Sustainable and Resilient Infrastructure

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tsri20

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To cite this article: Mohamed Salama, Mohamed Ezzeldin, Wael El-Dakhakhni & Michael Tait (2022) Temporal networks: a review and opportunities for infrastructure simulation, Sustainable and Resilient Infrastructure, 7:1, 40-55, DOI: 10.1080/23789689.2019.1708175

To link to this article: https://doi.org/10.1080/23789689.2019.1708175

Published online: 04 Feb 2020.

SUSTAINABLE AND RESILIENT INFRASTRUCTURE
2022, VOL. 7, NO. 1, 40–55
https://doi.org/10.1080/23789689.2019.1708175

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REVIEW ARTICLE

Temporal networks: a review and opportunities for infrastructure simulation

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ABSTRACT

Complex network theory (CNT) has been providing the platform to simulate, analyze, and visualize different complex interdependent networks. Despite the successes of simulating and analyzing infrastructure networks based on their static topological characteristics using CNT, there remain some challenges pertaining to considering the temporal variation within such networks. This is an important aspect, especially that most infrastructure (e.g., transportation and power) networks are dynamic (i.e., evolve over time) and vary not only spatially but also temporally. In this respect, the current study focuses on first presenting a review of temporal network topological characteristics and modeling approaches. The different graphical representation techniques of temporal networks are then summarized and compared to their static counterparts. Finally, the study highlights the fact that considering the time dimension in simulating complex networks is a relatively new research field that presents new research frontiers for breakthrough opportunities in simulating complex interdependent infrastructure networks.

ARTICLE HISTORY
Received 19 March 2019
Accepted 30 October 2019

KEYWORDS
Complex network theory; dynamic network; infrastructure networks; temporal network; time-varying graphs; temporal centrality

1. Introduction

The use of complex network theory (CNT) analysis techniques has extended to a wide spectrum of applications in different fields (Costa et al., 2011). Within the context of CNT (Newman, 2010), the main components of the network are simulated by nodes (e.g., bus stops in transit networks and substations in power networks), whereas links represent the interdependencies between these nodes within such a network (e.g., bus routes in transit networks and transmission lines in power networks). In other words, links mimic the relational connections among the nodes (Ouyang, 2014). Such links can be related to physical, cyber, geographical location, or logical interdependencies between nodes (Rinaldi et al., 2001). For example, the link may indicate a physical connection between two nodes or that two nodes sharing the same resources or are managed/controlled by the same entities.

Such an elegant simulation approach facilitates the quantification of the interdependence between the components comprising such networks. CNT analyses also facilitate the identification of the underlying network topological characteristics, and its most influential nodes and links (Tang et al., 2010b; Wang et al., 2017). In addition, other characteristics, such as network robustness, can be evaluated by subjecting the underlying network to dynamic stress tests (Barabási & Pósfai, 2016; Wang & Rong, 2009; Wang et al., 2010), within which, the systemic risk (e.g., domino-type cascade failure consequence) would mainly depend on the network topology (Wang, 2013).

Most published research studies have focused on simulating and analyzing networks using static approaches. Such approaches assume that the network nodes and links remain unchanged over time (Barabási et al., 2000; Guimerà et al., 2005; Latora & Marchiori, 2002; Sen et al., 2003). However, most real networks evolve, where their links can emerge and decline over time. This can be exemplified by the temporal nature of social media (Sanlı & Lambiotte, 2015), phone call (Saramäki & Moro, 2015), email (Eckmann et al., 2004), biology (Holme, 2016) and infrastructure networks (Borgnat et al., 2013; Rocha, 2017). For all such networks, the links may be present only for a small duration (i.e., according to the corresponding application), and their statuses always fluctuate (Holme & Saramäki, 2012). As such, neglecting the time dimension in studying such networks may result in erroneous interpretations of network behaviors (Pan & Saramäki, 2011; Tang et al., 2013; Wu et al., 2014). Accordingly, several recent studies have focused on extending static network modeling approaches to simulate the dynamic network behavior.

Such studies, however, generated multiple nomenclatures and evaluation approaches for essentially identical network characteristics. To name but one example, the

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term *temporal networks* have been used interchangeably with *dynamic networks* (Caceres et al., 2011), *time-varying graphs* (Nicosia et al., 2012; Tang et al., 2010c), *temporal graphs* (Wu et al., 2014), *dynamic graphs* (Kim & Anderson, 2012), or *evolving graphs* (Xuan et al., 2003).

The current study thus focuses on reviewing temporal network metrics, simulation approaches, and applications in infrastructure by adopting the following structure subsequent to this Introduction section: Section 2 reviews several critical topological temporal network characteristics; Section 3 introduces and analyzes temporal centrality measures reported in literature; Section 4 outlines the different graphical representations of temporal networks; Section 5 describes different classes of infrastructure network-based models; Section 6 highlights infrastructure networks simulation opportunities; and, finally, the study summary and overall conclusions are provided in Section 7.

2. Topology and characteristics of temporal networks

The analysis of static networks mainly relies on specific characteristics pertaining to the network topology. In the current paper, the authors give specific attention to various characteristics and performance measures of temporal networks, as applied to infrastructure systems. For example, most infrastructure systems such as power grid or transportation networks can be modeled by nodes and links, such networks continuously evolve over time (Borgnat et al., 2013; Rocha, 2017), regardless of the underlying applications (Holme 2015; Holme & Saramäki, 2012). In addition, centrality measures, as will be shown in the next section, highlight the role played by certain key nodes in networks, while, the significance of this role is translated according to the corresponding application (Nicosia et al., 2013; Tang et al., 2010b). As such, this section presents the extension of such network characteristics from their static simulation approach to considering the time dimension within the temporal simulation approach.

2.1. Time window and temporal scale

A temporal network can be simulated as a sequence of static network *snapshots*. Each snapshot represents the network nodes and links within a specific time interval referred to as the *time window* (Tang et al., 2010a). The selection of the time window is key when simulating temporal networks. For example, if a network is analyzed using an overly coarse resolution (i.e., too large a time window), the temporal variations of the nodes and links may not be properly identified. Nonetheless, the use of too fine a resolution (i.e., too small a time window) may result in only a very few changes within the selected time window (Caceres & Berger-Wolf, 2013; Caceres et al., 2011). Accordingly, the appropriate time window is based on the underlying application, the availability of data, and the required level of the study (Holme 2015; Li et al., 2017). For example, Borgnat et al. (2013) selected a time window of two hours in studying the temporal behavior of a France shared bicycle system to detect communities in the network and evaluate their weekly dynamical behavior. In case of evaluating the system performance at failure propagation or restoration process, the time window needs to be short enough (e.g., seconds or minutes) to capture the accelerated dynamic of network topology. In particular, studying power grid outages involves various dynamics with different timescales. Line tripping due to overload or the load shedding usually last a few seconds, whereas, the overhead lines outages due to vegetation contact or overheat usually last for a few minutes (Yao et al., 2015).

The main criterion for selecting an optimal time window to analyze temporal networks is to maintain the balance between the level of resolution and the target outputs. For this reason, several studies have proposed different approaches to select the optimal time window of the networks based on their underlying applications. For example, Tang et al. (2013) selected the time window according to the maximum available resolution of the data. This approach can be appropriate for some networks, where their dynamic (flow) data are collected at intervals coincident with the corresponding interactions between the nodes. However, substantial recent advances in data collection and storage have resulted in high-resolution dynamic information that requires optimizing the framework considered to select the appropriate time window. Moreover, the study by Sulo et al. (2010) revealed that there are various possible temporal scales, each scale demonstrates distinct measure for the same network.

2.2. Reachability

Reachability is also key for simulating the structure of any static or temporal network. In general, reachability describes the connectivity between any two nodes. For example, node F is *directly reachable* from node A, if and only if there is one direct link, without any bridge nodes, between nodes F and A. If node F is connected to node A through other bridge nodes, then node F is *indirectly reachable* to node A (Nicosia et al., 2013).

The time dimension significantly influences the reachability between nodes, when the status of links (i.e., emerging or declining over time) is considered (Holme & Saramäki, 2012; Nicosia et al., 2013). This is a key aspect in simulating temporal networks that is typically not considered in their static counterparts (Grindrod et al., 2011). As shown in Figure 1(a), node A is not connected to node F due to the time order of the links; however, the same two nodes appear connected if the focus is only on the aggregated static network, as shown in Figure 1(b). This explains the potential overestimate of the reachability when only the static state of a network is considered.

2.3. Temporal path, length, and distance

The definition of reachability is geared towards the notion of *path*. In static networks, the path represents the set of links traversed to reach from one node to another. The length of such a path is evaluated as the number of traversed links. Thus, the temporal path can be defined as the sequence of links that exist in an ascending time order (Göbel et al., 1991; Kempe et al., 2002; Nicosia et al., 2013).

The temporal path length can be described through two different approaches (Nicosia et al., 2013). First, similar to the definition of the path length in static networks, the *topological length* is the number of links in the path between any pairs of nodes. From a static network perspective, the shortest path is the one that contains the minimum number of links (i.e., minimum topological length). However, in many temporal networks, the time taken to transfer from one node to another becomes more critical than the minimum number of links between these nodes (i.e., how quick a bus can move from one station to another throughout the transportation network). Second, the *temporal length* can be evaluated as the duration of the path in terms of the number of time windows, w. For example, in Figure 1(a), there are several temporal paths from node A to node E (A-B-E, A-D-C-E, A-B-D-C-E). The first path A-B-E has the smallest topological length (i.e., two links), while its temporal length is equal to $4w$. The second path A-D-C-E has the smallest temporal

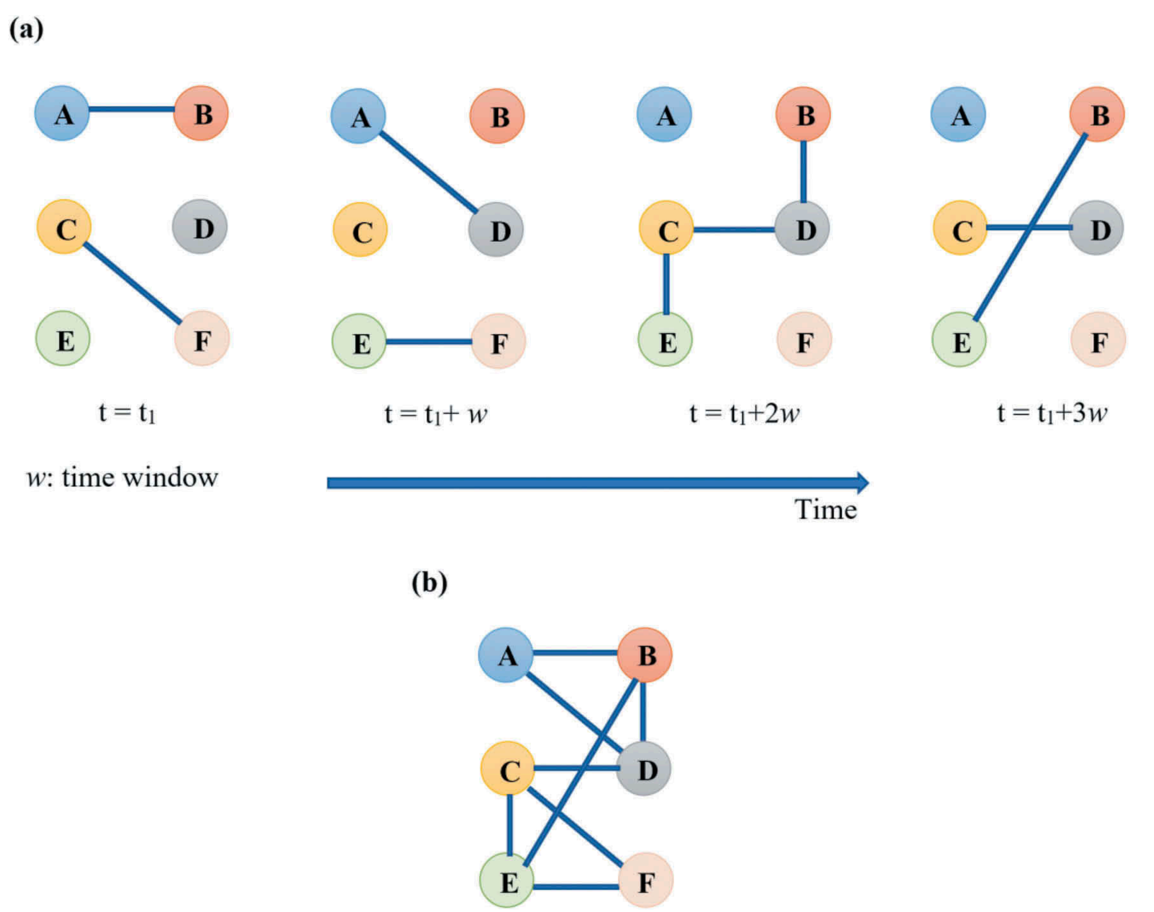

Figure 1. A network consists of six nodes: (a) temporal network presentation with four snapshots; and (b) static network presentation with one graph.

length (i.e., $2w$), while its topological length is equal to three links.

Several definitions for the shortest/minimum temporal path have been introduced based on the underlying applications (Nicosia et al., 2013; Pan & Saramäki, 2011; Tang et al., 2009, 2010a; Wu et al., 2014; Xuan et al., 2003). For example, Xuan et al. (2003) presented three definitions of a *minimum journey* (i.e., path): 1) shortest journey (minimum hop count); 2) foremost journey (earliest arrival date); and 3) fastest journey (minimum duration). The same authors termed temporal graphs as a sequence of subgraphs (i.e., timed snapshots) and provided algorithms to evaluate temporal paths. Other research studies (Pan & Saramäki, 2011; Tang et al., 2009, 2010a) defined the shortest temporal path between two nodes as the temporal path with the minimum duration (e.g., path A-D-C-E between nodes A and E in Figure 1). More recently, Wu et al. (2014) investigated four different measures to evaluate the temporal path: 1) shortest path (minimum distance); 2) fastest path (minimum duration); 3) earliest-arrival path; and 4) latest-departure path. Unlike the work of Xuan et al. (2003) that only considered the hop count, the latter four measures take into consideration the traversal time (e.g., phone call duration or flight duration) in quantifying the shortest path.

Hence, the *temporal distance* or *latency*, d_{ij}, is the duration for the shortest temporal path between nodes i and j (Nicosia et al., 2013; Pan & Saramäki, 2011). Subsequently, the average temporal distance between all pair of nodes can be expressed by calculating the *characteristic temporal path length* (Tang et al., 2009) in the network as:

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij} \tag{1}$$

where, N is the total number of nodes in the network.

According to Equation (1), if two nodes are disconnected, their temporal distance is infinity. Such infinite value influences the characteristic temporal path length quantification and subsequently yields unrealistic results. To address this issue, the definition of *temporal global efficiency*, as shown in Equation (2), is the inverse of temporal distance, becomes more practical (Tang et al., 2010c).

$$\varepsilon = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{2}$$

As a summary, Table 1 lists previous research studies that presented definitions of the shortest/minimum temporal path.

3. Temporal centrality measures

CNT is not only concerned with evaluating the complex interdependence between nodes through links but also with revealing the influences of different nodes on the overall network behavior. For this reason, several network centrality measures have been widely utilized in different applications to identify critical nodes in the relevant networks. Such applications range from identifying influential individuals in social networks (Kempe et al., 2003) to bottlenecks in transportation networks (Hossain & Alam, 2017; Zhao et al., 2017, Abdelaty et al., 2019). As such, several studies recently extended the different static centrality measures to temporal networks and subsequently compared their correlation to static network applications (Pan & Saramäki, 2011; Tang et al., 2010b; Taylor et al., 2017). This section summarizes the most common centrality measures within both static and temporal networks.

For notational consistency, the temporal network measures discussed next are based on a set of nodes, N, connected by a set of links, L, where links change over time. This network also has a finite time interval that starts and ends at t_{start} and t_{end}, respectively. The temporal network can be represented by a set of static graphs $[G_1, G_2, \ldots G_m]$, where each graph captures some network information for specific duration of time, referred to as the time window size, w. The number of the time intervals or the number of the snapshots, m, equals to the integer value of the quotient $((t_{end} - t_{start})/w)$.

Table 1. Temporal path definition according to different studies.

Ref.	Temporal path	Definition	Application
Xuan et al. (2003)	-Shortest journey -Foremost journey -Fastest journey	-Minimum hop count. -Earliest arrival time. -Minimum duration.	-Non specific
Tang et al. (2009) Pan and Saramäki (2011)	-Shortest path	-Minimum duration.	-Mobile and email networks
Wu et al. (2014)	-Shortest path -Fastest path -Earliest-arrival path -Latest-departure path	-Minimum distance. -Minimum duration. -Earliest arrival time. -Latest departure time.	-Applied to twelve real temporal networks

3.1. Degree centrality

For static networks, the degree centrality of a node is the total number of links connected directly to this node normalized (divided) by the maximum number of links that can be connected to the same node (Freeman, 1978), as presented in Equation (3). In directed networks, there are two types of degrees: an *in*-degree and an *out*-degree. According to the degree centrality, the node with the highest degree is the most central node (i.e., hub) (Barabási & Pósfai, 2016).

$$D_{C_S}(i) = \frac{1}{(N-1)} \sum_j \mathrm{L}_{ij} \tag{3}$$

where, $\mathrm{L}_{ij} = 1$ if, and only if, there is a link between nodes i and j, and $\mathrm{L}_{ij} = 0$ otherwise.

To extend the degree centrality measure to temporal networks, Kim and Anderson (2012) developed a time-ordered graph that facilitates evaluating the centrality measure for such networks. The time-ordered graph simulates the temporal network topology as a static network with directed flows, as shown in Figure 2. Accordingly, the temporal degree centrality of a node can be evaluated first from this graph as the sum of all the *in* and *out* links connected to this node in a time interval (i.e., from t_{start} to t_{end}). Subsequently, this summation is normalized through dividing by $2m(N-1)$, as presented in Equation (4). In other words, the temporal degree centrality of a node is the average value of its *in*- and *out*-degrees over a set of the snapshots, m.

$$D_{C_t}(i) = \frac{1}{2m(N-1)} \sum_t (\mathrm{K}_{in} + \mathrm{K}_{out}) \tag{4}$$

where, K_{in} and K_{out} are the number of *in* and *out* links connected to the node, respectively.

3.2. Closeness centrality

The closeness centrality measures how close a node is to other nodes in the same network. In static networks, the closeness centrality of a node is evaluated as the inverse of the average static distances from this node to all other nodes (Freeman, 1978), as expressed in Equation (5). Where the static distance S_{ij} is the minimum number of the links that connects nodes i and j.

$$C_{C_S}(i) = \frac{1}{N-1} \sum_j \frac{1}{S_{ij}} \tag{5}$$

Tang et al. (2010b) extended the concept of closeness centrality to temporal networks by using the temporal distance. Therefore, the temporal closeness centrality can be expressed in terms of the average of the total shortest temporal distances from a given node to all other nodes:

$$C_{C_t}(i) = \frac{1}{m(N-1)} \sum_j d_{ij} \tag{6}$$

Again, having disconnected nodes in the network would lead to an infinite temporal distance value, and therefore, the closeness centrality can be defined as (Pan & Saramäki, 2011):

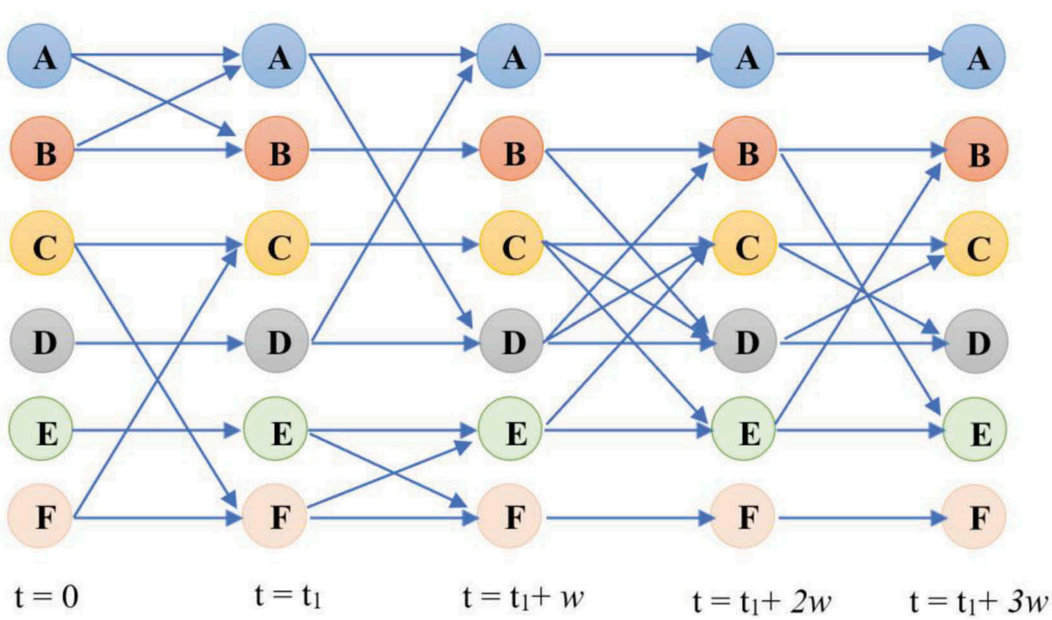

Figure 2. The time-ordered graph of the network presented in Figure 1.

$$C_{C_{II}}(i) = \frac{1}{m(N-1)} \sum_j \frac{1}{d_{ij}} \tag{7}$$

Tang et al. (2010b) demonstrated that the closeness centrality of a node is useful to identify the most influential *spreaders* throughout the network. For example, an infected individual (node) with high a closeness centrality value (compared to other exposed individuals) is potentially the most effective distributor for spreading virus or cascade systemic risks throughout the network. In the case of infrastructure networks, closeness centrality provides a potential indicator to the critical nodes that are, for example, responsible for blackouts in power networks or traffic jams in transportation networks. In addition, Pan and Saramäki (2011) emphasized that some nodes might appear too close in a static network; however, considering the temporal dimension, such nodes might actually be even not connected or have a long temporal path. Therefore, in a temporal network, some nodes might possess low closeness centrality values relative to their counterparts when the same network is evaluated as a static network.

Moreover, Kim and Anderson (2012) proposed a formula to calculate the closeness centrality of a node by considering the shortest temporal path distance for all time intervals from t to t_{end} (i.e., $t_{start} \leq t < t_{end}$), as presented in Equation (8). This definition differs from that presented in Equation (7) that focused only on the overall time interval (i.e., from t_{start} to t_{end}).

$$C_{C_{III}}(i) = \frac{1}{m(N-1)} \sum_t \sum_j \frac{1}{d_{ij}[t, t_{end}]} \tag{8}$$

where $d_{ij}[t, t_{end}]$ is the shortest temporal distance between nodes i and j within a time interval from t to t_{end}.

Table 2 presents the closeness centrality values calculated according to Equations (7,8) (Kim & Anderson, 2012; Pan & Saramäki, 2011) to facilitatedirect comparison. As can be seen in Table 2, nodes B, C, D, and E have the same closeness centrality value according to Equation (7) suggested by Pan and Saramäki (2011). Conversely, according to Equation (8) proposed by Kim and Anderson (2012), node C possesses a unique large value over nodes B, D, and E. This difference in closeness centrality values is mainly attributed to the variation of temporal paths as the time increases. More specifically, according to Equation (7), the temporal centrality is governed by the shortest temporal path within the overall time interval $[t_{start}, t_{end}]$ and all other interactions are ignored. While, according to Equation (8), all possible time intervals $[t, t_{end}]$ are considered to include the dynamics of temporal paths between nodes.

Table 2. Comparison between different approaches to calculate Closeness centrality.

	Node					
Ref.	A	B	C	D	E	F
Pan and Saramäki (2011)	0.150	0.200	0.200	0.200	0.200	0.125
Kim and Anderson (2012)	0.221	0.196	0.371	0.363	0.325	0.175

3.3. Betweenness centrality

The betweenness centrality measure identifies nodes that play a central role between other nodes in the network (Lazega et al., 1995). In a static network (Freeman, 1977), this measure is calculated as:

$$C_{B_S}(i) = \frac{\sum_{i \neq j \neq k} \sigma_{jk}(i)}{\sum_{i \neq j \neq k} \sigma_{jk}} \tag{9}$$

where $\sigma_{jk}(i)$ is the total number of shortest paths between nodes j and k that passes through node i, while σ_{jk} is the total number of shortest paths between nodes j and k.

The definition in Equation (9) can be extended to temporal networks by considering the temporal paths in lieu of the static paths (Tang et al., 2010b). In a similar way, the temporal betweenness centrality of node i can be defined as the ratio between the number of shortest temporal paths between all pairs of nodes that pass through node (i) and the total number of the shortest temporal paths between all nodes in the network. Tang et al. (2010b) proposed an expression to calculate the temporal betweenness centrality to consider the waiting time (e.g., the difference between arrival and departure time at the bus station in a transit network). In this respect, the betweenness centrality of node i at time t can be expressed as:

$$C_B(i,t) = \frac{1}{(N-2)(N-1)} \sum_{j \neq i} \sum_{\substack{k \neq i \\ k \neq j}} \frac{u(i,t,j,k)}{\sigma_{jk}} \tag{10}$$

where, $u\ (i,t,j,k)$ is the number of the temporal shortest paths between nodes j and k that passes through node i at a time equals to or less than t. Hence, the betweenness centrality of node i over all time intervals is defined as:

$$C_{B_I}(i) = \frac{1}{m} \sum_t C_B(i,t) \tag{11}$$

4. Graphical representation of temporal networks

Graphical representation of temporal networks is a critical aspect to visualize the network structure. This section provides a review of the different representation techniques proposed in previous studies to visualize temporal network data (e.g., links time, links order and duration).

4.1. Time-labeled graph

A simple technique to represent a temporal network is by using a *time-labeled graph* (Kempe et al., 2002), in which each link is labeled with the time of contact between its pair of nodes, as shown in Figure 3. Therefore, the temporal path is strictly committed to follow an ascending order through these labels (Kempe et al., 2002). Such a graph is also referred to as *contact sequences* (Holme, 2005) or *time series of contacts* (Holme 2015). Holme (2005) used this graph to illustrate the spreading processes in directed temporal networks. This representation technique illustrates the temporal data in a single graph, thus taking advantage of the static network layouts.

4.2. Sequence of static graphs

Another technique to represent temporal networks is to show the evolving network over time by a set of subgraphs, where each subgraph captures the network information at a specific time (Ferreira, 2004; Tang et al., 2009), as shown in Figure 1(a). Such a graph also termed *graph sequences* (Holme 2015) or *time-varying graph* (Nicosia et al., 2013, 2012). Such a representation depends mainly on the selected time window, as discussed earlier. One drawback of using this technique lies in its inability to consider the time spent to transfer the information (i.e., contact duration) within the same time window. For example, in Figure 1 (a), node B can connect to node E in one-time step through nodes D and C without any consideration to the time needed to reach from one node to another.

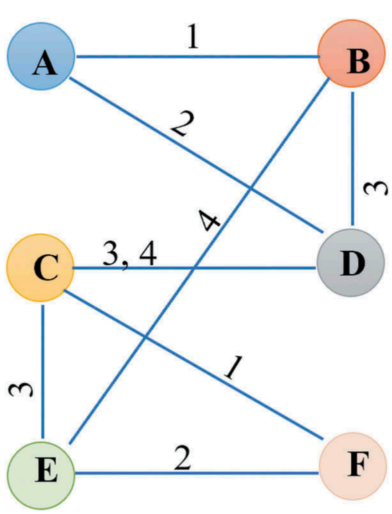

Figure 3. The time-labeled graph of the network presented in Figure 1.

4.3. Time-ordered graph

Another powerful technique to represent temporal networks is the time-ordered graph introduced by (Kim & Anderson, 2012). This graph has also been termed *directed acyclic graph* (Speidel et al., 2015; Takaguchi et al., 2016), *time-unfolded network* (Pfitzner et al., 2013), *static expansion* (Michail, 2016), or *time-node graphs* (Holme 2015). The concept behind this graph is to represent the temporal network by a single static network with directed links, as shown in Figure 2. This facilitates analyzing and visualizing any large temporal network using a simple organized equivalent static network (Kim & Anderson, 2012). This technique considers the contact duration, where no more than one interaction can occur at one-time step for each path.

4.4. Timeline graph

Timeline graph is an effective technique to illustrate the link status/evolution over time, where one axis represents the time and the other represents the nodes of the network, as shown in Figure 4 (Holme 2015). This technique provides a distinct visualization of the network, where the temporal path can be followed. However, the technique is limited to small networks as the graph can become too complex for networks with a large number of nodes.

4.5. Graphing/visualization tools

It is difficult to utilize the aforementioned visualization techniques for large networks without practical/efficient tools. The difficulty stems from the fact that the corresponding network graphs would become very dense and, subsequently, it would be challenging to visualize the temporal nature of the underlying networks. To address this matter, there are several temporal network visualization tools that are either stand-alone software packages or available within different programming languages such as C/C++, R, and Python. Table 3 lists some of the several software packages and libraries available for temporal network analysis.

5. Infrastructure network-based model classes

After highlighting the main differences in the previous sections between static and temporal networks, it is

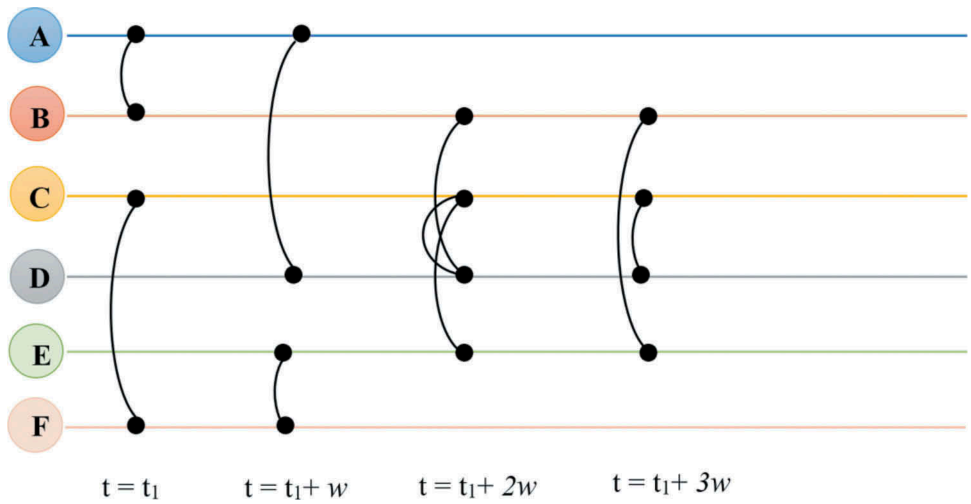

Figure 4. The timeline graph of the network presented in Figure 1.

Table 3. Software packages for network analysis.

Software	Stand-alone software	Software package used	Features: Visualization	Features: Analysis	Web-address
Cytoscape	✓		✓	✓	http://www.cytoscape.org
Gephi	✓		✓	✓	https://gephi.org
Graphviz	✓		✓		http://www.graphviz.org
Igraph		Python, R, C/C++	✓	✓	http://igraph.org
NetworKit		Python	✓	✓	https://networkit.iti.kit.edu
Networkx		Python	✓	✓	http://networkx.github.io
NodeXL		Microsoft Excel, Python	✓	✓	https://archive.codeplex.com
SNAP					http://snap.stanford.edu
Pajek	✓		✓	✓	http://mrvar.fdv.uni-lj.si/pajek/
SOCNETV	✓		✓	✓	http://socnetv.org

important to relate these two network models to different infrastructure network simulation applications. In general, studies that focused on evaluating infrastructure system performance, resilience, and robustness can be broadly classified into three groups: topology-based-, flow-based-, and physics-based models (LaRocca et al., 2015; Ouyang, 2014).

5.1. Topology-based models

Topology-based models would simulate an infrastructure network based only on the former's topology and connectivity properties. Such models disregard flows and physical properties of/within the network, and instead represent the underlying network in an abstract manner, as a set of nodes and links, without differentiation between the component physical functions/roles within the network (LaRocca et al., 2015; Ouyang, 2014). For example, when modeling a power grid, key stations would be treated simply as nodes with no distinction between generation-, distribution-, or sub-stations (Rosato et al., 2007). Some studies however adopted topology-based models with additional consideration for node heterogeneity (e.g., the different functions between network components) (Albert et al., 2004). Another example is the work of Kaluza et al. (2010) that investigated the global maritime transportation network, where ports were represented by nodes that were linked by shipping routes.

Although abstract in nature, topology-based models can provide a general indication of network behavior and vulnerability, albeit such models lack the ability to give a complete picture of infrastructure behavior. This is because all infrastructure networks are governed by the law of physics and subjected to constraints pertaining to their supply and demand capacities (Hines et al., 2010).

5.2. Flow-based models

Unlike network models based solely on topology, flow-based models consider also the flow or service delivered through the infrastructure network (Ouyang, 2014). In other words, such models combine the network topology with network flow models to represent loads, demands, and capacities within the network. However, these models do not incorporate real dynamic flow modeling (e.g., power flow analysis in power grid or hydraulic flow model in water network). For example, many network flow models proposed to consider power load and capacity according to shortest paths or centrality measures in studying power grid vulnerability and resilience (Ezzeldin & El-Dakhakhni, 2019; Fang et al., 2014; Motter & Lai, 2002; Wang & Rong, 2009, 2011).

Based on this concept, some studies focused on infrastructure networks and their interdependencies provided a more realistic simulation approach. For example, Lee et al. (2007) utilized a mathematical representation of network flow to model interdependence within infrastructure networks. Although such modeling approach considered different types of interdependencies to analyze and simulate network post-disruption and restoration processes, it only focused on a single level of the decision-making (i.e., the selection of components to repair or install to restore the network service). Such mathematical models can be integrated with optimization algorithms to incorporates the restoration planning and scheduling decisions (Cavdaroglu et al., 2013; Nurre et al., 2012). Nonetheless, high-fidelity models have to consider real system components properties, dynamics physical flow, and capacities especially for modeling the dynamics of cascade failure (Pagani & Aiello, 2013), systemic risk mitigation strategies, and resilience of infrastructure networks.

5.3. Physics-based models

The two network-based models described above do not fully capture the realistic dynamics physical flow within infrastructure systems (LaRocca et al., 2015). For example, a high-fidelity model of power grid should take into consideration the real power flow, the transmission lines electrical properties, and the generations supply and capacity (Bernstein et al., 2014; Li et al., 2018; Yang et al., 2017). Such physics-based models usually require significant computational time and required more data to simulate the functionality of network components, compared to their topology- and flow-based model counterparts. In particular, infrastructure network resilience analysis based on physics-based models is more realistic when considering the dynamic behavior of such complex networks. In real-life, infrastructure networks continuously evolve due to the changing of service demand, topological adjustments, the growth of the interdependencies, in addition to the post-event improvements such as enhancements of component capacities, implementation of new standards, the increase of situational awareness, and the integration with the new technologies (Goldbeck et al., 2019; Ouyang & Dueñas-Osorio, 2012).

In this respect, Ouyang and Dueñas-Osorio (2012) evaluated the resilience assessment processes of power infrastructure networks when the networks' future evolving processes are considered. Moreover, González et al. (2016) provided a simulation-optimization framework to optimize the resource allocation and recovery strategy in the restoration planning for interdependent infrastructure networks. Furthermore, other studies focused on evaluating interdependent infrastructure networks resilience, through a dynamic network flow model (Goldbeck et al., 2019) or a multi-objective restoration model (Almoghathawi et al., 2019), to maximize the network resilience while minimizing the total cost associated.

In closure, real infrastructure networks experience temporal variations of their topologies as well as the flow or service provided through them (Goldbeck et al., 2019; Rocha, 2017). Dynamics of network topology can be readily observed when evaluating failure propagation, recovery, systemic risk mitigation, as well as restoration and reconfiguration processes, whereas, the dynamics of flow are represented through the demand, supply, load, or service fluctuation through the network components (Hines et al., 2010; Ouyang, 2014). For example, in power grids or transportation networks, the network topology continuously varies due to maintenance scheduling of transmission lines or roads, closing roads or bridges due to accident or disruptive event, and/or failure propagation. Therefore, the temporal network approach provides a promising direction to model the dynamics of network topology. This approach can be also extended by an integration with physics-based models to also account for the dynamic of flow (Ouyang & Dueñas-Osorio, 2012; Yang et al., 2017).

6. Opportunities for infrastructure networks simulation

Modern societies are fully dependent on physical- and cyber infrastructure networks, that do not operate in isolation, but are instead interdependent on multiple levels (Ouyang, 2014). In fact, it can be argued that our prosperity and security rely on our future ability to understand and analyze not only the *intra*-dependence within each of such infrastructure networks but also their overall *inter*-dependence (Min et al., 2007). Although interdependence improves network efficiencies, it also increases their interdependence – induced vulnerability, which gives rise to systemic risk and may thus result in severe loss of functionality and recovery capability (Monsalve & de la Llera, 2019). In reality, multiple independent, possibly noncooperative, decision-makers are responsible for managing infrastructure networks (Smith et al., 2017). Furthermore, various layers of complexity play a role related to operating, maintenance, and recovery of infrastructure networks especially in case of catastrophic failure.

Another layer of complexity that needs to be tackled relates to the socio-technical aspects – the interface between the social networks with the underlying physical infrastructure networks. Specially, infrastructure networks are not only affected by physical components but also by human behavior, regulatory agencies, stakeholders, and government/private enterprise (Barrett et al., 2004). Recently, the work of Guidotti et al. (2019) highlighted the consequences of neglecting such interdependence between the social systems and physical infrastructure networks. It was concluded that disregarding the information from human response models may result in misleading conclusions including lower estimate of population dislocation; higher estimates demands on physical network compounds; and slower recovery process. Therefore, it is imperative to consider decentralized decision-making in modeling and simulation interdependent infrastructure networks. Moreover, it is quite challenging to develop informative and computationally high-fidelity modeling, especially with consideration of both time dynamics and interdependencies.

Another promising research area involves data-driven and game theory applications, especially for large-scale network analysis. For instance, Dueñas-Osorio and Kwasinski (2012) used the historical restoration curves through a time series method to quantify coupling strength and interdependencies between infrastructure networks. Furthermore, Monsalve and de la Llera (2019) presented a data-driven model to simulate the restoration process of interdependent infrastructure networks after a disruptive event. Some studies proposed data-driven models to generate a linear recovery operator from numerous disaster and failure scenarios (González et al., 2017). This operator can be used later to provide the optimal recovery strategies associated with any damage scenario. For consideration of multiple independent, utility network controllers, and decision-makers, game theoretic approaches have been used to resolve such crossed interactions between numerous players. Smith et al. (2017) proposed a game theoretic recovery model to address the decentralized related to infrastructure networks decisionmakers.

The following subsections highlight temporal network modeling research efforts and potential opportunities in transportation-, power-, and water distribution infrastructure networks. Overall extensive research is needed to simulate and analyze the infrastructure networks based on the temporal variation within the networks, rather than only the static topological characteristics. Especially when assessing infrastructure resilience, where the network topologies are evolving due to increase of service demand, retrofit, reconfiguration, and restoration processes (Goldbeck et al., 2019; Ouyang & Dueñas-Osorio, 2012).

6.1. Transportation networks

Transportation networks possess one of the most vivid temporal behavior in infrastructure networks. Recent computational advances coupled with the availability of detailed data that describes real-time interactions have also boosted the field of transportation network dynamical behavior research (Gallotti & Barthelemy, 2015). For example, the data collected by smart card systems can include accurate information about the corresponding time and space domains. A shared bicycle/car system is also a common example of a temporal network constructed using data from smart cards (Borgnat et al., 2013).

Air traffic networks present another mode of transportation that strongly evolves over time. Rocha (2017) provided a review of air traffic networks, where airports were represented by nodes and flights were represented by links between each pair of nodes. Studying such networks from a temporal perspective can demonstrate how flight delays propagate. This can be subsequently used to enhance network efficiency and connectivity by reducing the total travel time, optimizing resources, and maximizing profits. Moreover, Sun et al. (2015) studied the temporal evolution of air traffic networks within the European context. In their study, different network centrality measures have been analyzed over time to identify the hub nodes. It was found that these air traffic networks are dominated by seasonal (time) variation. Such results would assist stakeholders in managing and enhancing the performance of their air traffic networks.

Additional studies focused on other modes of transportation. For instance, Ducruet and Notteboom (2012) investigated the network structure for vessel movement data covering about all of the world's container fleets in 1996 and 2006. The study also analyzed the relative position of ports (i.e., centrality) in the global network with mapping the changing of ports centrality through time. In addition, Williams and Musolesi (2016) investigated the performance of four transport networks in the time and space dimensions. The same authors evaluated the behavior of these networks under random failures and targeted attacks.

In term of specific opportunities considering that transportation networks usually encompass multi modes that require different types of nodes and/or links, there remains a significant lack of understanding of multilayer temporal transportation networks. Multilayer (multiplex) networks include multiple layers representing the connectivity and the types of interactions between nodes. A comprehensive review pertaining to static multilayer networks have been discussed by de Domenico et al. (2013) and Kivela et al. (2014). Furthermore, it is worth mentioning that one way to reveal more complexity and provide a deep understanding of transportation infrastructure networks is to combine different concepts in simulation. For example, spatio-temporal networks typically integrate both space and time dimensions. These networks can develop a more accurate representation of several infrastructure networks, especially when multi-modal transit systems are analyzed (George & Kim, 2013; Goforth et al., 2019). Another example, adaptive dynamic networks combine the dynamics of nodes and/or links and their influences on the temporal network topology, where links shift adaptively according to the network status. This leads to a dynamical interplay (Gross & Sayama, 2009) between the topology and the operation state of the transit network, especially in disaster situations and emergency traffic management.

6.2. Power networks

The temporal behavior of power networks can be easily observed in two aspects. First, power networks are typically subjected to load balancing between supply and demand. The supply may change frequently due to the fluctuation of renewable energy sources such as wind. In addition, power storage infrastructure has only limited capacities to store electric power; thus, any overproduced electric power must be transferred and consumed within the larger power network (grid). Moreover, the demand for electricity continuously varies throughout the day (Nardelli et al., 2014) and based on numerous factors including weather conditions. Subsequently, the electric loads on power stations and transmission lines vary continuously over time. Second, a blackout is a typical example of the dynamic nature of power networks (Carreras et al., 2001). A blackout can be initiated by several causes including those attributed to weather conditions, network component failures, or human errors. It should also be noted that a small disruption in some key components may lead to overload on other components and start a chain of cascade failures, which can spread throughout the network (Bernstein et al., 2014; Costa et al., 2011).

Several studies have investigated cascade failures by simulating failure propagation on power networks (Crucitti et al., 2005; Fang et al., 2014; Kinney et al., 2005; Motter & Lai, 2002; Pagani & Aiello, 2013; Sun et al., 2008; Wang & Rong, 2009, 2011; Wang et al., 2010). For example, Motter and Lai (2002) studied the cascade failures due to targeted attacks on several real undirected networks, including power networks. It was concluded that power networks have high robustness to random attacks, but once a node with high load fails, network-level cascade failures may be triggered, affecting the performance of the entire network. In addition, Rosato et al. (2007) analyzed power networks of Spain, Italy, and France to identify their critical links (i.e., transmitting lines) and improve the network connectivity (e.g., robustness and redundancy) by adding new links. Moreover, Wang and Rong (2009) studied the vulnerability of the US power network. Different attack scenarios have been applied through the removal of nodes in ascending or descending orders (in terms of their loads). The initial load of a node was assumed by integrating a node *degree* and its neighbors' degrees. After a node is successfully attacked and thus removed, the load is redistributed to that node's neighbors according to their initial loads. Although this research work contributed to the understanding the US power network behavior and evaluating its robustness under different attack scenarios, the model in the study by Wang and Rong (2009) did not consider actual power distribution, where the initial load of a node was assumed according to its corresponding degree. In addition, the model did not account for the overload on the links. Bernstein et al. (2014) modeled the cascade failure for US western interconnected with considering power flow distribution to identify the most vulnerable components in the grid. Recently, Yang et al. (2017) provided a large-scale model for the US – South Canada power network to investigate network vulnerability. The model was characterized by its large scale, the physical properties of power flow and a large amount of temporal data representing a wide range of system conditions over time.

Most previous research studies have focused only on cascade modeling, while a limited number of studies developed risk mitigation and resilience enhancement strategies. For example, Motter (2004) proposed a cascade control method based on minimal alterations to the network structure. These alterations consisted of removing a few selected nodes or links after the initial attack and prior to the propagation of cascade failures (e.g., similar to the function of the circuit breakers). Another risk mitigation strategy has been introduced by Wang (2013) to suppress the cascade propagation through load redistribution from the overloaded nodes to other neighboring nodes. This redistribution maintains the overloaded nodes' normal and efficient function.

Overall, there is an opportunity for temporal/dynamic behavior of power networks to be adopted in simulating changes in both network topology (i.e., cascade failures) and network flow. Such an approach would facilitate better understanding of network behavior and developing real-time defense and risk mitigation strategies of actions prior to and during cascade failures.

6.3. Water distribution networks

A limited number of studies have been conducted on water networks using CNT. For example, Jianhua et al. (2008) utilized different network topological characteristics (e.g., betweenness centrality and path distance) to identify the key nodes within a water distribution network. These key nodes can be used to accommodate sensors to detect contamination locations within the network. Furthermore, the same authors used the concept of *reachability* to formulate the receivability, which indicates the set of nodes that has paths to a certain node in a directed network. The receivability measure is useful to simulate the different risk scenarios and the corresponding mitigation strategies following any contamination events. Dueñas-Osorio et al. (2007) also investigated the water distribution networks, where tanks and pipelines were represented by nodes and links, respectively. Their work illustrated the network topology to evaluate the network vulnerability under both targeted and random disruptions. However, the network has been studied as an undirected network without any consideration to the flow direction. Furthermore, Yazdani and Jeffrey (2011) investigate four water distribution networks using several measurements to quantify the network's vulnerability and robustness. Finally, Perelman and Ostfeld (2011) used the network topology and connectivity analysis to study strongly and weakly connected clusters in directed water distribution networks.

In closure, water distribution networks are becoming more complex with the introduction of large-scale infrastructure components such as tanks, pumping stations, hydrants, valves, and pipelines. It is thus challenging to predict the network performance in case of failure scenarios or provide an efficient contaminant spread risk mitigation strategy (Perelman & Ostfeld, 2011). However, the use of temporal network modeling approaches might facilitate tackling such challenges. For example, temporal centrality could help enhancing water security by detecting contamination sources and highlighting critical locations to place sensors.

7. Discussion and conclusion

The recent revolution in collecting network-type data has boosted CNT studies and applications. In addition, current available datasets collected, for example, by mobile devices, sensors, or smart cards, include many details about the temporal (i.e., dynamic) behavior of the underlying network. In this respect, the current study provided a review and a fundamental background of the temporal simulation approach of complex networks. The static network topological characteristic extensions to temporal networks were also outlined. In addition, several temporal centrality measures and graphical representation techniques were discussed and investigated. Finally, opportunities and applications of infrastructure networks simulation using CNT were presented.

Previous studies demonstrated that temporal measures provide more realistic and accurate results compared to static measures. Therefore, the temporal network simulation approach can be considered a more appropriate framework to simulate and analyze infrastructure networks. However, there remains several gaps that need to be addressed. For example, the current review showed that, there is no consensus among researchers about the definition of some temporal metrics, with previous studies providing several definitions to the same measure (e.g., the shortest temporal path). It is also clear that the temporal closeness centrality measure can be evaluated by two different approaches: one that considers only the overall time interval, while the other considers all possible time intervals. The results of the two approaches were significantly different for the same nodes.

Although there is a significant amount of literature related to the robustness of infrastructure networks from a static perspective, a limited number of studies have been conducted considering the temporal nature of these networks. Furthermore, despite the significant progress in modeling cascade failures, there is still a lack of large-scale models for infrastructure networks that consider the dynamical changes in the network topology. For example, most previous studies consider power networks merely as undirected networks without any physical or electrical properties of actual infrastructure network. In addition, most of the proposed models do not account for the actual loads on the nodes and links (i.e., the power pass-through stations and transmitting lines), and the subsequent real load redistribution when any component fails. A high-fidelity model of power grid should take into consideration the real power flow, the transmission lines electrical properties, and the generations supply and capacity. In addition, a major obstacle still remains due to the lack of high quality and precise data which is typically restricted for security reasons. Subsequently, without feeding the models with the actual data, it is not possible to provide a realistic network vulnerability analysis to ensure the reliability and resilience of power grids. Developing such models remains an intriguing research area.

Overall, the current study indicates that using the temporal network as a simulating approach for infrastructure complex networks presents a promising framework to simulate and reveal complex infrastructure network characteristics, evaluate their interdependence, quantify their resilience, and mitigate their systemic risks.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research was supported by NSERC through the Canadian Nuclear Energy Infrastructure Resilience under Systemic Risk (CaNRisk) – Collaborative Research and Training Experience (CREATE) program of the Natural Science and Engineering Research Council (NSERC) of Canada.

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