estimate of the large-scale economic impacts of disruptions due to cascading failures at the local and international level. The criticality of system components can be ranked based on the severity of these impacts. Furthermore, by aggregating the losses caused in each region and in each industry for various failure scenarios, it is possible to identify the vulnerable regions and economic sectors that should be strengthened for the risk management of cascading failures.

This paper is structured as follows. Section II introduces the cascading failure analysis model, the MRIIM used for the interdependence study in the integrated model, and the metrics used for evaluating the societal impact of the cascading failures. The results of the case study on the Swiss electric network and the related countries and their implications are discussed in Section III. Section IV concludes the work and offers thoughts on future work.

II. METHODOLOGY

A. AC-PF based Cascading Failure Analysis

In cascading events, the initial contingency can be unexpected outages of generators or transmission lines, a sudden unanticipated increase of demand, fluctuations of the generator output, or outage of other equipment [21]. The outages may be local and terminate before causing power supply disruption, or they may propagate to wide areas and lead to blackouts. Cascading phenomena are complicated because there are many failure mechanisms involved, which include cascading overloads, failures of protection equipment, reactive power problems, and voltage collapse. Cascading line overloads is one of the most common propagation mechanisms [3]. When a transmission line is overloaded, it triggers a dynamic of automatic disconnection from the network by a circuit breaker to prevent system damage. The load that is originally carried by the disconnected line is redistributed to other lines, which may lead to additional line overloads. FACTS can be applied to nudge power flows in desired directions and mitigate the line overloads [22]. The topology change can cause island operation in the system, and in the case of large power imbalance in the island, frequency instability can occur, which can lead to power supply disruption. The

system may enter a state of voltage instability after sequential line tripping or other changes in system condition that can lead to a progressive and uncontrollable drop in voltage. Under Frequency Load Shedding (UFLS) or Under Voltage Load Shedding (UVLS) can be implemented, respectively, when there is a potential of frequency/voltage instability in the system. The imbalance of the power generation and load consumption in the island is compensated by primary and secondary frequency control. If there is not enough generation capacity in the island, load shedding has to be conducted to restore the power generation/consumption balance and to correct the frequency deviation.

To simulate the evolution of cascading failures and to assess potential adverse consequences, the steady-state operations of the power system is simulated with an approximate model. The model represents the dynamical process of cascading events that is consistent with some basic network and operational constraints. The cascading failure analysis is based on AC power flow. The linear nature of the DC PF method leads to efficient computation and applicability to large-scale systems. However, the voltage profile of buses and reactive power have significant impacts on the system conditions, and by disregarding their effects, the underlying assumptions in the DC PF method may provide underestimated results. This approach can model combinations of several types of failures such as cascading line overloads, frequency deviation, reactive power problems, and voltage drop. The non-sequential Monte Carlo method [23, 24] is applied to power system risk analysis, where the states of the components are sampled and a non-chronological system state is obtained. The model captures following phenomena: (i) it simulates critical scenarios that may trigger a cascading event; (ii) the post-contingency power flow on the transmission lines is computed with a AC power flow algorithm; (iii) primary and secondary frequency control of generators are activated in case of power generation/consumption imbalance in island operation [1], the frequency deviation are computed and the frequency control is modeled according to [25]; (iv) the lines are disconnected automatically when they reach the failure limit [26] [27]; (v) it identifies blackout conditions when there is frequency instability due to the large power imbalance in the island [1, 28], and UFLS is conducted when the frequency exceeds the acceptable threshold [28]; (vi) UVLS is performed when the voltage magnitude at a bus is under the limit [29]; and (vii) if there is not enough generation capacity in the island, load shedding is conducted as a last resort. Constant load demand from the customer during the cascading event is assumed. In addition, the probability of having additional random failures of transmission equipment in the evolution of the cascading event is very low and is not considered. Demand not served (DNS) is used to measure the consequences of the cascading event, which is a commonly used reliability measure for power systems [30] [1].

The cascading failure analysis evaluates the steady-state post-contingency system conditions [31]. The transient process after the failure (e.g., the dynamic frequency characteristics of the generator/load) is not involved in the analysis.

1) Frequency Control

The steady state frequency deviation after the cascading failure is evaluated according to the following equation [32]:

$$\Delta f = \frac{-\Delta P}{\sum_{h=1}^{N_{bus}} 1/D_{d,h} + \sum_{h=1}^{N_{bus}} 1/R_h} \quad (1)$$

where ΔP is the power imbalance in MW. $D_{d,h}$ and R_h are the frequency characteristics of the demand and generator at bus h , respectively.

Here we restrict ourselves to a single-area system, where the objective of secondary control is power balancing within the area and to release the capacity used for primary frequency control. The contribution of each generator to secondary frequency control is computed from the nodal balance at bus h [25]

$$0 = P_{g,h}^{\text{nom}} + P_{g,h}^{\text{primary}} + P_{g,h}^{\text{secondary}} - P_{d,h} - \sum_{k \in n_h} P_{l,hk} \quad (2)$$

where $P_{g,h}^{\text{nom}}$ is the nominal power generation, $P_{g,h}^{\text{primary}} = -\Delta f / R_h$ and $P_{g,h}^{\text{secondary}} = u_{g,h}$ are the power delivery for primary frequency control and secondary control. $P_{d,h}$ is the power demand at bus h , n_h is the set of the buses that are connected to bus h and $P_{l,hk}$ is the flow on line $\{h,k\}$, respectively. By summing up (2) for all the buses, we obtain

$$\Delta f = \left(\sum_{h=1}^{N_{bus}} P_{g,h}^{\text{nom}} + \sum_{h=1}^{N_{bus}} u_{g,h} - \sum_{h=1}^{N_{bus}} P_{d,h} - \sum_{h=1}^{N_{bus}} \sum_{k \in n_h} P_{loss,hk} \right) \cdot \sum_{h=1}^{N_{bus}} R_h \quad (3)$$

where the left-hand side denotes the *measurable* system frequency deviation Δf , the term $P_{loss,hk}$ depicts the power loss on the transmission line $\{h,k\}$, and the term in brackets on the right-hand side denotes the total power imbalance. Observe that Δf is zero if and only if the power injections and losses are balanced by means of the secondary control input $u_{g,h}$. The secondary control action $u_{g,h}$ is implemented via integral control of the frequency error Δf with integral gain equal to the generation participation factor $\beta_{g,h}$ for each generator, which represents the ratio of generator h 's capacity to the total capacity, i.e., $\beta_{g,h} = P_{g,h}^{\text{capacity}} / \sum_{h=1}^{N_{bus}} P_{g,h}^{\text{capacity}}$. Thus, the

steady-state of the secondary integral control input achieving $\Delta f = 0$ is given by

$$u_{g,h} = \beta_{g,h} \cdot \left(\sum_{h=1}^{N_{bus}} P_{d,h} + \sum_{h=1}^{N_{bus}} \sum_{k \in n_h} P_{loss,hk} - \sum_{h=1}^{N_{bus}} P_{g,h}^{\text{nom}} \right) \quad (4)$$

The simulation algorithm, depicted in Fig. 1, is as follows:

1. For each failure scenario,

1.1 Initialize the system (topology, load/generation at each bus) with the output from the optimal power flow with the objective of generation costs minimization.

1.2 Run random component failure (for each component, a random number is sampled, the component is supposed to be failed if the number is smaller than the failure probability of the component, Pr).

1.3 Check for an island in the system based on the new topology.

2. For each island

2.1. Evaluate the system frequency deviation and the voltage

magnitude of each bus.

2.2. Apply UFLS if the frequency deviation exceeds the acceptable threshold [28] (e.g., 2.5Hz).

2.3. Apply UVLS if the voltage magnitude at a bus is lower than 92% of nominal [29].

2.4. Restore load/generation balance through primary and secondary frequency control.

2.5. Run the AC power flow model.

2.6. Remove lines with flow higher than the line tripping threshold T_l . If there are new islands, return to step 1.3.

3. Output total load shed (DNS) and total line outages.

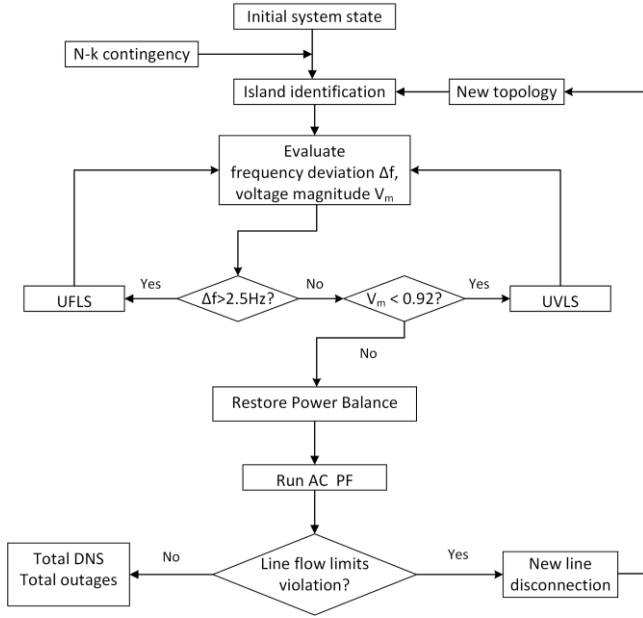


Fig. 1. Algorithm applied in the simulation model.

B. Inoperability Input-Output Model

The IIM is derived from Leontief's input-output (I-O) model [33], which is used to quantify the interconnectedness within sectors of the economy. Extending from the traditional I-O model, inoperability is expressed as a proportional lack of productivity relative to its "as-planned" production capacity [34]. This normalized production loss is calculated in (5).

$$\text{Normalized production loss} = \frac{\text{as-planned production} - \text{degraded production}}{\text{as-planned production}} \quad (5)$$

The IIM is constructed based on two assumptions. The first is the equilibrium assumption (i.e., all production is consumed). The supply inoperability of an industry is equal to the sum of the direct perturbation to the industry's production and cascading inoperability from interconnected industries. The second is that interdependent industries receive proportional impact from disruptive sectors. The basic formulation of IIM is found in (6), where $\mathbf{A}^*$ is an industry interdependency matrix that is modified from the Leontief technical coefficient matrix $\mathbf{A}$ according to [34] (i.e., $\mathbf{A}^* = \mathbf{1}/\hat{\mathbf{x}} \cdot \mathbf{A} \cdot \hat{\mathbf{x}}$. Matrix $\hat{\mathbf{x}}$ is the diagonal matrix derived the production vector $\mathbf{x}$. Each element a_{ij}^* describes the amount of inoperability occurred in industry i due to the inoperability in industry j . $\mathbf{f}^*$ is a vector of direct perturbation to a industry's production. The inoperability

vector $\mathbf{q}$ is a real-valued vector of normalized production losses for each industry at the national level. $q_i > 0$ and $q_i < 0$ represent the ratios of unrealized and excessive production with respect to the nominal production level of the sector, respectively. The unrealized production represents the proportional extent to which industries aren't producing. Inoperability can also be understood as the supply unreliability of a sector [35]: $q_i = 0$ if industry i is operating at its nominal level – it experiences no inoperability in such a case. $q_i = 1$ if industry i is completely inoperable relative to nominal. The element of $\mathbf{f}^*$, f_i^* is the change to the final demand with respect to nominal production output for industry i .

$$\mathbf{q} = \mathbf{A}^* \mathbf{q} + \mathbf{f}^* \Leftrightarrow \left\{ q_i = \sum_j a_{ij}^* q_j + f_i^* \right\} \quad (6)$$

Equation (6) estimates supply inoperability from intermediate economic exchanges between industries. To calculate the inoperability resulting from a given disruption, $\mathbf{q}$ is represented in (7) as a function of a pre-specified perturbation vector $\mathbf{f}^*$, the interdependency matrix $\mathbf{A}^*$, and a conformable identity matrix $\mathbf{I}$.

$$\mathbf{q} = (\mathbf{I} - \mathbf{A}^*)^{-1} \times \mathbf{f}^* \quad (7)$$

Note that (7) is linear in nature, therefore an increased perturbation results in a proportional increase in inoperability. Inoperability can be converted into economic loss by multiplying inoperability by the production vector $\mathbf{x}$.

To reflect the spatially explicit intraregional interdependencies, which are likely to differ from those at the national level, the IIM is regionalized by adding spatial explicitness to the model. Generally, the regional interdependency coefficients are estimated through the use of regional multipliers, which indicate the regional production compared to the national production. In [19], a specific type of regional multiplier called a location quotient is used for the estimation of regional interdependency coefficients. The location quotient represents the proportion of demand for industry i in region s that can be satisfied regionally, compared to the nation's ability to satisfy the nation's internal demand for industry i . The location quotient for industry i and region s , lq_i^s , is found in (8), where x_i^s and x_i^N indicate the overall production from industry i in region s and nation N , respectively, and x^s and x^N indicate the overall production from all sectors in region s and nation N , respectively. Equation (9) provides the calculation for a_{ij}^{*s} , the amount of inoperability incurred in industry i due to the inoperability in industry j specifically in region s . a_{ij}^* is the amount of inoperability experienced in industry i due to total inoperability in industry j in the nation. When lq_i^s is less than 1, it means that the production output of industry i is insufficient to satisfy the regional supply demand, otherwise there is no adjustment to a_{ij}^* .

$$lq_i^s = \frac{x_i^s / x^s}{x_i^N / x^N}, \quad (8)$$

$$a_{ij}^{*s} = \begin{cases} lq_i^s a_{ij}^*, & lq_i^s < 1, \\ a_{ij}^*, & lq_i^s \geq 1, \end{cases} \quad (9)$$

To assess the international impact of a disruption that occurs in one country, a multiregional IIM was introduced to connect all countries based on international trade [36]. The bilateral trade data between countries is used to construct an interregional matrix, T_i^{rt} , which indicates the percentage of commodities and services in industry i that are produced in country r and consumed by country t , as illustrated in (10).

$$T_i^{rt} = \begin{cases} \frac{m_i^{rt}}{x_i^t + m_i^t - e_i^t}, & \text{if } t \neq r \\ \frac{x_i^t - e_i^t}{x_i^t + m_i^t - e_i^t}, & \text{if } t = r \end{cases} \quad (10)$$

where m_i^{rt} is the value of industry i 's commodities and services that are imported by country t from country r , m_i^t and e_i^t are country t 's total imports from and exports to all other countries included in the model for industry i . The commodities and services that are both produced and consumed in country t are represented as T_i^{tt} . Both exports and imports are included in the calculation in order to ensure that T_i^{rt} captures all the production in industry i and that $\sum_r T_i^{rt} = 1$. The interregional matrix $\mathbf{T}$ is shown in (11), where each T_i^{rt} is of size n and the i th element on the diagonal is T_i^{rt} . Variable b is the number of countries that are considered in the model.

$$\mathbf{T} = \begin{bmatrix} \mathbf{T}^{11} & \mathbf{T}^{12} & \dots & \mathbf{T}^{1b} \\ \mathbf{T}^{21} & \mathbf{T}^{22} & \dots & \mathbf{T}^{2b} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{T}^{b1} & \mathbf{T}^{b2} & \dots & \mathbf{T}^{bb} \end{bmatrix} \quad (11)$$

The IIM is extended to the multiregional IIM by incorporating the interregional matrix as shown in (12). For notational simplicity, the notation $\mathbf{y}^{a:b} = [(\mathbf{y}^a)^T, (\mathbf{y}^{a+1})^T, \dots, (\mathbf{y}^b)^T]^T$ is adopted to represent a vector of length $n(b - a + 1)$ for countries $a, a + 1, \dots, b$, where $\mathbf{y}^c$ is a vector of interest (e.g., production, final demand, changes in production). The square matrix is of order nb , where $\mathbf{T}^* = \mathbf{1}/\hat{\mathbf{x}} \cdot \mathbf{T} \cdot \hat{\mathbf{x}}$. The right-hand side of (12) illustrates how the demand level in one or more countries can affect the production in b countries.

$$\mathbf{q}^{1:b} = \mathbf{T}^* \mathbf{A}^* \mathbf{q}^{1:b} + \mathbf{T}^* \mathbf{f}^{*1:b} = (\mathbf{I} - \mathbf{T}^* \mathbf{A}^*)^{-1} \mathbf{T}^* \mathbf{f}^{*1:b} \quad (12)$$

The IIM enterprise has successfully deployed to provide an account of how a disruption that adversely impacts a particular industry can lead to inoperable conditions in other industries in several domains, including waterways [16, 17, 37], inventory [38, 39], and electric power outages [14, 40]. The IIM enterprise, and more broadly interdependency models of multi-industry impact, were among the 10 Most Important Accomplishments in Risk Analysis: 1980-2010 [41]. The assumption of model linearity is overshadowed by the amount of real data describing interdependencies ($\mathbf{A}^*$) and total production from the US Bureau of Economic Analysis (BEA), the Organization of Economic Cooperation and Development (OECD), and dozens of other countries worldwide.

C. Integrating Cascading Failures with Interdependent Impacts

As introduced in [14], in a blackout event, the initial sector perturbation $\mathbf{f}^*$ can be decomposed into: (i) the direct impact of

a power supply disruption in electric power sector, and (ii) the direct impact of reduced workforce productivity in each sector with reliance on power supply. The former is only applied to electric power sector directly, while the latter can have impacts practically on all the sectors and is the largest source of the overall economic losses [42]. For example, Anderson et al. [14] concluded that the Northeast Blackout 2003 caused an approximately \$6.5 billion reduction of earnings, of which \$4.2 billion could be attributed to the income losses suffered by the workers and investors. It is difficult to capture the perturbation effects of an electric power disruption in a macro-level analysis (i.e., without looking at industry-specific operations in each disrupted region). The workforce perturbation is meant to work as a proxy for the lack of productivity in industries that rely on electric power, particularly in workforce-intensive industries.

1) Losses Resulting from Unfulfilled Electric Power Demand

To evaluate the direct effect on the electric sector and the higher order effect on other dependent sectors, the percentage of demand not served at the national and regional level are translated in (13) and (14) as an electricity sector perturbation in the national and regional IIM, where $f_{\text{electricity}}^{*N}$ and $f_{\text{electricity}}^{*s}$ are used as a perturbation to the electricity sector in the national and regional IIM, respectively. DNS^N and DNS^s are the demand not served values in nation N and in region s , respectively. P_{load}^N and P_{load}^s denote the national total load demand and load demand in region s , respectively.

$$f_{\text{electricity}}^{*N} = \frac{\text{DNS}^N}{P_{\text{load}}^N} \quad (13)$$

$$f_{\text{electricity}}^{*s} = \frac{\text{DNS}^s}{P_{\text{load}}^s} \quad (14)$$

2) Losses Resulting from Workforce Impacts

Inoperability due to unfulfilled electric power demand does not provide the complete picture of how industries require and use electric power. Another perspective accounts for a lack of productivity due to facilities being inoperable. A proxy for measuring the effects of this disruption is to estimate the extent to which productivity requires labor, suggesting that workforce unavailability resulting from a power supply disruption leads to reduced productivity [42]. For instance, in the manufacturing industry, a proxy for measuring the production that is interrupted in a blackout could be a function of labor requirements. An electric power blackout may affect the mobility of the workforce in terms of unavailable power-dependent transportation modes [42]. There are two layers of interdependencies: the workforce's dependence on the electric power and the industry's dependence on the workforce. First, by examining each industry's contribution to the workforce, the effect on the workforce due to a perturbation originating from the electric power sector is estimated. To quantify an industry's dependence on the workforce, the amount spent on labor costs is estimated. To do so, the local area personal income (LAPI), which reflects the amount of an industry's economic production spent on workforce, is used. Therefore, it is assumed that the effect on industry i of a disruption in the workforce is proportional to LAPI. The direct

workforce effects can cause other higher-order effects on the productivity of interdependent sectors.

The procedure to construct the perturbation vector considering the effect of workforce unavailability is:

1. For each industry i , evaluate $LAPI_i$, which is the product of personal income in industry i and the number of people employed in industry i .
2. Calculate the ratio of $LAPI_i$ to total production in industry i by dividing $LAPI_i$ by the industry's output x_i to estimate the proportional contribution of workforce to the total output of industry i .
3. Estimate the direct workforce perturbation to sector i at region s with (15).

$$\hat{f}_{i,workforce}^{*s} = \hat{f}_{i,electricity}^{*s} \times \frac{c_i}{x_i} \times \frac{LAPI_i}{x_i} \quad (15)$$

This equation is based on two assumptions: (i) the direct impact of workforce unavailability on the productivity of each sector is estimated by converting the supply constraints into equivalent demand reduction (i.e., $\hat{f}_{i,electricity}^{*s} \times c_i/x_i$ where c_i is the final demand in industry i) and (ii) workforce intensity is proportional to the percentage of an industry's total economic output that is spent on salaries (i.e., $LAPI_i/x_i$).

Repeat steps 1-3 for all industries and regions to find the vector of the direct workforce perturbation at each region s , $\hat{f}_{i,workforce}^{*s}$. The national direct workforce perturbation $\hat{f}_{i,workforce}^{*N}$ is calculated as $\sum_s \hat{f}_{i,workforce}^{*s}$.

3) Integrating the Failure and Impact Models

The cascading failure analysis is integrated with the regional IIM (RIIM) and the multiregional IIM to capture the direct and higher-order effects of the consequence of a cascading event, illustrated in Fig. 2.

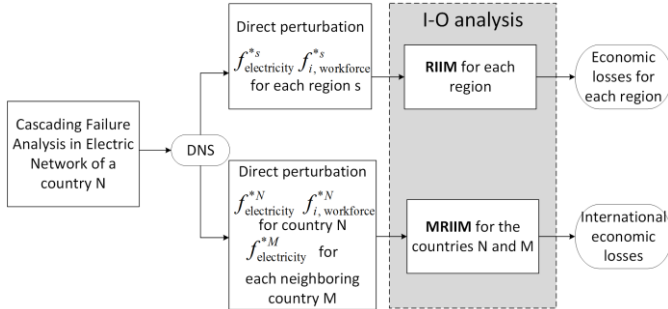


Fig. 2. The integration of cascading failure and interdependent impact models.

The cascading failure analysis evaluates the DNS for a cascading event in a country N . The DNS at each substation is mapped into the DNS at each region of the country. To evaluate the economic losses in each region, the DNS is used to construct the direct perturbation $\hat{f}_{i,electricity}^{*s}$ and $\hat{f}_{i,workforce}^{*s}$, which are the inputs for each regional IIM. The disruption of the power exchange between the neighboring countries M is modeled as the direct perturbation on the electricity sector of country M (i.e., $\hat{f}_{i,electricity}^{*M}$). The international economic impact can be estimated by introducing the inputs of direct perturbation on country N (i.e., $\hat{f}_{i,electricity}^{*N}$ and $\hat{f}_{i,workforce}^{*N}$), and the direct perturbation on the dependent countries M (i.e.,

$\hat{f}_{i,electricity}^{*M}$ in the multiregional IIM).

The severity of the consequence of a cascading event in the electric transmission system is measured as the DNS to customers and the economic losses at the regional and international levels. The risk of a cascading event is evaluated by incorporating the probability of the initial contingency (i.e., $\prod_{i=1}^k Pr_i$ for k initial line failures) and the severity of the consequence.

III. CASE STUDIES

We deploy the framework to estimate national and international impacts following a cascading disruption in the Swiss electric system.

A. Validation of the Cascading Failure Analysis

The validation of the cascading failure analysis is essential, because it is inherently infeasible to include all the cascading failure mechanisms, and assumptions have to be made in choosing the mechanisms to be modeled in particular applications [43]. In this paper, the cascading failure analysis model is validated on a reduced Western Electricity Coordinating Council (WECC) network system [44] by comparing the simulation results with real blackout data. In the WECC network, the main source of blackouts data is the frequency of blackouts from 1984 to 2006 [45], which is provided by the North American Electrical Reliability Council (NERC). Another available failure data set is the TADS transmission line outage data for 8864 outages, which was recorded by a utility company in WECC for a period of 10 years [46].

The parameters of the cascading failure analysis model (i.e., the probability of random line failure, Pr and the tripping threshold of overloaded lines, T_l) are calibrated to reproduce historical WECC blackout statistics. When $Pr = 0.001$ and $T_l = 110\%$ of the line capacity, the distribution of the load shedding after the simulated cascade event captures the distribution of the historical blackout size as shown in Fig. 3. Furthermore, the probability distribution for the total line outages is consistent between the model results and the historical data for cascading events involving up to six line outages as shown in Fig. 4. This effort is important as it represents one of the first attempts to validate cascading failure models against real power outage statistics.

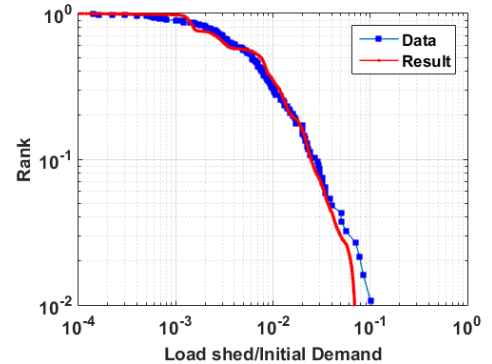


Fig. 3. Rank function for the normalized load shed from cascading failure analysis for the reduced WECC network (red line) compared with the data for the western interconnect (blue line).

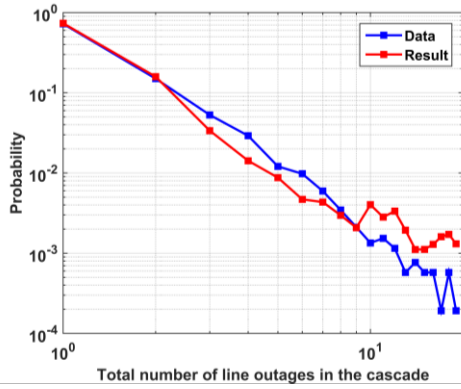


Fig. 4. The distribution of the total outages from cascading failures for the reduced WECC network (red line) compared with the historical data (blue line).

B. Test System

For the electric network, the cascading failure analysis is built on the data describing the Swiss grid system. The Swiss transmission network consists of 161 buses, 34 generation units, and 229 transmission lines (220kV and 380kV). The snapshots, provided by Swissgrid, served as a basis for estimating power demand. The total generation capacity is 10098 MW, and the total load consumption in the given snapshot is 5214.4 MW. To simulate different operating conditions, the power demand is scaled with a Load Factor (LF). Due to the deficiency of reliability data for the Swiss network transmission lines, the line failure probabilities are derived from the fault data of the electric components in the German transmission network for 2004-2011 [47]. The system is modeled in accordance with the modeling approach described in Section II.A.

The Organization of Economic Cooperation and Development (OECD) [48] provides I–O data and bilateral trade data in U.S. dollars for all of the OECD countries and for 11 non-OECD countries in Asia and South America. Each national economy is divided into 34 industries. Data from 2011 (the most recent available) are used, and it is assumed that the coefficients for the economic structure do not change drastically over time. Seven countries in addition to Switzerland are included in the model: Austria, China, Germany, Italy, France, the United States, and the United Kingdom. These countries represent more than 80% of all of Switzerland’s importing activities. The technical coefficient matrices and the vectors for the production and final consumption are constructed based on the I–O data. The location quotient and the LAPI are developed from the data provided by Swiss Federal Statistical Office. Bilateral trade matrices for 19 of the 34 industries are available from OECD. An assumption is made that the fraction that country t imports from country r for the other 15 industries is equal to the overall proportion that country t imports from that country r . The T matrix for OECD countries is generated based on the trade data.

In the IIM, the economic losses are typically estimated on an annual basis. When a load shedding is operated, it is assumed that the load shedding recovery will take one day. Therefore, a uniform-loss assumption is made that losses are evenly distributed throughout the year, and the annual losses divided by 365 gives an estimate of the daily economic loss [14].

Different duration of load shedding recovery can be modelled in the current framework, and the associated economic consequences of a loss of power supply can be estimated. There are 26 cantons in Switzerland, as shown in Fig. 5, with all the substations geographically located in 18 cantons. To evaluate the economic losses at each Canton, the IIM is regionalized by the locational quotient.

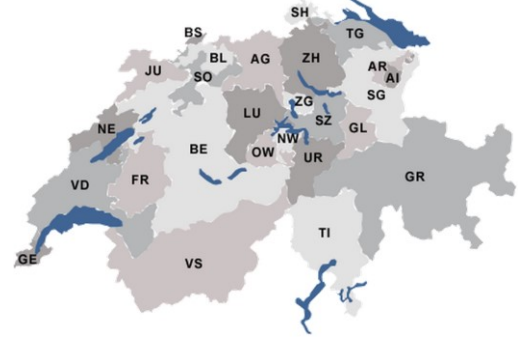


Fig. 5. Cantons in Switzerland [49]

C. Results for Application of the Integrated Model

Contingencies in the power system caused by the random line outages (i.e., independent line failure and common mode failure) are simulated with respect to increasing loading conditions (i.e., load factor = 1.1, 1.15, 1.2, 1.25). An optimal power flow is used to solve the economic dispatch problem at the four load conditions and to determine the initial output of each generator. For each loading condition, 100,000 simulations were conducted considering a low failure probability of transmission lines and to ensure the convergence of the results. The percentage of single-line failure or multi-line failures are determined by the failure probability of each transmission line. In this study, there are 99.32% of simulations with single-line failure, 0.68% of simulations with double-line failure and 0.0004% of simulations with triple-line failure. Furthermore, 30% of the initial failures can lead to cascading failures. Each cascade simulation takes 0.057 second on average on a desktop with Core i7 processor and 16GB RAM. The load shedding caused by the cascading events at each substation is mapped into the DNS at each canton. The economic losses for the DNS at each canton is evaluated with the regional IIM for each canton. The electric power imports and exports between Switzerland and other neighboring countries can be disrupted when load shedding is conducted at the nodes on the border. The economic losses due to the direct perturbation on each sector of Switzerland (i.e., unfulfilled electric power demand and workforce unavailability), and the direct perturbation on the electric sectors of the countries which have power import/export with Switzerland are evaluated with the MRIIM for Switzerland and the dependent countries.

1) Correlation: Power Supply Losses and Economic Losses in Switzerland

For each scenario, the economic losses in Switzerland estimated with the regional IIM (from direct power perturbation and workforce unavailability) are plotted against DNS with respect to the initial power demand, which is the perturbation input $f_{electricity}^{*s}$ to the IIM. In Fig. 6, the comparison with the linear regression trend line indicates that

the economic impact of a power loss of supply does not scale proportionally with the DNS. This is due to the fact that the power dependence of economic sectors varies in different cantons. Therefore, when different cantons are affected by the power disruption, the same DNS can translate into different magnitudes of economic losses.

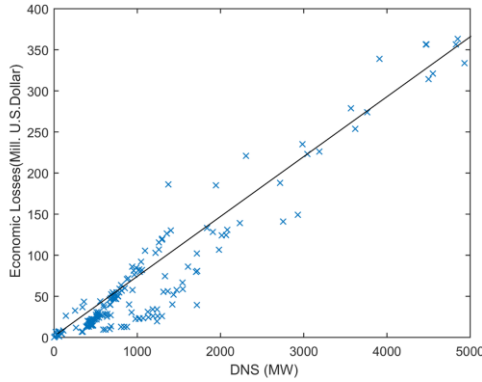


Fig. 6. Correlation plot for the risk of economic losses from the regional IIM (vertical axis) and the risk of DNS (horizontal axis) given the same scenario.

2) Risk Analysis of Cascading Events

The consequences of a cascading event (e.g., DNS and economic losses) are plotted against the probability of the initial contingency in Fig. 7 and Fig. 8.

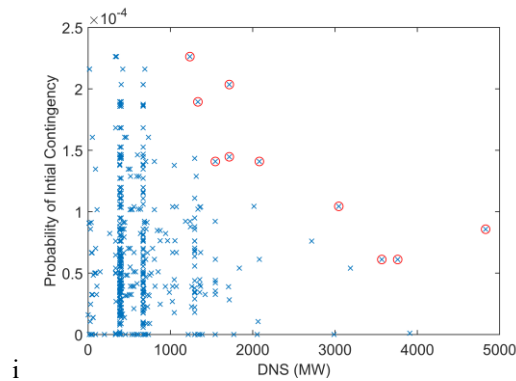


Fig. 7. Probability of the initial contingency against the DNS in a cascading event.

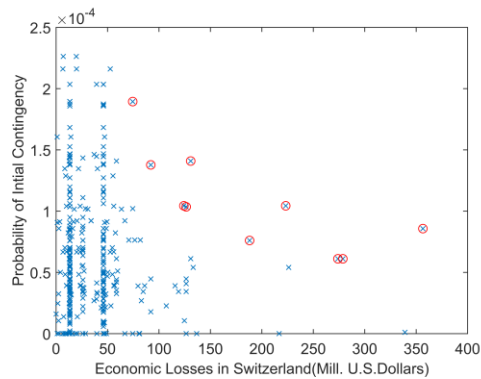


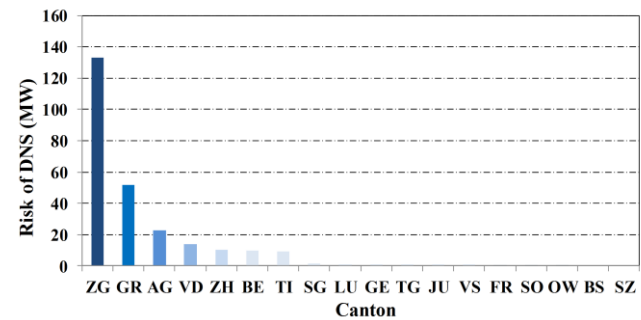
Fig. 8. Probability of the initial contingency against the economic losses in each cascading event.

The cascading events in the bottom left corner have a low level of risk. As illustrated in the figures, most of the events are associated with relatively lower consequences (i.e., lower than 2000 MW in terms of DNS and less than \$150 million in multi-industry economic losses). It can be observed that the contingencies with different probabilities can lead to the same consequences. This is due to the fact that when different

contingencies occur, the same island condition with certain generation insufficiency can be formed when the cascade stops. The cascading events towards the top right corner have higher risk. These events, marked with red circles in Fig. 7 and Fig. 8, are associated with a higher priority in risk management because they have a high probability of occurring and can cause large DNS and economic losses.

3) Regional Vulnerability

In Fig. 9, the risk of DNS caused at each canton for these scenarios is plotted. It can be observed that canton Zug (ZG), Graubünden (GR), and Aargau (AG) suffered the largest DNS in the scenarios. The losses in Canton Zug (ZG) are twice the losses experienced by the second most impacted canton. The power losses are translated into the economic losses through the RIIM, and Fig. 10 illustrates the cumulative economic losses at each canton.

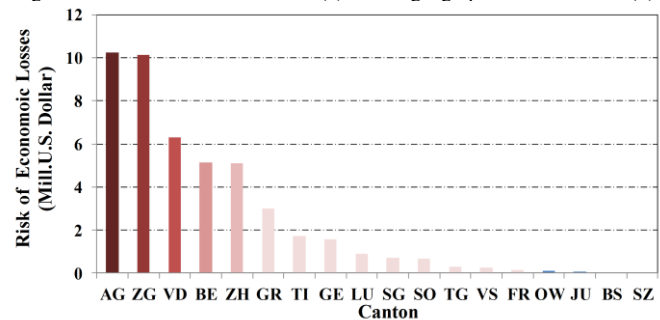


(a)



(b)

Fig. 9. Risk of DNS at each canton (a) and its geographical distribution (b)



(a)

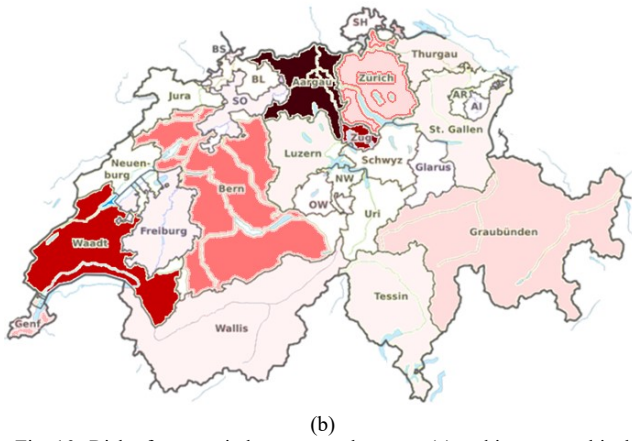


Fig. 10. Risk of economic losses at each canton (a) and its geographical distribution (b)

The result demonstrates that the power supply robustness of each canton is ranked differently based on the risk of DNS and on the risk of economic losses. For instance, Canton AG has the third largest power supply losses but ranked on the top of economic losses among regions because this canton has many energy intensive companies and therefore a strong dependence on the electric power supply.

Fig. 11 provides important insight in the interdependent impacts that large disruptions might have in different countries. In Europe, Switzerland assumes a key role as an electricity hub of Europe. Switzerland imports power from Germany, Austria, and France and exports power to Italy. Table I shows the amount power that is imported and exported between Switzerland the neighboring countries for the considered operating condition.

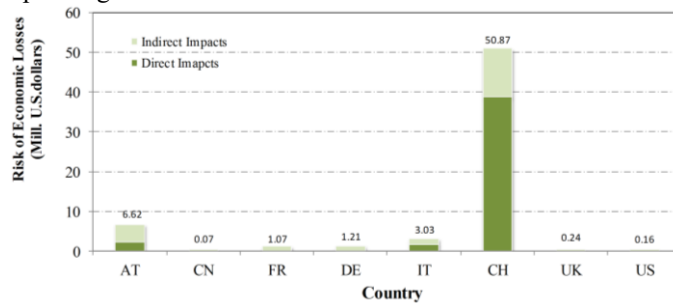


Fig. 11. Economic losses in each country.

Due to the strong dependency of the electricity supply between Switzerland and the neighboring countries, a power supply disruption caused by cascading events in Switzerland can lead to a significant change in production in the electric sectors of neighboring countries. The neighboring countries that have grid connection and electricity exchange with Switzerland (i.e., Austria, France, Germany, and Italy) suffered more significant impacts in this disruptive scenario than the countries without electricity exchange with Switzerland (i.e., China, U.K., and U.S.). The power that exports from Austria to Switzerland is 15% of Austria's total electric power consumption, therefore Austria is the most impacted country. The direct perturbation can lead to further economic losses in interdependent industries. The higher order impacts on the interdependent industries are obvious. For instance, the indirect economic losses Switzerland constitute 20% of the total

TABLE I

THE AMOUNT OF POWER, IN MEGAWATTS, THAT SWITZERLAND IMPORTED FROM AND EXPORTED TO EACH COUNTRY.

Countries	Austria	France	Germany	Italy
Import	845.7	1144.2	2212.7	0
Export	0	157.9	165.9	2560.8

economic losses, and for Austria the indirect economic losses are higher than the direct losses.

4) Industry Vulnerability

To identify the most susceptible sectors to power supply disruption, the distribution of the overall economic losses among sectors is analyzed. We aggregated the 34 industries into 10 related industries and explore the impacts in each. Fig. 12 shows the interdependent economic losses in each industry in Switzerland for the disruption scenario. It can be observed that the economic losses caused by the workforce unavailability significantly contribute to total losses. As expected, the *energy, utility and construction industry* suffered the greatest production losses, as these losses consist of the impact of disruption in electric sector and the workforce unavailability in the construction sector. The *wholesale and retail trade, business services, and education and health* industries have high economic losses caused by workforce unavailability as these industries are labor intensive. The electric disruption scenario also caused economic losses in the *transportation and telecommunication services*, which requires electricity for operating facilities.

Fig. 13 demonstrates the macroeconomic impact on the selected countries. Disaggregating the production losses by industry reveals that except from the *energy, utility and construction industry*, the cascading event that occurred in Switzerland also has a strong international impact on the *business services* sector.

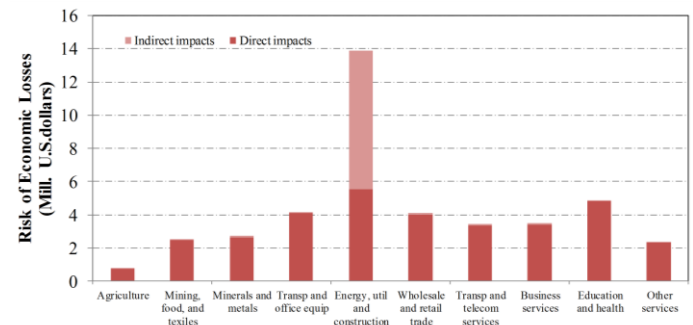


Fig. 12. Economic losses in Swiss industries.

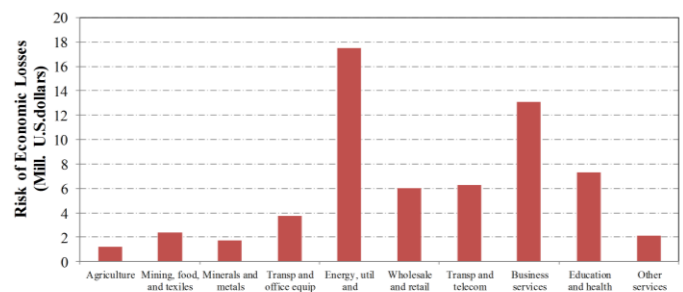


Fig. 13. Economic losses in the industries of the selected countries.

5) Criticality of Transmission Lines

For each transmission line, its contribution to the risk of DNS and economic losses is analyzed. Fig. 14 and Fig. 15 display the criticality of the lines measured in the terms of DNS and economic losses in Switzerland, respectively. It can be observed that the criticalities of lines are ranked differently when measured with these two metrics. In Fig. 14, there are two lines significantly contributed to the DNS, line 35 and line 198, which are associated with risk of DNS for 10.93 MW and 13.35 MW, respectively. Although line 35 and line 198 are ranked as the most critical lines in DNS in Fig. 14, they are less critical compared to the line 200 in economic losses in Fig. 15.

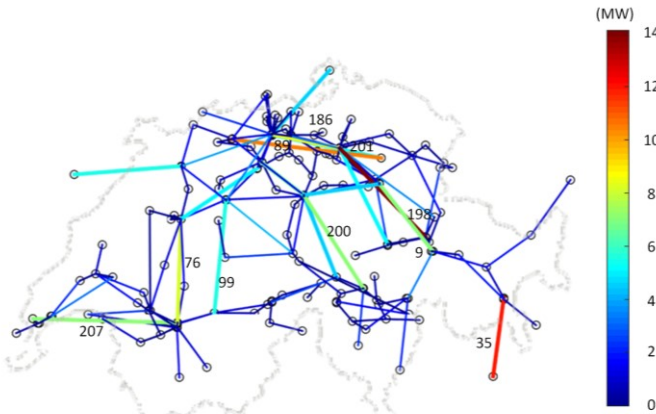


Fig. 14. Line criticalities ranked based on the risk of DNS occurring in Switzerland.

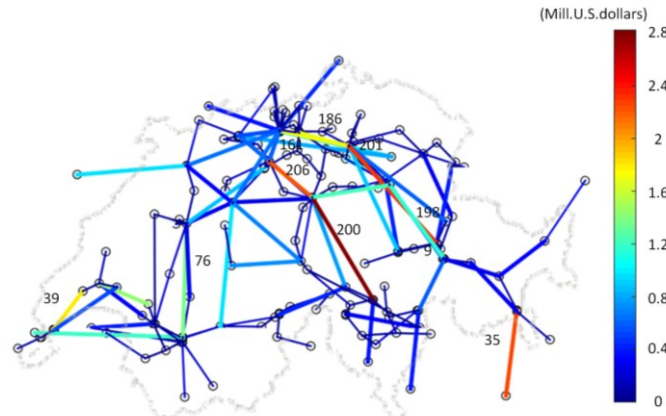


Fig. 15. Line criticalities ranked based on the risk of economic losses occurring in Switzerland.

To better understand the observations, Fig. 16 illustrates the DNS that is caused by the failure of lines 35, 198, and 200 in each canton. As expected, the line failures lead to high losses in Canton ZG, AG and Canton GR, which are identified as the most vulnerable regions in power supply disruption in Section III.C.3. The failure of line 200 leads to high DNS in region AG, which is the region with strong dependence on the power supply and therefore the DNS is translated into high economic losses. In Fig. 17, the international impacts of the cascading events are considered for line criticality. Note that line 35, which exports power from Switzerland to Italy, has the highest criticality. The failure of this line can lead to direct power supply disruption of 1773 MW. The high economic losses caused within Switzerland adding the international economic losses make line 35 as the most critical line in terms of the

multi-country economic losses. The results demonstrate the necessity of using economic impact as a measure for the component criticality. Table II illustrates the 10 most critical lines ranked based on the risk of DNS, risk of economic losses in Switzerland, and risk of international economic losses that can be caused by the failure of the line. The line criticality ranks vary for different criteria, and decision makers can determine which criterion to use based on their interests (e.g., reducing power supply losses versus economic losses), or apply a multi-criteria decision analysis.

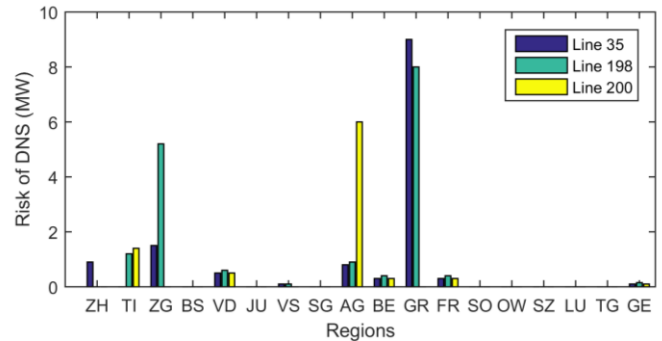


Fig. 16. The risk of DNS caused by the failure of lines 1, 2, and 4 in each region.

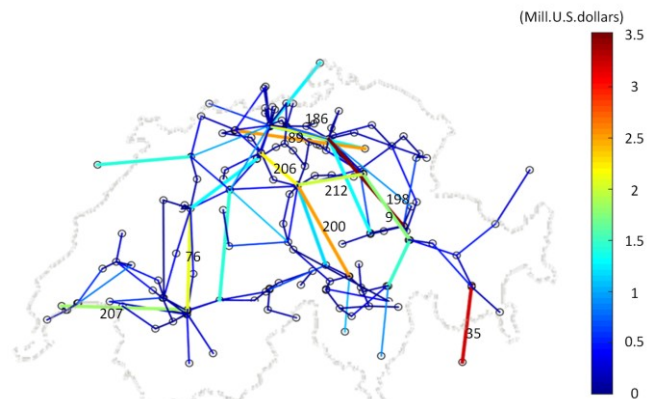


Fig. 17. Line criticality ranks based on international economic losses occurring in selected countries.

TABLE II
CRITICALITY RANK OF LINES IN TERMS OF RISK OF DNS, RISK OF ECONOMIC LOSSES IN SWITZERLAND, AND RISK OF INTERNATIONAL ECONOMIC LOSSES

Rank	Risk of DNS	Economic losses (Switzerland)	Economic losses (international)
1	198	200	198
2	35	198	35
3	89	35	200
4	186	206	89
5	76	201	206
6	200	39	186
7	9	186	76
8	207	192	212
9	201	161	9
10	99	76	207

IV. CONCLUSIONS AND OUTLOOK

The effects of regional blackout events spread across multiple industries and regions. Moreover, they not only directly impact the electric power sector, but they have distributed direct impacts on many other sectors due to reduced productivity. Due to the complexity of the impacts, no single metric can adequately measure the consequence of such a

disruption and provide information for identifying system vulnerabilities. To quantify the direct and higher order effects that can result from a cascading event in a large-scale and complex system, we propose a framework that integrates (i) cascading failure analysis for the electric power network with (ii) a multi-regional, multi-industry interdependent impact model.

The Swiss electric power case study, with impacts to several related countries, demonstrates the significance of including societal consequences as an additional metric for measuring the vulnerability of a system and the criticality of components in the infrastructure. The dependence on power of different industries varies in different cantons, thus the DNS and economic losses caused by the cascading event provide different perspectives, and are thus different, for the same canton. The framework identifies the cantons that are more dependent on the power supply and are vulnerable to power supply disruption (e.g., canton Aargau (AG) has the third largest DNS and the highest economic losses). I-O analysis provides complementary insight into the impacts on individual industries. Except from the electricity sector, the sectors that are labor intensive (e.g., *wholesale and retail trade, business services and education and health industry*) and the sectors that require electricity to operate the facilities (e.g., *transportation and telecommunication services*) can have high economic losses. Based on the results, policymakers can decide which region should increase the redundancy of the power supply or which industries may be best suited to have backup power generation capabilities. Additionally, ranking the criticality of components based on the societal consequences can provide a complementary insight for strengthening the component in the electric network. The inter-regional cascading effects of economic losses are captured by the commodity and service exchange among countries. If the cross region impact is neglected, the total societal consequence due to a power supply reduction may be underestimated. The case study based on the OECD member countries demonstrates the significance of capturing the cascading effects of economic consequences across the border through the MRIIM.

In the future work, the risk management strategies would be proposed and compared to mitigate the risk of cascading failures. The restoration duration has an impact on the economic losses evaluation (e.g., for big cascades), longer restoration time is required. More specific restoration time data for cascading events of different sizes would be used. Further, economic and other societal impacts can help guide recovery optimization decisions.

ACKNOWLEDGEMENT

The authors would like to acknowledge the CTI - Commission for Technology and Innovation (CH), and the SCCER-FURIES - Swiss Competence Center for Energy Research - Future Swiss Electrical Infrastructure, for their financial and technical support to the research activity presented in this paper.

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