RESILIENCE ASSESSMENT FOR COMPLEX NETWORKS BASED ON RECOVERY STRATEGIES

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

The vulnerability of complex networks to unexpected disruptive events could be reduced by increasing network resilience through the efficient recovery of the damaged network. To find the most efficient recovery strategy among the existing variety of strategies, a resilience-based framework was proposed and implemented for both localized attacks and cascading failures. For localized attacks, preferential recovery based on nodal weights (PRNW), periphery recovery (PR) and localized recovery (LR) were assessed. Additionally, probability-based recovery (RS1) and recovery of neighboring or boundary nodes (RS2) methods were evaluated for cascading failures. Considering the advantages and disadvantages of these strategies, a hybrid recovery strategy was proposed to achieve high network resilience in a timely manner with a manageable amount of cost. Overall, this study aids in the assessment and the development of a cost-effective resilience-based recovery strategy.

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I like to take this opportunity to express the deep sense of gratitude to my parents, who gave everything they could to make me what I am today. Their touching care and love provided me the necessary strength to withstand the pressure of my research program. Their contributions to this work, though invisible, are invaluable to me.

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LIST OF SYMBOLS

k……………………………………........Degree

$P(k)$…………………………………......Degree distribution

$g(v)$ ……………………………………... The betweenness centrality of a node

$\sigma_{st}(v)$ …………………………………….The number of those paths that pass through node v

σ_{st}…………………………………………The total number of shortest paths from node s to node t

$I_{A \rightarrow B}$………………………………………Interdependency between two networks

L………………………………………….. Load of a node

C...Capacity of nodes

β…………………………………………...Tolerance parameter

$\Delta L_{ij}(t)$…………………………………… The amount of extra load

p_{rc}………………………………….…….. Recovery probability for coupled nodes

p_{ri} ……………………………………………. Recovery probability for uncoupled nodes

$P_R(t)$ ……………………………………….The real performance curve

$P_T(t)$ ……………………………………….The targeted performance curve

A_R ………………………………………….The area under the real performance curve

A_T ………………………………………….The area under the targeted performance curve

R……………………………………......Resilience

t_d …………………………………………. Time after the disaster stop propagating or the start of the recovery strategy

t_r …………………………………………. Time at which the recovery is completed

d_{ij}……………………………………………The shortest path length connecting node i and j

N…………………………………………..The number of nodes

E…………………………………………..Network Efficiency

Sets

r……………………………………….......Set of recovery strategies

t………………………………………... Set of time steps

e……………………………………….......Set of edges to be repaired

n……………………………………….......Set of nodes to be repaired

s……………………………………….......Set of resources

w……………………………………….......Switching point

Parameters

t_t……………………………………….......Total recovery time required

T……………………………………….......Maximum allowable time

C_{tr}………………………………………… Cost of recovery at time t for strategy r

E_{rt}………………………………………… Network efficiency at time t after applying strategy r

E_o…………………………………………Network efficiency at the original stage

P_{tr}………………………………………… Recovered performance by strategy r at time t

N_{ert}……………………………………….......Number of edges recovered by strategy r at time t

N_{nrt}……………………………………….......Number of nodes recovered by strategy r at time t

C_e…………………………………………Cost for repairing edge e

C……………………………………….......Total cost for strategy r

B………………………………………... Budget

C_n………………………………………… Cost for repairing node n

V_{se}…………………………………………The required amount of resources to recover each edge

V_{sn}…………………………………………The required amount of resources to recover each node

S……………………………………….......The total amount of available resources

C_w…………………………………………Cost for switching recovery strategy

P_w... Recovered performance at the switching point

Decision Variables

γ_r... Binary variable

1. INTRODUCTION

1.1. Current State and Challenges

Critical infrastructure systems, such as power distribution network, water distribution network, gas network, communication network, etc. plays a crucial role in the successful functioning of modern society. These networks are often interconnected and interdependent for their proper functioning. The collection of such interconnected networked infrastructure systems could be viewed as complex networks. These networks are often vulnerable to failure due to unexpected natural, technological or intentional disruptive events. Natural disasters, such as earthquakes, hurricanes, flood, etc. are quite unpredictable and have devastating effects on the networked infrastructure systems resulting in negative impacts on the social and economic structure of a country. For instance, damage from hurricanes hitting the U.S. between 1980 and April 6, 2018 cost totals $862 billion, where, the cost of an average hurricane is $21.6 billion [1]. Hurricane Harvey was predicted to be the most expensive natural disaster in the history of the United States at over $180 billion, surpassing $160 of Hurricane Katrina [2]. In April 2015, Nepal experienced the most devastating earthquake in its history causing the damage of $10 billion, which is half of its gross domestic product (GDP) [3]. Moreover, the interconnection and interdependency between networks make the systems more vulnerable. Because damage in one network might cause damage to the other dependent network resulting in the collapse of the total system. In September 2003 a tree fell on a transmission line in Switzerland and triggered a cascade of failure all the way to Italy that left more than 53 million people in the dark [4, 5]. In order to reduce the undesirable consequences and mitigate the follow-up risks, there is no alternative to preparing for the post-disaster recovery.

An efficient recovery strategy aids the achievement of system resilience. Resilience is a multidimensional concept that refers to the ability of a system to be prepared for any unexpected disruption, withstand adapt to such events and recover from its damaged state to normal operating condition [6, 7]. It is known to be one of the most important metrics for measuring the capability of a system to cope with changes [8, 9]. The resilience of complex networks is highly associated with the recoverability of the system. That is why the successful implementation of recovery strategies is essential to make complex networks more disaster resilient. The necessity of studying the vulnerability and the resilience of complex networks has influenced many researchers to focus on resilience-based network recovery. A variety of recovery strategies were developed considering failure patterns and network properties. Hu et al. [10] proposed two recovery strategies from natural disasters, modeled as localized attacks in a two-dimensional lattice network application. Di Muro et al. [5] proposed a recovery strategy for two interdependent infrastructure networks under a cascading failure. The devastating effects of cascading failures have encouraged many other researchers to work on this field. Hong et al. [11] developed recovery strategies against cascading failures in interdependent networks. A further extended version of it was developed for spatially interdependent networks [12]. Wang and Quyang [13] proposed a joint recovery model to support interdependent systems' resilience assessment. A localized recovery method was proposed by Shang [14] which could be beneficial to recover from any failure. Some recovery strategies were developed based on recovery priorities. Sun and Zeng [15] proposed a target recovery method where the most important nodes are selected for recovery. Moreover, many real-world dynamic complex systems are said to be able to spontaneously recover after an inactive period of time. For example, stock market pricing, or sudden economic crashes in finance. Majdandzic et al. [16] developed a framework for understanding the mechanism of spontaneous recovery in dynamic networks. Most of the existing recovery strategies are compiled in ref. [17]. Although these proposed methods could be very effective in different circumstances, many other factors, like, recovery cost, resources, recovery time, etc. are necessary to be considered before implementation. This increases the complexity of choosing a suitable recovery strategy. To address this challenge, many optimization models were developed to design resilience-based recovery. Almoghathawi [18] developed a resilience-driven restoration model for interdependent networks. A resilience optimization model was proposed by Liao et al. [19] for transportation network recovery. For post-disaster recovery, a stochastic optimization model was introduced by Turnquist and Vugrin [20]. Figueroa-Candia et al. [21] formulated a resilience-based optimization model for the evaluation of restoration policies. A resilience-based model designed for a supply chain network by Margolis et al. [22]. Fang and Sansavini [23] investigated the effects of several uncertainties on post-disaster restoration and proposed a two-stage optimization model to solve this problem. To minimize resilience loss during the restoration plan, Chen [24] solved a restoration scheduling problem.

1.2. Scope of the Study

Based on the current state of research, the damage-specific recovery strategies are yet to be evaluated on the scale of resilience. Although, a variety of recovery strategies have been proposed by researchers in different circumstances, evaluating them through resilience assessment is crucial before the implementation. From the assessment of the recovery strategies considering the goal of recovery, the most efficient recovery strategy could be selected. In this purpose, a framework for the assessment and comparison of the recovery strategies could be developed.

Moreover, the assessment of recovery strategies could be a significant way of identifying the drawbacks of the current methods. It would also encourage improving recovery methods and developing a more efficient recovery strategy.

1.3. Objectives of the Study

In this study, an attempt has been made to address all the scopes identified and intend to achieve the following goals: (i) to propose a resilience-based general comparison framework, (ii) implement the proposed framework for both localized attacks and cascading failures, (iii) identify the major drawbacks of the existing recovery strategies, and (iv) develop an improved and resilient recovery strategy.

The rest of the study is detailed in four chapters. Literature review containing basic complex network properties, failure patterns in complex networks, recovery strategies against different failures and network resilience is presented in Chapter 2. The proposed methods applied in this study are given in Chapter 3. Chapter 4 provides the implementation of the proposed methods through three case studies. Finally, Chapter 5 summarizes the key findings and suggests future research directions in the same field of study.

2. LITERATURE REVIEW

This study is mainly focused on the achievement of resilience in complex networked infrastructure systems through restoration after failure. This review attempts an in-depth analysis of basic complex network properties, failure mechanisms that occur in complex networks, different strategies to recover from such failure, and network resilience.

2.1. Properties of Complex Networks

Infrastructure systems, such as power distribution networks, transportation networks, water distribution network are often represented by complex networks in the form of a graph consisting of nodes and edges, where nodes represent the entities of the system, and edges represent information interactions or other relations among entities [25]. The significance of network components may vary according to the system properties. Nodes can represent sources and demands in distribution networks, service stations in a supply network, locations in a transportation network, suppliers or distributors in a supply chain, genders in a social media network, components in a product, and so on. On the other hand, the edges in a network represent the connection between the nodes primely, while carrying edge weights. These weights could represent the rate of flow to the given directions (unidirectional or bidirectional), geographical distance between locations, etc. However, networks can be more complex than just a set of nodes and edges in many ways. The properties of network structures may vary both in different ways. Some networks can have several hierarchical structures that are commonly known as 'multi-leveled or multi-layered networks'[26]. The difference between the structure of a single-layered network and a multi-layered network is shown in Figure 1. Additionally, more than one types of a node or more than one type of edges could be present in a network. For instance, the multi-layered network shown in Figure 1 has two types of edges, edges within a layer and between layers. The complexity of multi-layered networks could also be increased through the interdependency between interconnected components. In the sociology applications, networks that have edges categorized by their types, are also known as 'multiplex networks' or 'multi-relational networks' [27].

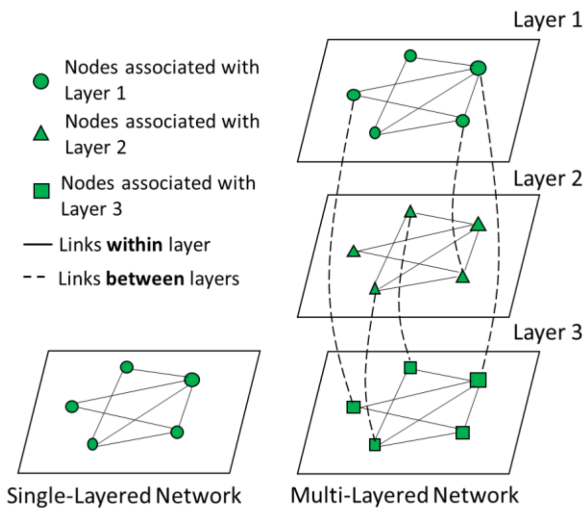

Figure 1: General network structures [17]

In reality, most infrastructure networks work together to perform and deliver services that are crucial to the community wellbeing. For example, both the telecommunication network and internet/cyber network are dependent upon the power grid network. That is why representing current infrastructure system configuration through interconnected and interdependent networks would be the most realistic representation of modern complex systems. However, the interconnectedness and interdependency in complex networks have caused some unforeseen challenges to the surface. One of the most threatening parts is that when any kind of damage occurs in a network, other interconnected networks could also be affected leading to the breakdown of the total system. This phenomenon has influenced researchers to analyze the relationship of the components in complex networks and their behavior under different circumstances.

To understand the structural and operational behavior of the network properly, it is necessary to have knowledge of the basic terms related to networks. Some of the commonly used terms in defining and analyzing network systems are:

Degree: The degree of a node in a network is the number of connections or edges of a node to other nodes. In this study, the degree of a node is denoted as k. For example, in Figure 2, node 1 is connected to 2 other nodes. Thus, the degree of node 1, k_{n1} is 2 and the degree of node 2, 3, 4, 5 and 6 is respectively 5, 3, 4, 2 and 1.

Degree distribution: The degree distribution, $P(k)$, of a network is the fraction of nodes in the network with degree k. If there are a total of n nodes in a network and n_k of them have degree k, $P(k)=n_k/n$. This indicates the probability of a randomly selected node to have degree k. For example, in Figure 2, the probability of a randomly selected node to have degree 3, $P(3)$ is 1/6.

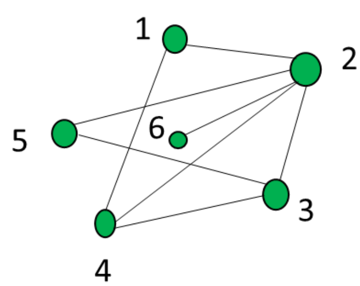

Figure 2: Illustration of the fundamental terms of a network [17]

Betweenness centrality: For each node, the number of shortest paths that pass through the node is known as betweenness centrality. The betweenness centrality of a node n, $g(v)$, is given by:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{1}$$

where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through node v [15]. For example, in Figure 2 the total number of the shortest path from node 1 to node 5 is 2. And the number of those paths that pass through node 3 is 1. The betweenness centrality of node 3 is ½.

Giant component: The largest connected component of a network that contains the majority (more than half) of the nodes of the entire graph's nodes.

2.2. Failures in Complex Networks

Failures in complex networks may occur in various ways due to distinct network properties and unpredictable attacks. Typical failure behaviors that are commonly observed in complex networks are summarized in Figure 3. Failures in the network are the results of attacks that have devastating impacts on both structures and network performance.

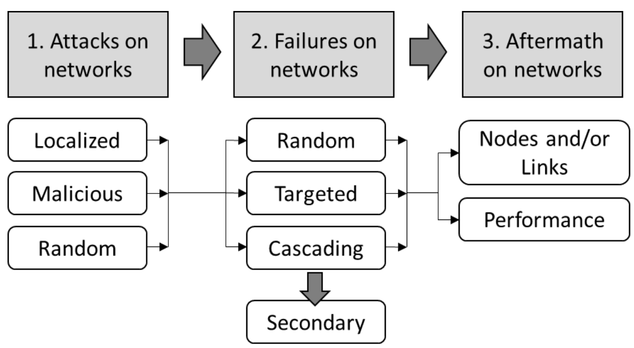

Figure 3: Commonly observed failure scenarios in complex networks

The attack scenarios could also vary under different circumstances. One of the most common attacks are localized attacks (LA) which occur geographically specific areas. These are mostly natural disasters (earthquake, hurricane, etc.), internal critical components failures, or mass/multiple attacks in a specific location [10]. From the point of complex networks, localized attacks could be demonstrated by the failure of a group edges concentrated in a particular geographical domain resulting adjacent isolated nodes. The failure mechanism of localized attack is illustrated in Figure 4.

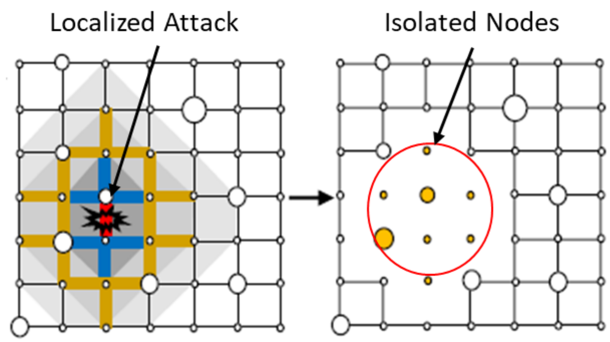

Figure 4: A typical aftermath of localized attacks [10]

Secondly, there are malicious attacks (MA) that disrupt the most important parts of a network and may cause severe damage by resulting heavily impaired the networked system's functionality [10]. This type of attack is typically identified by the state where the edges in a complex network are removed in order of the largest betweenness centrality leading to the emergence of several separated sub-networks, as shown in Figure 5.

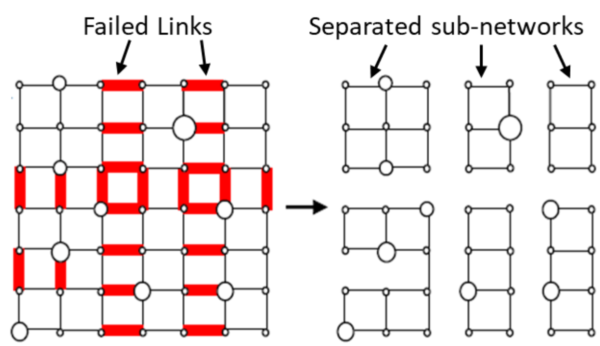

Figure 5: A typical aftermath of malicious attacks [10]

Thirdly, failures in a complex network may occur randomly due to random attacks (RA). In RA, the edges are damaged randomly following an attack as shown in Figure 6 [10].

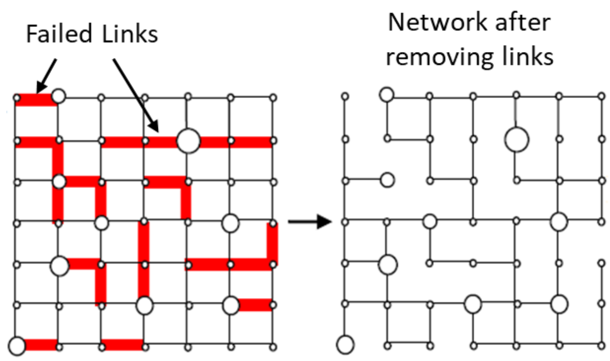

Figure 6: A typical aftermath of random attacks [10]

Generally, failures in a network could occur in two ways: random failure or targeted failure. If any of the network components (nodes/edges) fails randomly after a disruptive event, it is known as a random failure. On the other hand, a targeted failure is the outcome of any intentional attacks that could be intruded into a network from outside. These result in the removals of or damages to certain nodes or edges.

One of the most discussed network failures in recent times is known as cascading failure. A cascading failure is a failure process in which the failure of one or more components in a network (edges/nodes) can trigger the failure propagation to the overall network. Cascading failures are commonly observed in interdependent networks where the components of a network are dependent on the components of other networks [4]. Most infrastructure networks (power, water, transportation, communication, etc.) are often connected to each other and interdependent for their proper functioning. The main reason behind the initiation of such failure could be the overloading of nodes and the interdependency between networks. When one node in a complex network fails, its load is redistributed among the neighboring nodes. This extra load may cause overloading of the neighboring nodes leading to failure of them. If this continues, the failure could propagate to the whole system. Due to the interdependency between networks, the cascade of failure may also spread from one network to another. To model cascading failure, Watts and

Strogatz [28] generated two networks Network *A* and Network *B* based on the spatial proximity of nodes in the same two-dimensional area. Interdependence across the two networks are modeled with the dependency matrix,

$$I_{A\to B}: I_{ij} = \begin{cases} 1, \ if\ node\ j\ in\ Network\ B\ is\ dependent \\ \qquad on\ node\ i\ in\ Network\ A \\ 0, \ otherwise \end{cases} \tag{2}$$

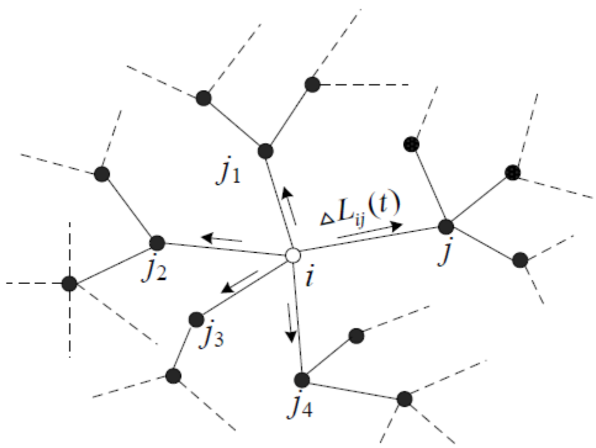

Figure 7: Redistribution of loads [29]

The capacity of each node is assumed to be linearly proportional to its initial load. If the initial load of node i is $L_i(0)$, the capacity of that node would be

$$C_i = (1+\beta)L_i(0), \ \ i = 1,2, \ldots., N_A \tag{3}$$

where β ($\beta \geq 0$) is a variable called tolerance parameter. It limits the node load so that it does not become infinite. If a node fails, its load becomes 0 and a load of failed node redistributes among the neighboring nodes in the manner shown in Figure 7. The amount of this extra load could be expressed as,

$$\Delta L_{ij}(t) = L_i(t)\frac{L_j(t)}{\sum_l L_l(t)} \tag{4}$$

If $L_j(t+1) > C_j,$ node j fails and the nodes of Network B, linked to the lost node are failed due to dependency link and failure propagates through the total system [29]. From the cascading failure, a secondary failure could also occur, which is explained in Ref. [30].

As an aftermath, a failure could cause structural damage as well as the performance degradation of a network. The failure affecting network structure had been observed as any of these three ways: (1) edges failures, (2) nodes failures, and (3) both edges and nodes failures.

2.3. Recovery Strategies

Restoration of a system after the occurrence of any disruptive event is one of the most important parts of a resilient system. In order to recover a system faster, a proper recovery strategy should take into account the recovery order, allocated time and resources, and other significant network properties. To restore a damaged network from different kind of attacks or failures, a variety of recovery strategies have been developed in recent years. These recovery strategies could be categorized according to their applicability for given failure scenarios. In this subsection, the existing recovery strategies against both localized attacks and cascading failures will be discussed.

2.3.1. Recovery Strategies against Localized Attacks

Many researchers have worked on developing recovery strategies against localized attacks. Hu et al. [10] proposed periphery recovery (PR) and preferential recovery based on nodal weight (PRNW), and Shang [[10, 14] proposed the localized recovery (LR) method. The three strategies are illustrated in Figure 8. After localized attacks occurred, a group of edges failed and removed from the network. In Figure 8 (A) the edges colored red, blue and yellow were the failed edges. Consequently, the nodes connected through those edges become isolated, as shown in Figure 8 (B). The three recovery strategies for localized attack can be summarized as:

Periphery recovery (PR): In this method, recovery priorities are given to the most populated isolated node at the boundary of the functional component. In Figure 8 (C1) the blue edges with arrowhead are the damaged edges adjacent to the functional components of the network. The red node $n1$ is the most populated boundary node of the functional network. According to this recovery strategy, either edge $m1$ or $m2$ would be repaired first randomly. In this case, $m1$ is selected to be restored first and colored green. After all the isolated nodes are connected, $m2$ is repaired and colored yellow. At the next step, the node $n2$ in Figure 8 (C2) is the most populated boundary node of the functional network, and either edges $m3$ or $m4$ is supposed to be repaired randomly. The process would be iterated until all the isolated nodes were connected to the functional network, as shown in Figure 8 (C3). In the end, the yellow edges are repaired randomly one by one until all are repaired.

Preferential recovery based on nodal weight (PRNW): The edges that could connect the most populated isolated nodes to the functional component of the network are preferred to be repaired. In Figure 8 (D1), the red node $n3$ has the largest population among all the isolated nodes, and edge $m5$ connects $n3$ to the network. According to the PRNW algorithm, the edge $m5$ is repaired first and colored green. Following the same procedure, the most populated node $n5$ is connected to the functional network through the edges $m6$ and $m7$. The steps are iterated until all the isolated nodes are connected to the network, as shown in Figure 8 (D4). At last, the yellow edges are repaired randomly one by one until all edges are repaired. PRNW could be highly efficient in connecting the most populated area while reducing the recovery time. It can also provide a rational solution with limited available resources.

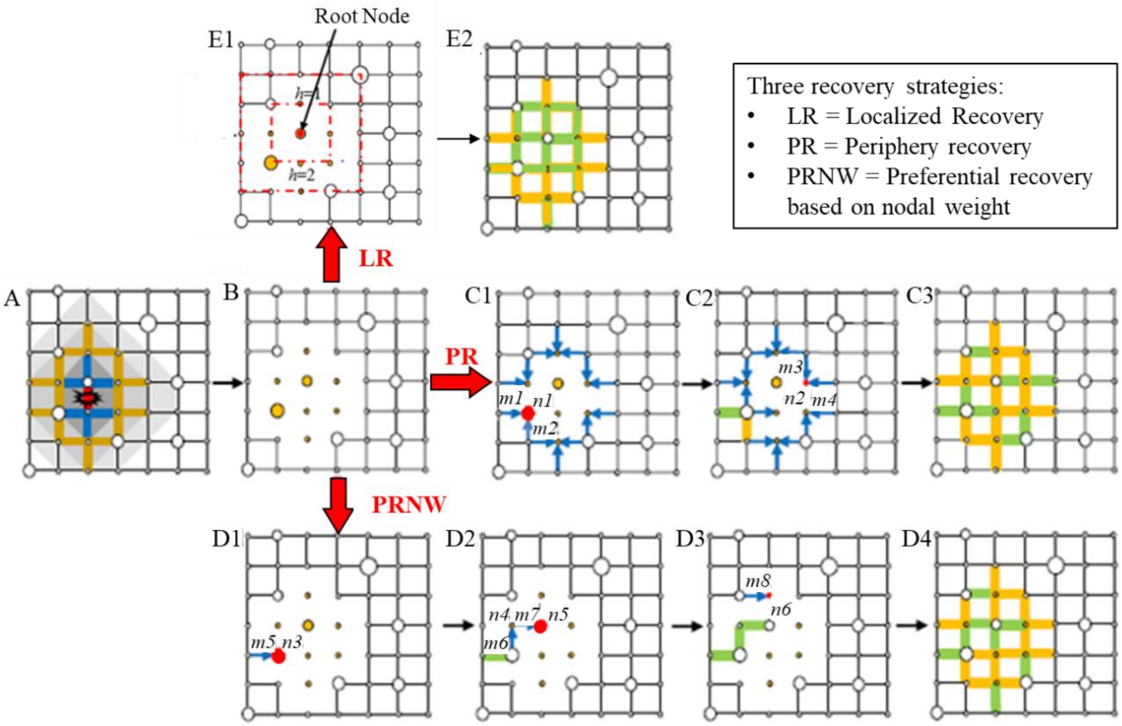

Figure 8: The illustration of various strategic repair processes after a localized attack on a two-dimensional square lattice network with heterogeneously populated nodes [10, 14]

Localized recovery (LR): In the localized recovery process, the priority of being recovered is given to the edges of a root node as well as its neighboring nodes respectively [10, 14]. This recovery process begins with the selection of root nodes. The rest of the nodes are listed in order of their distance from the root node as shown in Figure 8 (E1). Nodes being in the same distance from the root node are placed in the same shell. The edges of the root node are recovered first with the edges connected to it. Then the nodes in the same shell h are randomly selected and their edges are further recovered. After all the nodes in the first shell *h*=1 are recovered, recovery in the next shell *h* +1 starts. The recovery process stops when all the edges are recovered, as shown in Figure 8 (E2).

2.3.2. Recovery Strategies against Cascading Failures

The severity of the effect of such failure could be easily comprehensible from this. That is why finding possible strategies to prevent the breakdown of the total system is crucial. So far a variety of recovery strategies against such failures have been proposed. These strategies mostly follow either a probability based recovery or neighboring node recovery rule. Some of these strategies can be summarized as:

Probability-based recovery: Hong et al. [11, 12] analyzed cascading failure and proposed an active in-process recovery strategy in interdependent networks. In this purpose, two isolated networks with the same number of nodes were investigated where the networks were connected with interdependent edges. Figure 9 represents the interdependent network model, where the edges in Network A and B are shown as green and red lines respectively and the interdependent edges between two networks are shown as black short dash lines [11].

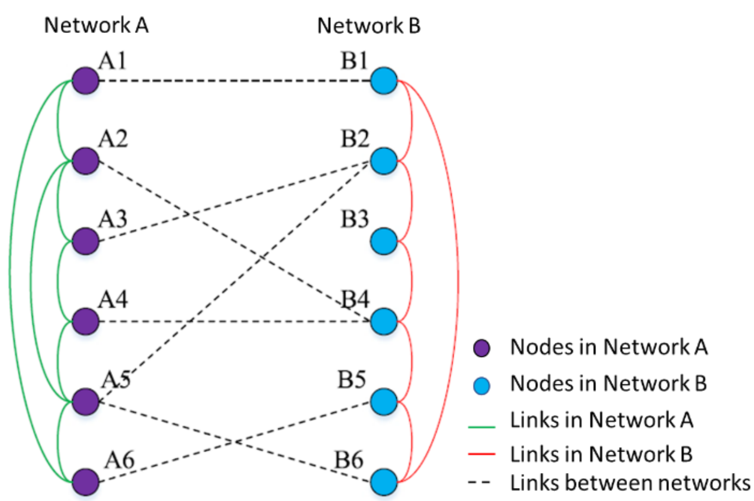

Figure 9: Interdependent network model [11]

The recovery action starts as soon as the cascading failure process begins. In this process, the recovery priority is given for coupled nodes. It was assumed that the recovery probability for uncoupled nodes is p_{ri} and for coupled nodes, the probability is,

$$p_{rc} = \mu \, p_{ri} \tag{5}$$

where μ is used to adjusting the recovery priority. A higher value of μ indicates higher priority and probability of being restored. If a node is restored, its edges and load are restored to its initial status. In the meantime, the remaining nodes suffer the recovery disturbance as loads of the failed nodes are redistributed to the remaining nodes according to the same redistribution strategy. The failure propagation to the interconnected network ends if no nodes are overloaded. The process repeats unless the cascading failure stops.

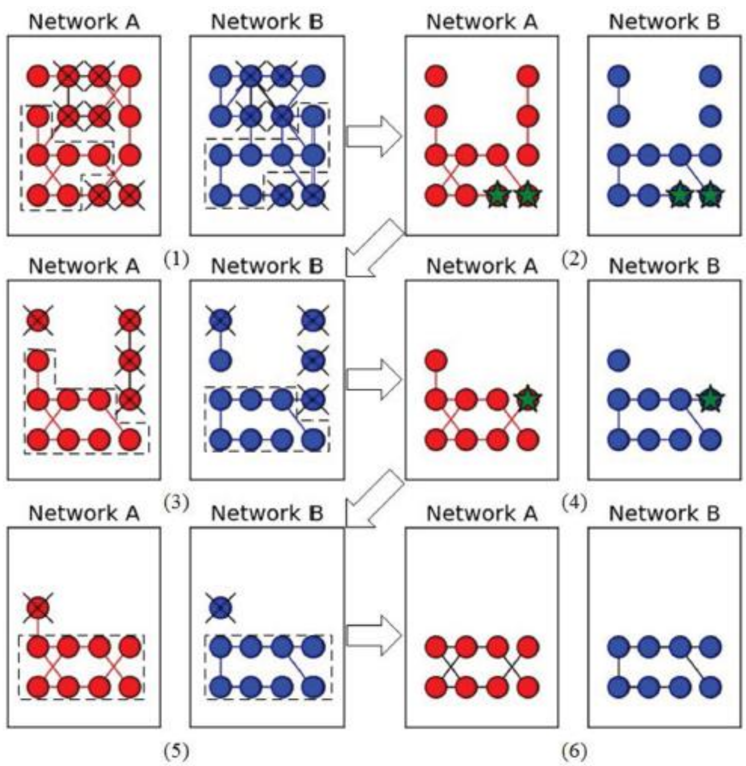

Figure 10: The cascading failure process with recovery [12]

Hong et al. [12] also demonstrated a method for the recovery of spatially interdependent networks which is illustrated in Figure 10. Two single spatially interdependent Networks *A* and *B* were considered. As the failure propagates in both networks and a pair of failed nodes connected to the giant component is recovered with probability γ. This process was repeated until the steady state of the fully recovered network had been achieved.

Recovery of neighboring or boundary nodes: Di Muro et al. [5] proposed a recovery approach that repairs failed nodes in the boundary of the functional network and reconnect the failed nodes to the network. According to them, the recovery process should be applied immediately after the cascading failure was identified in order to avoid or delay the collapsing of the total system. In this recovery model, the pair of failed nodes that belongs to the mutual boundary of both networks were recovered. The boundary of a network here denotes the nodes at a distance $l = 1$ from its giant component. When a node of the boundary is restored, its connections with both the giant component and other restored nodes from the same network are recovered. These steps repeat until a steady state is reached. On the other hand, the failed node pairs will not be recovered immediately if the interdependent failed node does not belong to the boundary $l > 1$. The whole process could be illustrated in Figure 11.

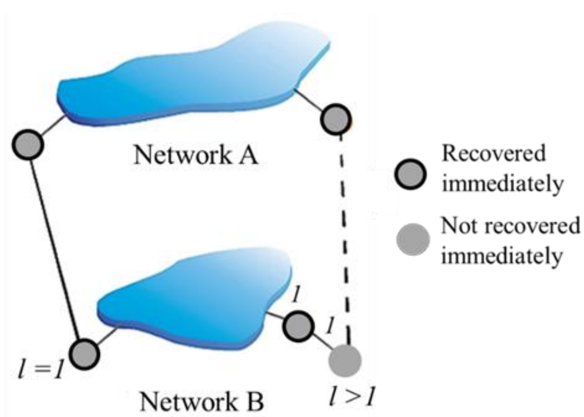

Figure 11: A recovery strategy for interdependent networks [5]

This recovery process could be more practical because in many real systems it is convenient to repair boundary nodes. It is also claimed to be able to prevent further failures of the nodes that are not in the boundary. However, the load distribution of the nodes is not considered in this model. The after-recovery effect on load distribution could make the boundary nodes to be more vulnerable to failure. That is why considering load distribution while repairing failing nodes is crucial [5].

2.4. Network Resilience

Resilience is the ability of a system to withstand any kind of disruptive event while maintaining a certain level of performance and recover immediately from a failed state to a normal operating state. In other words, resilience is a characteristic that represents system performance under unusual conditions, recovery speed, and required actions for recovery to its original functional state [31]. It is a component importance measure related to network reliability and recovery after an attack or failure [32, 33]. According to C. Whitson et al. [34], resilience is a composite of (1) the ability of a network to provide service despite external failures, and (2) the time to restore service when in the presence of such failures. Bruneau et al. [35, 36] defined resilience with four dimensions: robustness (the ability to withstand extreme events and deliver a certain level of service after the occurrence of disruptive events), rapidity (the speed of recovering from a disaster), redundancy (the substitutable components within the system), and resourcefulness (the availability of resources to respond to a disaster). Ouyang et al. [37] described the resilience of an infrastructure system as its joint ability to resist, prevent, and withstand any possible hazards, absorb the initial damage, and recover to normal operation.

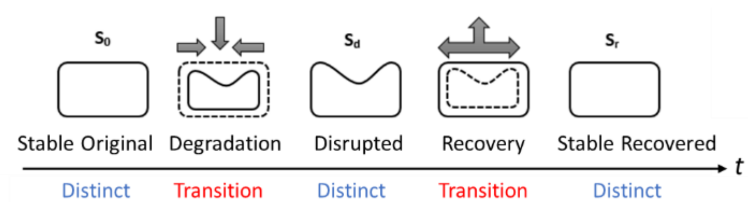

Figure 12: Resilience-based system state transitions [38]

A system experiences three distinct states (stable original, disrupted, and stable recovered) and two state transitions (degradation and recovery) if any unexpected disruptive event occurs. The trend of state transitions could be explained in Figure 12.

To portray both distinct and transitions states of the system a resilience curve is often employed, as shown in Figure 13. A system performance function $P(t)$ is introduced as a measure to describe different system states at time t. The pre-disaster operating condition of a system is denoted as the original state S_0. Once the disruptive event e occurs at time t_e, the system performance degrades gradually until it converges to a stable disrupted state S_d at time t_d. The system performance function corresponding to this disrupted state is denoted as $P(t_d)$, which is typically lower than its original value $P(t_o)$. After a duration of $t_s - t_d$, the recovery action is taken at time t_s. Through a recovery strategy, the system restores from the disrupted state S_d to a new stable state S_r with system performance function value $P(t_r)$ at time t_r [39].

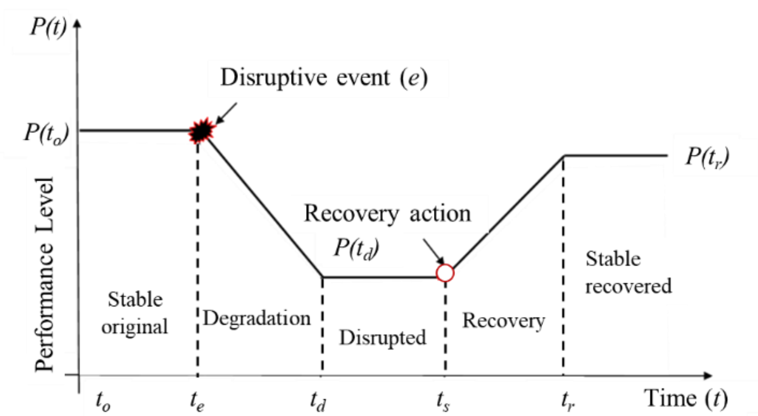

Figure 13: Concept of system resilience [39]

According to Ouyang et al., the resilience assessment framework for most networked systems can be divided into various stages: (1) a disaster prevention stage ($t_o \leq t \leq t_e$), (2) a damage propagation stage ($t_e \leq t \leq t_d$), and (3) an assessment and recovery stage ($t_d \leq t \leq t_r$) and (4) a stable state after the recovery process is fully completed ($t_r \leq t \leq T$), as shown in Figure 14.

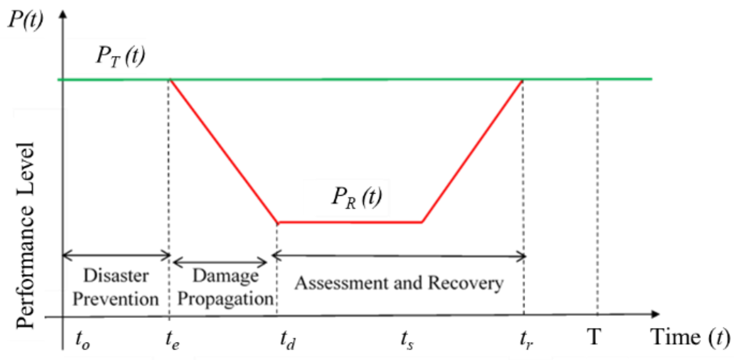

Figure 14: Performance process of an infrastructure system during disruptive events [37]

From this three-stage framework, resilience can be quantified by the ratio of the area under the real performance curve $P_R(t)$ (A_R) and the targeted performance curve $P_T(t)$ (A_T) and as:

$$R(t) = \frac{\int_{t_0}^{T} P_R\,(t)\,dt}{\int_{t_0}^{T} P_T\,(t)\,dt} = \frac{A_R}{A_T} \tag{6}$$

The above-mentioned perspective of resilience indicates that the recovery of a complex network after the damage is the most important part of the network resilience scheme. A networked system could become disaster resilient if it could recover from particular damage and resumes proper functionality within the desired time. This is one of the reasons where an effective recovery strategy is crucial in order to achieve a higher resilience level. It should be noted that the network resilience in this section is associated with infrastructure applications. Although a variety of resilience metrics were developed with different applications [8, 40-43]. more detailed information regarding resilience property or resilient systems could be found in some of system resilience literature in reference [32, 39, 44-48].

3. METHODOLOGY

This study is mainly focused on the resilience assessment of the existing recovery strategy for a given failure scenario and finding the most efficient strategy. A resilience-based assessment framework was proposed here in this purpose. After analyzing the limitations of the current strategies, a hybrid recovery strategy was also proposed. In this chapter, the proposed methods are described in detail.

3.1. Resilience-Based Recovery Assessment Framework

The proposed resilience-based assessment framework could be found in Figure 15. At the beginning of the assessment of the recovery process, the failure characteristics and the reasons behind such failure are analyzed. Different types of attacks (localized, malicious, random, etc.), as well as their resulting failure patterns (random, targeted, cascading, secondary, etc.), are taken into account in this step.

The next step is to build a comparison matrix to perform the comparison among the recovery strategies for the given failure pattern. According to the goal of recovery, multiple objective functions could be formulated. For example, while achieving the highest system resilience could be the main aim of an optimum recovery strategy, it can be achieved with the combination of maximizing performance, minimizing recovery time, and minimizing recovery cost. There are many other factors that should be considered during the recovery process, such as, recovery cost, budget, allowable time, available resources, etc. With the presence of all these constraints, the formulated objective valued could be calculated to find the most suitable recovery strategy for the given circumstances. This could lead to the formulation of a multi-objective optimization problem. A recovery strategy that could achieve the maximum possible resilience level and satisfies other objectives should be considered as an efficient strategy.

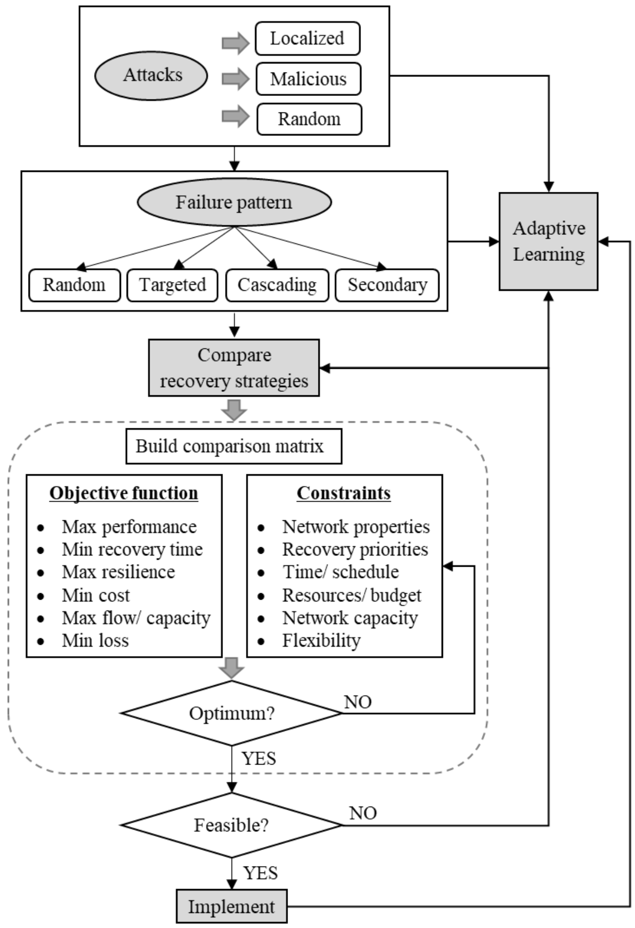

Figure 15: General resilience-based recovery assessment framework

While evaluating a recovery process the optimality and feasibility analysis are crucial prior to the implementation stage. A recovery strategy could increase the recovery speed with a high cost and enormous resources. Due to the limitations in budget and available resources, it might not be possible to provide the required amount of resources and expenses for a faster recovery. On the other hand, a recovery process could be cost-effective and implemented with minimum resources but typically it could be time-consuming. A trade-off between these factors is needed while selecting a recovery strategy for further implementation. Considering cost, resource, and time constraints, it is possible to find an optimum recovery strategy. The strategy that satisfies all the given constraints could be considered as the optimal solution. Among all the optimal solutions, only the one that satisfies the objective values should be selected.

After performing the optimality and feasibility analysis, the desired network recovery strategy could be chosen for the implementation. The results found from the implementation of the selected recovery strategy might provide insight towards further improvement in the current method and developing a more robust and efficient recovery strategy. Thus, an adaptive learning process can be introduced in each step of the assessment to preserve significant information that might affect the recovery process. This information might include but not limited to the root causes and patterns of failures, applicability, effectiveness/ineffectiveness and limitations of the strategies selected for implantation. Through the adaptive learning capability, the scopes for possible advancements could be identified and implemented. Another objective of adaptive learning is that it could be useful in compiling the recovery strategies and the condition associated with them. This could be beneficial in protecting complex networks in the future while similar circumstances are observed. Although the proposed is a generalized framework, it could be modified according to the given circumstances.

3.2. A Hybrid Recovery Strategy

The implementation of the proposed comparison framework provides a clear vision of the advantages and disadvantages of employing the existing recovery strategies. Some strategies are efficient for faster recovery while being quite expensive. These strategies could be more effective in achieving higher system resilience. On the other hand, some strategies could be slower but cost-effective. In a real scenario, while choosing a recovery strategy after any disruptive event, many factors are needed to be considered together, such as recovery time, overall cost, available resources, percentage of performance recovered, system resilience, and so on. It is quite challenging to consider all these factors while employing a single recovery strategy throughout the recovery time. To address this challenge, a two-stage time-dependent hybrid recovery strategy was proposed.

3.2.1. Algorithm and Mathematical Model

When a disaster occurs in the lifetime of a networked infrastructure system, immediate recovery is required to maintain a certain level of performance so that the system is functional. Even if the network is not recovered fully, an immediate faster recovery for a time being may aid to achieve that goal. As employing a faster recovery process throughout the recovery time requires more resources and so, expensive. That is why switching the recovery strategy from a faster and expensive process to a slower and cost-effective process after recovering a critical percentage of performance would be an optimized method of employing the existing recovery strategy. Considering this, a two-stage optimized hybrid recovery method was proposed. The algorithm of the proposed hybrid recovery is shown in Figure 16. The objective of the first stage recovery is set on minimizing the recovery time which indicates a faster recovery is required immediately after the failure. This would retrieve most of the lost network performance and increase network resilience as well. After applying a faster recovery strategy for a given time duration until the network performance in retrieved to a given percentage, the method of recovery will switch to a cost-effective process. This point is named as the switching point. If the switching point is set to more than 50%, this could be more effective in achieving system resilience. Because, in this way, most lost performance will be recovered fast and lesser performance will be recovered slowly. Although it will depend on the requirements of specific circumstances. This is the second stage of the hybrid recovery. The objective of this stage is to minimize recovery cost. A strategy with the lowest recovery cost will be employed here. During the total recovery period, other constraints, such as time, cost, budget, resources, etc. are considered. An optimization model was developed in this purpose. All the variables and parameters could be found in Table 1. The general multi-objective formulation for resilience can be expressed as:

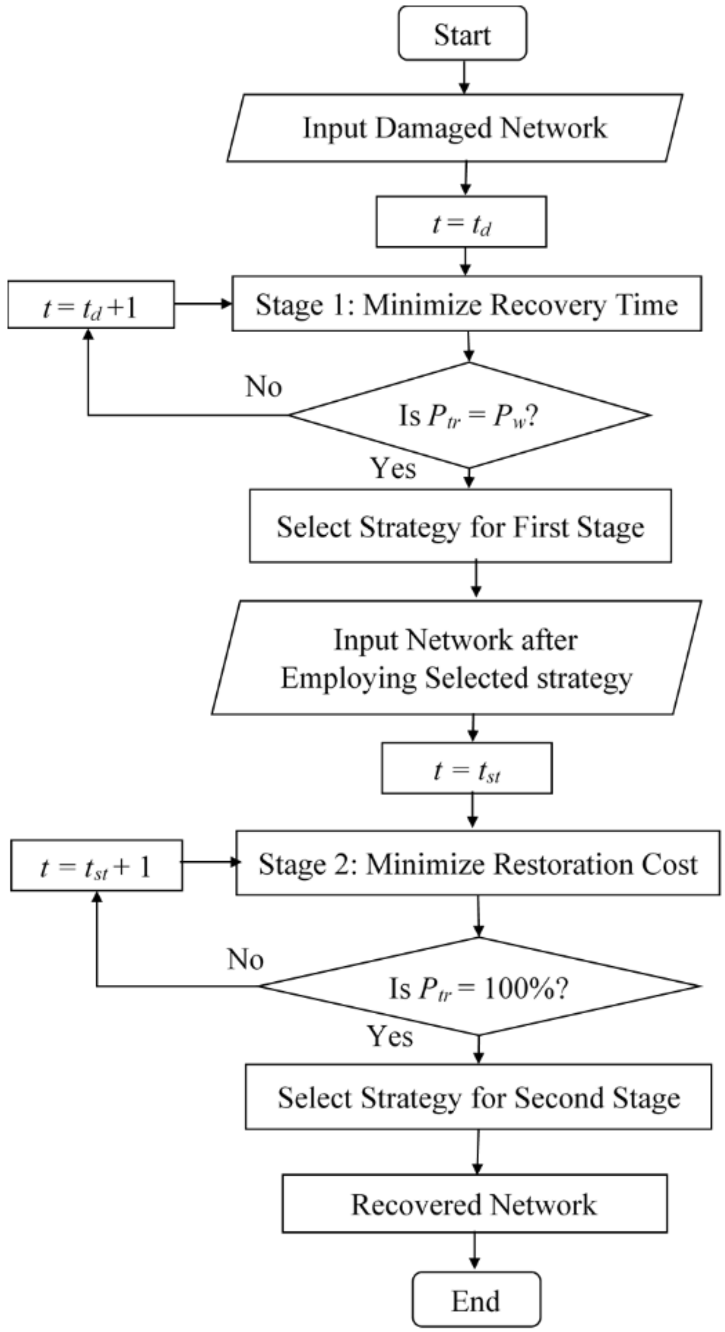

Figure 16: Algorithm for hybrid recovery

Table 1: Symbols and descriptions of parameters and variables

Sets		Parameters		Decision Variables	
r	Set of recovery strategies	R	Resilience	γ_r	Binary variable (1 if strategy *r* is selected, 0 otherwise)
t	Set of time steps	t_d	Time after the disaster stop propagating or the start of the recovery strategy		
		t_r	Time at which the recovery is completed		
		t_t	Total recovery time required		
		T	Maximum allowable time		
		C_{tr}	Cost of recovery at time *t* for strategy *r*		
		E_{rt}	Network efficiency at time *t* after applying strategy *r*		
		E_o	Network efficiency at the original stage		
		P_{tr}	Recovered performance by strategy *r* at time *t*		
e	Set of edges to be repaired	N_{ert}	Number of edges recovered by strategy *r* at time *t*		
		N_{nrt}	Number of nodes recovered by strategy *r* at time *t*		
		C_e	Cost for repairing edge *e*		
		C	Total cost for strategy *r*		
		B	Budget		
n	Set of nodes to be repaired	C_n	Cost for repairing node *n*		
s	Set of resources	V_{se}	The required amount of resources to recover each edge		
		V_{sn}	The required amount of resources to recover each node		
		S	The amount of available resources at time *t*		
w	Switching point	C_w	Cost for switching recovery strategy		
		P_w	Recovered performance at the switching point		

Model Formulation:

Stage 1:

$$\mathit{Objective\ function,} \qquad \mathit{minimize}\ t_t \tag{7}$$

$$\mathit{Subject\ to,} \qquad P_{tr} = \frac{E_{rt}}{E_o} \tag{8}$$

$$t_d + \sum_r \gamma_r \,(t_r - t_d) = t_t \tag{9}$$

$$t_t \leq T \tag{10}$$

$$C_{tr} = C_e E_{rt} + C_n N_{rt} \tag{11}$$

$$C = \sum_t C_{tr} \gamma_r \tag{12}$$

$$C \leq B \tag{13}$$

$$V_e N_{ert} + V_e N_{nrt} \leq S \tag{14}$$

$$\gamma_R = 0{,}1 \tag{15}$$

The objective function, Eq. (7) minimizes the total time. The percentage of recovered performance can be quantified by Eq.(8). Eq.(9) defines the total recovery time required when applying recovery strategy r. Eq. (10) indicates that the total time cannot exceed the maximum allowable given time, T. Eq. (11) is the constraint that measures the cost of recovery at time step t while implementing strategy r. The total cost of recovery includes the cost of recovering both the nodes and the edges. Eq. (12) is the total cost of recovery and Eq.(13) is the budget constraint. Eq.(14) is the resource constraint. Finally, Eq. (15) is the binary decision variable constraint.

Stage 2:

$$Objective\ function, \qquad minimize\ C_{tr} \tag{16}$$

$$Subject\ to, \qquad P_{tr} = \frac{E_{rt}}{E_o} \tag{17}$$

$$t_d + \sum_r \gamma_r \,(t_r - t_d) = t_t \tag{18}$$

$$t_t \leq T \tag{19}$$

$$C_{tr} = C_e E_{rt} + C_n N_{rt} \tag{20}$$

$$C = C_w + \sum_t C_{tr}\gamma_r \tag{21}$$

$$C \leq B \tag{22}$$

$$V_e N_{ert} + V_e N_{nrt} \leq S \tag{23}$$

$$\gamma_R = 0{,}1 \tag{24}$$

In the second stage, the objective function Eq. (16) minimizes the total recovery cost. However, the constraints of Eq. (17)-(20) and Eq. (22)-(24)are identical to the constraints of the first stage except for the total cost of Eq (21). Unlike the first stage, the recovery cost includes a switching cost which refers to the expenses due to the change in recovery arrangements. After solving the two-stage optimization problem, a combination of two recovery strategies, one for each will be selected, which refers to the hybrid recovery. The next step is to verify whether the found combination of recovery strategies would result in the highest resilience or not.

3.2.2. Resilience Assessment

The main goal of recovery is to achieve network resilience. From the hybrid recovery, a combination of two recovery methods is selected. At each stage, a recovery strategy is selected to employ considering the objectives and the constraints. The reason behind designing the selection criterion in such a way is to achieve maximum network resilience at minimum cost. To verify this claim, resilience assessment for strategy combinations are necessary. The algorithm for the resilience assessment of the hybrid recovery process is shown in Figure 17.

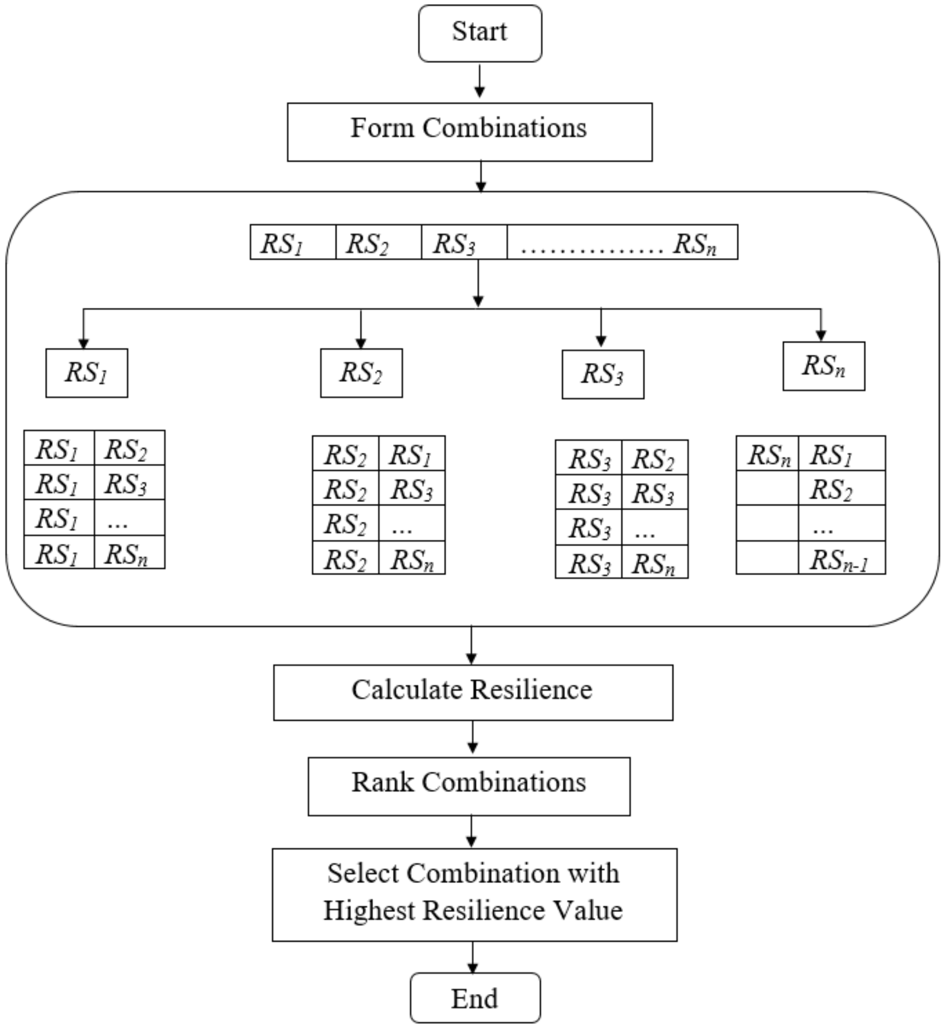

Figure 17: Algorithm for resilience assessment of hybrid recovery

According to the algorithm, the resilience assessment for combinations starts with forming combinations of two recovery strategies from the list of existing strategies. From *n* number of recovery strategies, a combination of two will be selected and tested for resilience at each time until all the combinations are taken into account. All of the formed combinations are ranked according to the resilience value and the combination with the highest resilience will be selected to be applied.

4. CASE STUDIES

The efficiency of the proposed comparison framework and the application of the hybrid recovery process could be better comprehensible through case studies. In this chapter, three different case studies will be presented. Case study I and case study II explains the resilience assessment and comparison of the existing recovery strategies against localized attacks and cascading failures respectively. And finally, case study III portrays the application of the proposed hybrid recovery method.

4.1. Case I: Resilience Assessment and Comparison of Strategies under Different Failures – Localized Attack, Lattice Network

This case study was designed for the resilience assessment of recovery strategies against localized attacks in the context of the proposed comparison framework. In this subsection, a description of the designed case study will be presented, and the results found will be discussed.

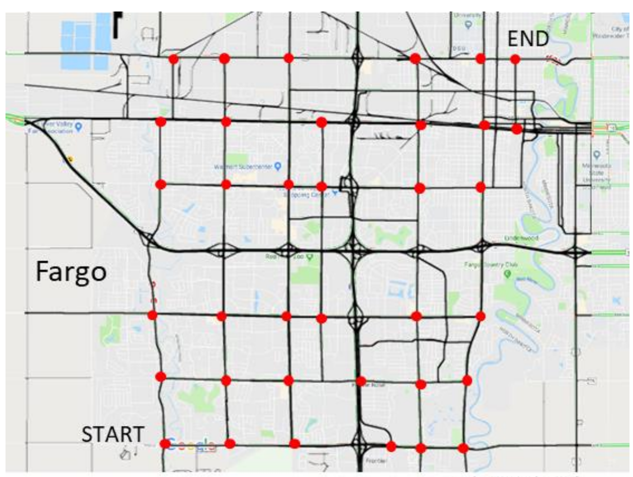

Figure 18: A water distribution network case study

Many of the real infrastructure systems are often modeled with lattice networks. Although this type of networks may seem too ideal, the weights of both nodes and edges resemble the real scenario. Inspired by the water distribution network used in Ref. [49] a lattice network consisting of 36 nodes and 60 edges were considered for this case study, which is shown in Figure 18. The weights of the nodes represent the demand of the nodes. Both the length of each edge and the amount of flow in each edge were considered as edge weight. The failure of the network was modeled as localized attacks, initiated at a random node and the impact of the attack propagated over time. As a result, 8 nodes were isolated randomly, and 24 edges connected to them were damaged and removed to result in a region of isolated nodes.

To illustrate the challenges in resilience assessment, there are two critical performance measures considered in this case study, the maximum flow and the shortest path distance. The maximum flow path and the shortest distance path from node 1 to node 36 are highlighted in Figure 19. The maximum flow quantifies the amount of load this network can carry from a source node to a target node and follows the concept of "the more, the better". The shortest path indicates the best route with the least travel distance. Opposite from the maximum flow, the shortest path distance follows the concept of "the least, the better". Due to the damage caused by localized attacks, the maximum flow decreases from 75 to 48 units, and the shortest path length increases from 192 to 229 units. The transition of network performance from its original state to after attack state is shown in Table 2.

Table 2: Degradation propagation from original to degraded state

Time	Critical Performance		Description
	Max flow	**Shortest path**	
0	75	192	Original state
1*	75	206	1 node was isolated
2	75	206	2 nodes were isolated
3	75	206	3 nodes were isolated
4	75	229	4 nodes were isolated
5	75	229	5 nodes were isolated
6	75	229	6 nodes were isolated
7	75	229	7 nodes were isolated
8**	48	229	8 nodes were isolated

* Failure occurred at time step 1. ** Failure stopped propagating at time step 8

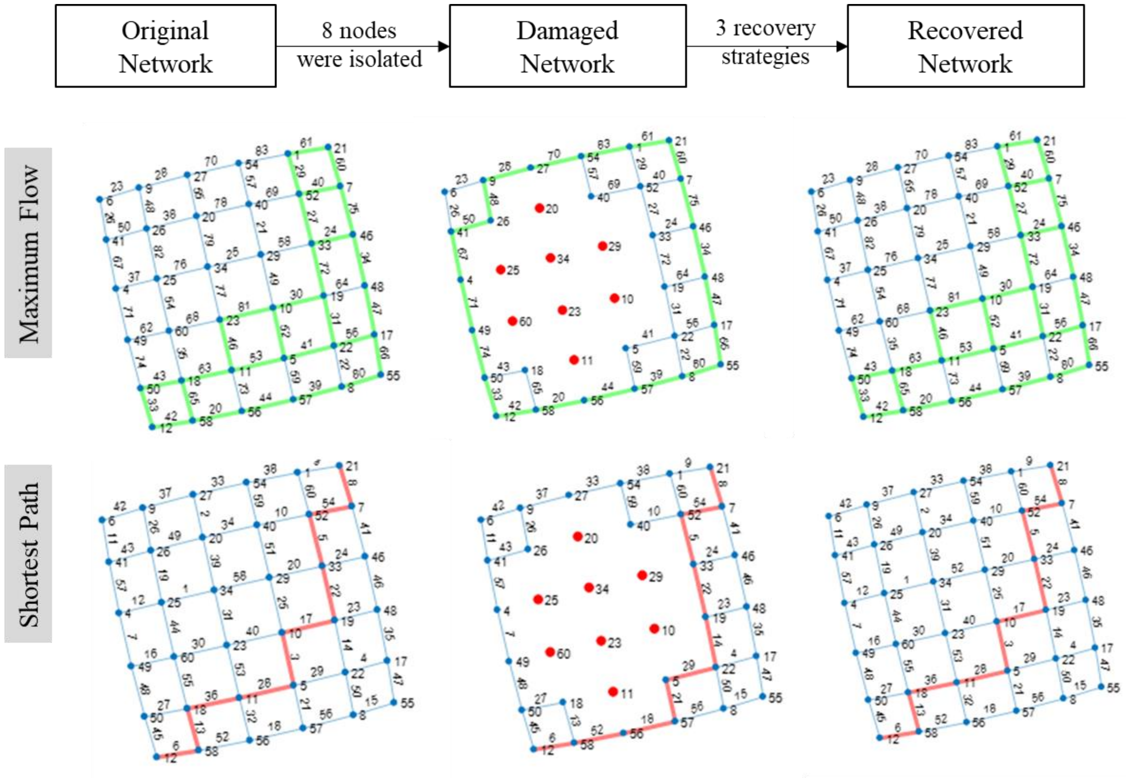

Figure 19: The assessment model in different stages of resilience

As mentioned in subsection 2.3.1, there are three recovery strategies that could be appropriate for recovering network that suffers from a localized attack: (1) preferential recovery based on nodal weight (PRNW), (2) periphery recovery (PR), and (3) localized recovery (LR). All three recovery strategies are implemented on the damaged network. It is assumed that the network will recover fully (100%) after implementing any recovery strategy, given that the iteration properties could differ. As the damage propagation stopped at time step 8, and the recovery starts immediately at time step 9. The changes in system performance during the recovery stage are shown in Table 3and the transitions in the structure of networks at different stages are shown in Figure 19.

Table 3: Changes of max flow and shortest path distance during recovery (shaded area indicates that the recovered state was reached)

Time	PRNW**		PR**		LR***	
	Max Flow	**Shortest Path**	**Max Flow**	**Shortest Path**	**Max Flow**	**Shortest Path**
9*	48	229	48	229	75	229
10	48	229	48	229	75	192
11	73	229	48	229	75	192
12	73	229	75	229	75	192
13	73	229	75	215	75	192
14	75	229	75	192	75	192
15	75	215	75	192	75	192
16	75	192	75	192	75	192
17	75	192	75	192	75	192
18	75	192	75	192	75	192
19	75	192	75	192	75	192
20	75	192	75	192	75	192

* Recovery started at time step 9, ** Recovery stops at time step 17-fully recovered state reached, *** Recovery stopped at time step 12- fully recovered state reached.

The main aim of repairing the damaged network is to achieve system resilience by regaining the highest possible percentage of initial network performance. Here the system resilience R is quantified by using Eq. (6), which can be defined as the ratio of the area below the targeted performance curve (A_T) and the real curve (A_R). The resulting resilience curves after employing all three recovery strategies are shown in Figure 20(a) for maximum flow, and Figure 20(b) for the shortest path.

Table 4: Resilience assessment of recovery strategies

	PRNW		**PR**		**LR**	
	Max flow	**Shortest path**	**Max flow**	**Shortest path**	**Max flow**	**Shortest path**
$\boldsymbol{A_R}$	1413	4312	1392	4238	1473	4104
$\boldsymbol{A_T}$	1500	3840	1500	3840	1500	3840
$\boldsymbol{R}$	0.94	1.12	0.93	1.1	0.98	1.07

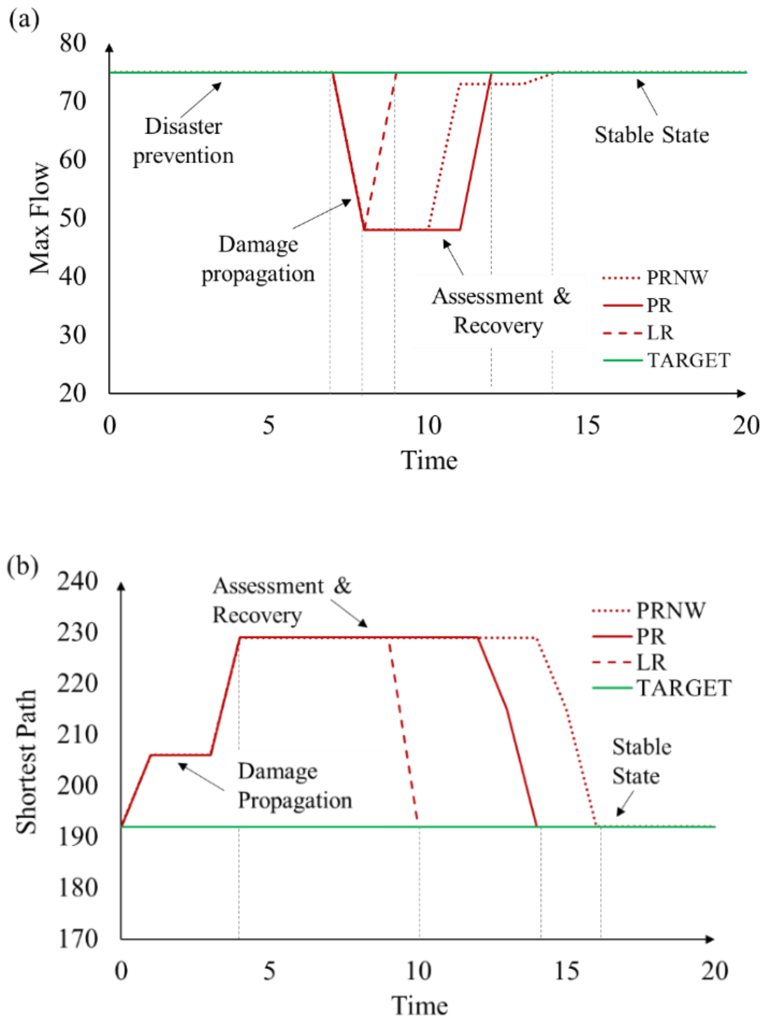

Figure 20: Resilience curve based on (a) maximum flow and (b) shortest path

All the results found from the resilience assessment of recovery strategies are summarized in Table 4. For maximum flow, the area under the real performance curve (A_R) values are 1413, 1392, and 1473 respectively for PRNW, PR, and LR and the area under the targeted performance curve (A_T) value is 1500. As the value of A_R is always lesser than A_T, the resilience value should be less than 1. The found resilience values are 0.94, 0.93 and 0.98 for PRNW, PR, and LR indicating LR showing the highest resilience. Because the maximum flow follows 'the larger the better' concept. On the other hand, A_R values for the shortest path are 4312, 4238, 4104 respectively for PRNW, PR, and LR and A_T value is 3840. As A_R is always greater than $A_{T,}$ in this case, the resilience values 1.12, 1.1, and 1.07, greater than 1. However, this also indicates that LR is the most resilient strategy as the shortest path follows “the smaller the better” concept.

One of the most important factors that affect the recovery process is the recovery cost. Before going for the implementation, the probable expenses should be analyzed. Because there are always budget constraints that could restrict the recovery process in various ways. While considering system resilience, the recovery strategy with the lowest cost should be selected. The results found from cost analysis are summarized in Table 5.

Table 5: Recovery cost during each recovery step

Time Steps	**Cost ($)**		
	PRNW	**PR**	**LR**
1-8	*Damage Propagation Stage*		
9	7,300	7,300	42,300
10	4,700	7,300	24,400
11	13,100	7,700	3,400
12	3,300	8,700	0
13	6,300	9,800	0
14	12,600	4,700	0
15	15,100	10,000	0
16	8,700	15,600	0
Total	71,100	71,100	70,100

For cost analysis, the recovery cost at each time step was calculated based on the weight of the edges that need to be recovered. For each time step of the recovery process, an amount of $200 was assumed to be the fixed cost. Additionally, the repair cost for each unit of recovered edges was assumed to be $100 and added to the fixed cost to find the total cost. From the cost analysis, it is observed that the total recovery cost for PRNW and PR is $71,100, while for LR it is $70,100 indicating LR is the most cost-effective strategy. However, the initial recovery cost for LR is higher than both PRNW and PR. In the initial two steps recovery cost for LR are $42,300 and $24,400, for PRNW are $7,300 and $4,700, and for PR are $7,300 and $7,300. Although the overall cost for LR is lower, the higher initial costs may exceed the budget resulting in the selection of a different recovery strategy. The changes in costs at each time step can be compared with the cost vs time graph given in Figure 21.

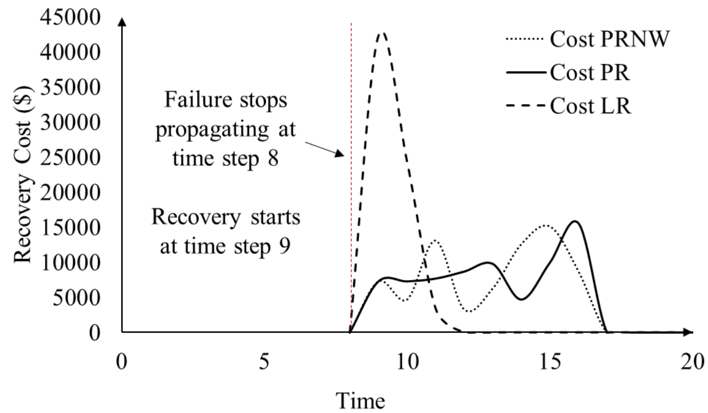

Figure 21: Changes in recovery cost in each time step

In many real cases, immediate recovery is needed after any disaster which contributes to the system resilience in a significant manner. That is why a faster recovery should also be taken into account while considering system resilience and recovery cost. Considering these facts, the recovery strategies were evaluated based on the restoration sequence and the amount of time required for complete recovery. In Table 6, the found results are summarized. It is observed that PRNW and PR take 8-time steps and LR takes only 3-time steps to restore the network completely. It is also observed from Table 6 that the water supply infrastructure network system performances, maximum flow, and shortest path, were restored prior to the network being connected fully. The maximum flow for PRNW was restored at time step 14, and the shortest distance was restored at time step 16 while the overall network connection was restored at time step 17. Although PR required an equal amount of time step to reconnecting the network completely, the maximum flow based was restored at time step 12 and the shortest path performance was regained at time step 14 by PR. Considering the ability to restore the individual network performance, it can be claimed that PR is capable of faster recovery than the PRNW. Additionally, LR managed to restore the network's maximum flow and shortest path at time step 9 and 10, respectively indicating LR would be a much faster process compared to PRNW and PR strategies. Although not as fast as LR, PRNW and PR are two recovery strategies that could be quite effective for post-disaster recovery in a shorter time period. Because of their low computational complexity, it is easy to employ PRNW and PR immediately.

Table 6: Iteration details of recovery strategies

Time step	**PRNW**		**PR**		**LR**	
	Recovered edges*	**Sum of weights**	**Recovered edges***	**Sum of weights**	**Recovered edges***	**Sum of weights**
9	23,15	71	23,15	71	28,36,38,39,25,27,26,30,37,47,41,49	421
10	26,36	45	40,41	71	14,16,15,17,19,23,29,34,40,50	242
11	38,40,41	129	26,34,37	75	6	32
12	34,37	31	47,49,50	85		
13	25,28	61	6,14,16	96		
14	39,47,49,50	124	19,29,30	45		
15	6,14,16,17	149	36,38,39	98		
16	19,27,29,30	85	17,25,27,28	154		
17-20	*Stable State*					

* Restoration sequence was sorted from the first to the last node restored

Considering the results, it is clear that the localized recovery (LR) process should be selected from the perspective of network resilience, overall recovery cost and recovery time. However, at the presence of budget constraint at each time step PRNW or PR would be more appropriate in keeping the initial cost in the lower range. More details of this case study will be found in ref. [50].

4.2. Case II: Resilience Assessment and Comparison of Strategies under Different Failures – Cascading Failures, Interdependent Network

To evaluate the recovery strategies against cascading failures and find the most efficient strategy, the proposed comparison framework was employed in a case study. The efficiency of the framework for comparing different strategies and resilience assessment could be easily comprehensible through the case study. For this case study, two interdependent power-water networks were considered. Both the networks are consist of 30 nodes each with an average node degree of $<k>=3$. Each node in the water network depends on the geographically nearest power nodes. The power network is denoted as Network *A* and the water distribution network is denoted as Network *B*

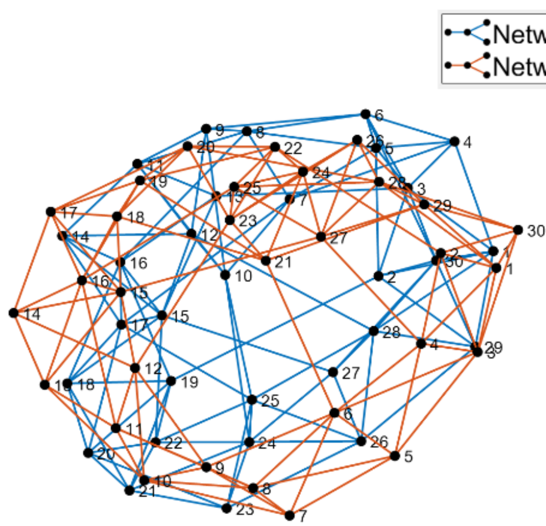

Figure 22: Interdependent power-water networks

To measure network performance, network efficiency was used. The network efficiency can be measured with the average shortest path length. To avoid the infinity caused by the disconnection between two nodes, the average reciprocal shortest path length is can be used as

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{25}$$

where E is the network efficiency, N is the number of nodes and d_{ij} is the shortest path length connecting node i and j. It quantifies the effectiveness of flow within nodes. Low efficiency indicates that the flow between any two nodes in this network will take a longer path and more time or resources.

Table 7: Changes in network efficiency during failure and recovery

Time steps	**Efficiency**				**Description**
	Probability-Based Recovery (RS1)		**Recovery of neighboring or boundary nodes (RS2)**		
	Network *A*	**Network *B***	**Network *A***	**Network *B***	
0	0.537	0.527	0.537	0.527	Original state
1	0.537	0.527	0.537	0.527	
2	0.537	0.527	0.537	0.527	
3	0.537	0.527	0.537	0.527	
4	0.163	0.175	0.163	0.175	Failed state
5	0.226	0.231	0.417	0.359	Recovery starts
6	0.288	0.285	0.537	0.527	
7	0.328	0.326	0.537	0.527	
8	0.376	0.339	0.537	0.527	
9	0.386	0.426	0.537	0.527	
10	0.448	0.443	0.537	0.527	
11	0.480	0.455	0.537	0.527	
12	0.495	0.489	0.537	0.527	
13	0.511	0.502	0.537	0.527	
14	0.523	0.502	0.537	0.527	
15	0.535	0.516	0.537	0.527	
16	0.537	0.527	0.537	0.527	
17	0.537	0.527	0.537	0.527	Stable state

At the normal operating condition, the efficiency for Network *A* is 0.537 and Network *B* is and 0.527 respectively. After the cascading failure occurs, The efficiency degrades to 0.163 and

0.175 for Network *A* and Network *B* respectively. The recovery starts in between the cascading process. Two existing recovery strategies: probability based recovery (RS1) and neighboring nodes recovery (RS2) are implemented. In the RS1 process, all the nodes are randomly assigned with a probability of recovery which indicates the restoration priority. In the RS2 process, the neighboring nodes of the connected components are recovered. For both, the network and the change in the network structures, are shown in Figure 23. The change in network efficiency during failure and recovery is shown in Table 7.

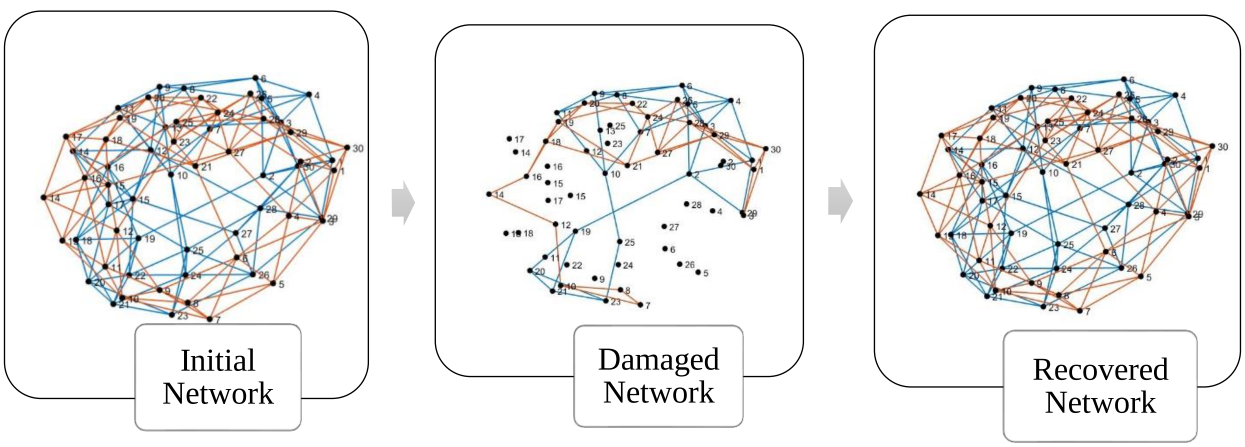

Figure 23: Network structures in different stages

After implementing both of the strategies it is observed that RS1 takes 13 steps and RS2 takes only 2 steps to recover completely. This indicates that RS2 is a faster process compared to RS1. As the recovery time is lesser for RS2 than RS1, RS2 would be more resilient. To verify this, a resilience assessment of recovery strategies was performed. Resilience metric *R* from Eq 1 was used again for this purpose. Resilience curves for both recovery strategies for Network *A* and Network *B* are shown in Figure 24.

Table 8: Resilience assessment for recovery strategies against cascading failures

	Strategy 1(RS1)		**Strategy 2(RS2)**	
	Network *A*	**Network *B***	**Network *A***	**Network *B***
$\boldsymbol{A_R}$	7.9783	7.6497	9.1723	8.9591
$\boldsymbol{A_T}$	9.6660	9.4788	9.6660	9.4788
$\boldsymbol{R}$	0.8254	0.8070	0.9489	0.9452

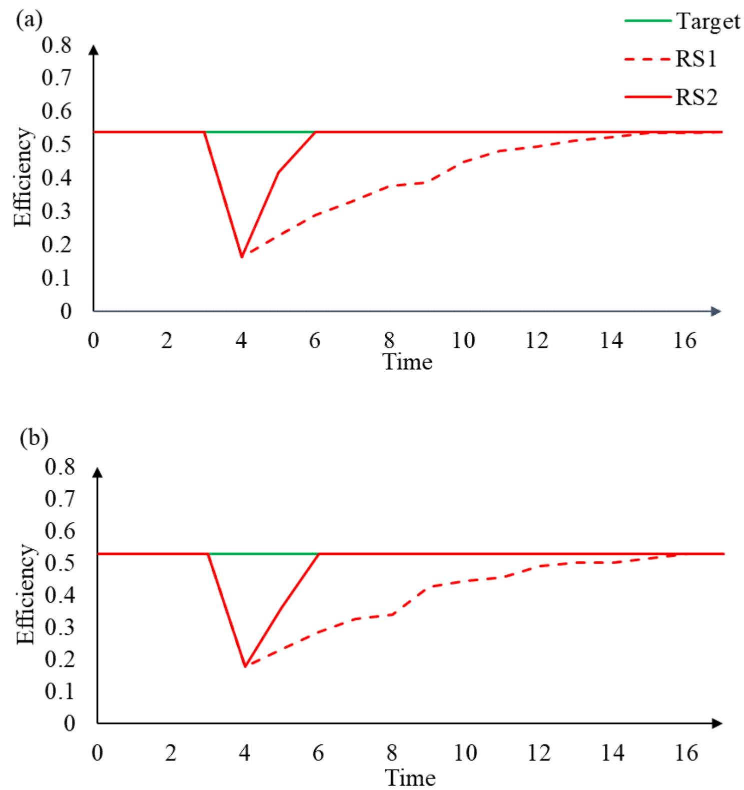

Figure 24: Resilience curve for (a) Network *A* and (b) Network *B* under RS1 and RS2

The results from the resilience assessment are summarized in Table 8. In the case of RS1, the area under the real performance curve are 7.9783 and 7.6497 for Network *A* and Network *B* respectively and the area under the targeted performance curve are 9.6660 and 9.4788. This results in the resilience value of 0.8254 and 0.8070 for RS1. For RS2, the area under the real performance curve is 9.1723 and 8.9591 for Network *A* and Network *B* respectively. The resulting resilience value Network *A* and Network *B* are 0.9489 and 0.9452 respectively. The results from the resilience assessment verify the previous claim indicating RS2 is more resilient compared to RS1.

Table 9: Recovery cost at each time step with RS1 and RS2

	RS1		RS2	
Time	**Network A**	**Network B**	**Network A**	**Network B**
5	800	900	3900	3700
6	800	700	4200	4100
7	800	800	0	0
8	700	700	0	0
9	400	700	0	0
10	800	800	0	0
11	700	600	0	0
12	800	600	0	0
13	700	700	0	0
14	700	700	0	0
15	600	600	0	0
16	300	0	0	0
17	0	0	0	0

Although, RS2 is more resilient that RS1, it could be costly for the time being. Because in RS2, many nodes and edges are recovered at each time step. As a result, it recovers most network components in a lesser time period. In a real scenario, it is hardly possible to implement such kind of recovery method due to budget and resource limitation. To find the trend of cost while implementing both recovery strategies, a cost analysis was performed. The recovery cost for each node and each edge was assumed to be \$200 and \$100 respectively. The total recovery cost at each time step under both recovery strategies are summarized in Table 9 and the trend of the cost could be found in Figure 25.

It is observed that the recovery cost at each time step is below \$1000 over the recovery period with RS1. On the other hand, the cost for recovering Network *A* and Network *B* with RS2 was \$3900 and \$3700 at the first step of recovery and \$4200 and \$4100 in the second step. In this process, the recovery cost at each time step is significantly higher, which may not satisfy the budget limitations. Although, the total cost would be the same as the number of recovered components are equal.

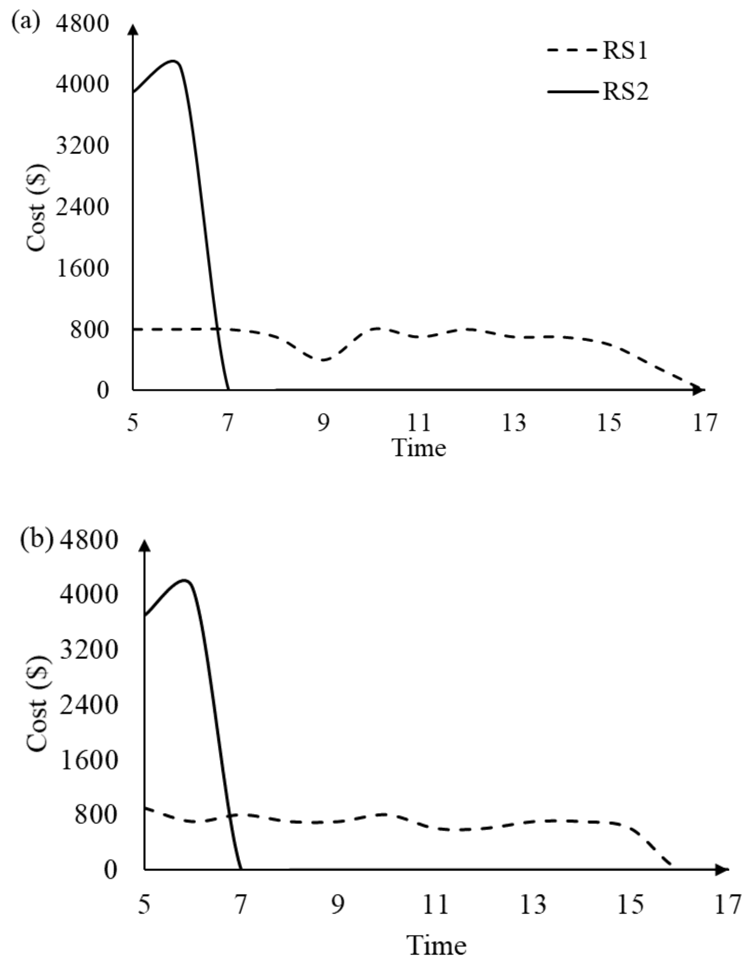

Figure 25: Changes of recovery cost for (a) Network A and (b) Network B with both recovery strategies

4.3. Case III: Implementation of Hybrid Recovery

To validate the proposed hybrid recovery, a case study was developed. In this subsection, a description of the designed case study will be presented, and the results found will be discussed.

In this case study, an IEEE-14 bus system and a 20 nodes gas system was considered as shown in Figure 26. Between these two networks, bidirectional interdependency is present. The power distribution network is dependent on the gas network for electricity generation and the gas network consumes electricity to operate the compressors. The gas system consists of 17 load nodes, 2 compressor stations, and 1 supply node and the power network consists of 14 busses and 5 generators.

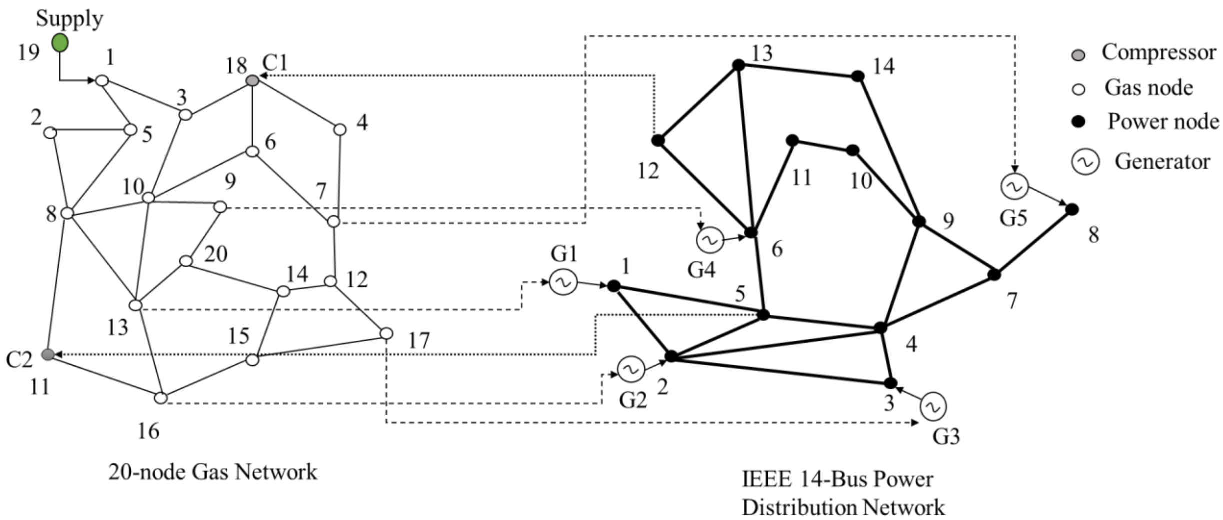

Figure 26: Interdependent power-gas network

In the gas network, the supply of gas starts at the supply node (19) to the other demand nodes. Between these nodes, there are edges which represent gas pipelines to transport gas from the supply node to demand nodes. There are 2 compressors (18, 11) that help in transporting gas from one node to another through the pipelines by pressurizing it constantly. These compressors need a power supply which is provided by the power node 12 and 5 of the power distribution network. In the power distribution network, there are 14 busses to which other components, like, generator, loads, transformers, etc. are connected. Generators at nodes 1,2,3,6 and 8 get gas supply from gas nodes 13, 16, 17, 9 and 7 to generate power. Each node of both networks can carry different loads and have different capacity levels.

Table 10: Degradation propagation due to cascading failure

Time	**State Description**	**Efficiency**	
		Gas Network	**Power Network**
0	Original operating state	0.4459	0.5223
1		0.4459	0.5223
2		0.4459	0.5223
3	Cascading failure	0.0741	0.1447
4		*Recovery starts*	

The cascading of failure was initiated in node 9 of the gas network. Due to the interdependency, the failure propagated from the gas network to the power distribution network. To measure network performance, network efficiency was used as (25) The change of network efficiency due to the cascading of failure could be found in Table 10. Both the networks are in normal operating condition during the time step 0-2. The failure is initiated at time step 3 resulting degradation of the efficiency of the gas network from 0.4459 to 0.0741. Due to the cascade of failure the power distribution network efficiency degrades from 0.5223 to 0.1447. As the cascading process continues, it was stopped forcefully at time step 4 and the recovery starts here. The damaged network is shown in Figure 27.

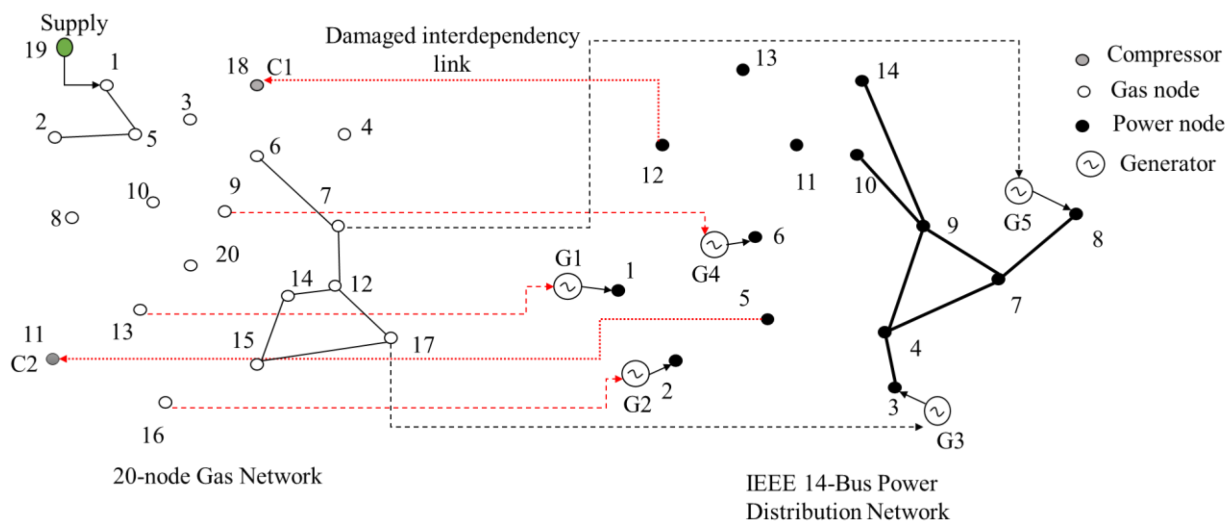

Figure 27: The damaged network

Both the previously mentioned recovery strategies against cascading failures: probability-based (RS1) and neighboring nodes recovery (RS2) were considered for the hybrid recovery. The parameter values used for solving the problem for hybrid recovery could be found in Table 11.

Table 11: Parameter values

Parameter	Value
T	20
P_s	60%
C_e	200
B	3000
C_n	100
V_{se}	5
$\mathrm{V_{sn}}$	2
S	15
C_w	100

Table 12: Change of network efficiency at each recovery step with an individual recovery strategy

Time	RS1		RS2	
	Gas Network	Power Network	Gas Network	Power Network
4	0.0873	0.2601	0.1406	0.3123
5	0.1374	0.3491	0.2836	0.5090
6	0.2059	0.3929	0.4459	0.5223
7	0.2634	0.4822	0.4459	0.5223
8	0.3200	0.5057	0.4459	0.5223
9	0.3327	0.5223	0.4459	0.5223
10	0.4459	0.5223	0.4459	0.5223
11	0.4459	0.5223	0.4459	0.5223
12	0.4459	0.5223	0.4459	0.5223

***** Shaded area = stable state reached

Table 13: Change of network efficiency at each recovery step with hybrid recovery

Time	RS1-RS2				RS2-RS1			
	Gas Network	P_{tr}	Power Network	P_{tr}	Gas Network	P_{tr}	Power Network	P_{tr}
4	0.0873	0.1957	0.2601	0.4979	0.1406	0.3153	0.3123	0.5978
5	0.1374	0.3082	0.3491	0.6683	0.3155	0.6360	0.4579	0.8766
6	0.2059	0.4618	0.3929	0.8766	0.4266	0.8744	0.5223	1
7	0.2634	0.5908	0.5223	1	0.4459	1	0.5223	1
8	0.4459	1	0.5223	1	0.4459	1	0.5223	1
9	0.4459	1	0.5223	1	0.4459	1	0.5223	1
10	0.4459	1	0.5223	1	0.4459	1	0.5223	1
11	0.4459	1	0.5223	1	0.4459	1	0.5223	1
12	0.4459	1	0.5223	1	0.4459	1	0.5223	1

RS1 and RS2 were also implemented individually to observe the changes in network efficiency. It was observed that RS1 requires the highest time and RS2 requires the lowest time to recover completely. The changes in network efficiency with both individual and hybrid recovery are summarized in Table 12 and Table 13.

For the second stage, the aim is to select a strategy that would be cost effective. Cost analysis was performed in this purpose. The recovery cost at each time step with both individual and hybrid recovery is summarized in Table 14.

Table 14: Recovery cost at each time step

	RS1		**RS1-RS2**		**RS2-RS1**		**RS2**	
Time	**Gas**	**Power**	**Gas**	**Power**	**Gas**	**Power**	**Gas**	**Power**
4	400	500	400	500	1200	1300	1200	1300
5	400	500	400	500	1800	1200	1800	1300
6	900	500	900	500	800	400	1200	300
7	1000	1200	1000	1200	400	-	-	-
8	900	1000	1500	-	-	-	-	-
9	400	500	-	-	-	-	-	-
10	200	-	-	-	-	-	-	-
11	-	-	-	-	-	-	-	-

It was observed that with RS1, the recovery cost is quite low at each time step. But with RS2 it is always high. The costs for the combinations of recovery strategies are also analyzed. As the gas network reaches the switching point the recovery cost reaches to $1000 an $1800 with RS1 and RS2. After switching, it becomes $1500 and $1200 with RS2 and RS1. The same trend occurs for power network from $500 and $1300 to $1200 and $400. The trend indicates that For RS1-RS2 combination, the cost increases after switching point. On the other hand, the recovery cost decreases after switching point for RS2-RS1 combination. The trend of recovery cost could be found in Figure 28. Considering the two objectives, RS2-RS1 should be selected.

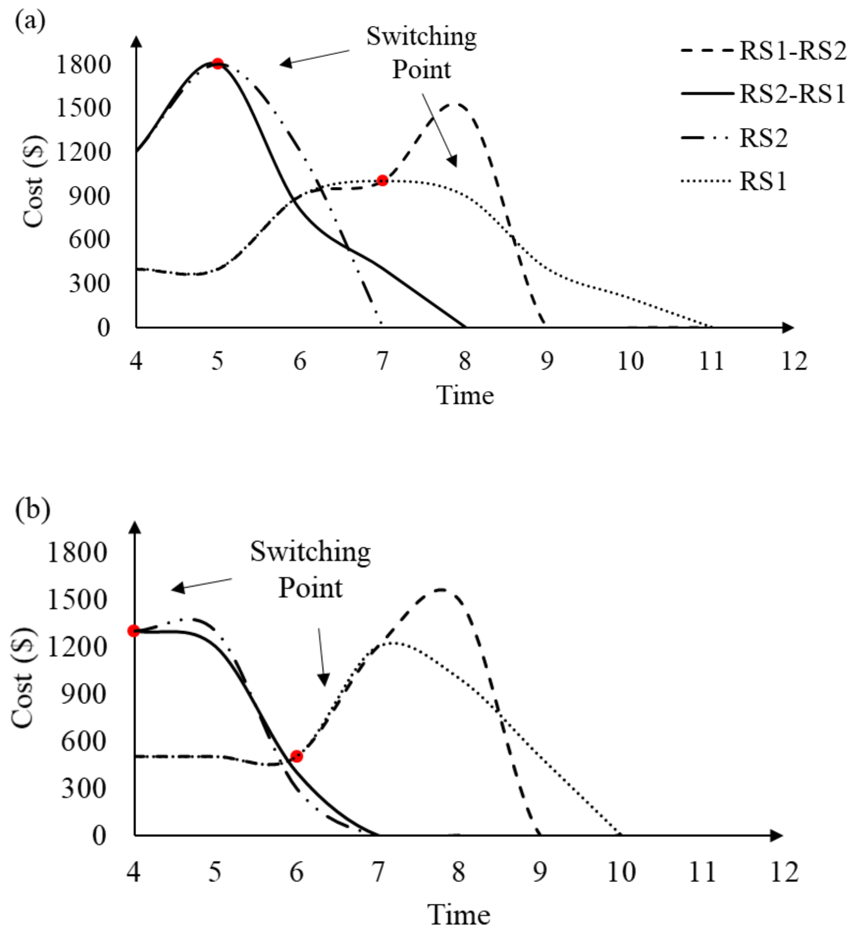

Figure 28: Cost analysis for (a) Gas network and (b) Power network

As the main goal of hybrid recovery was to find a recovery pattern that would achieve the highest possible resilience with a balance on cost and time. In this purpose, resilience assessment was performed by using Eq. (6) The found results are summarized in Table 15. For RS1, the resilience values are 0.6822 and 0.8405 for gas and power network and for RS2, these values become 0.8431 and 0.9040. The resilience value Gas network with combination RS1-RS2 is 0.7269, which increases to 0.8326 with RS2-RS1. For power network, this value increases from 0.8496 with RS1-RS2 to 0.8959 with RS2-RS1. It should be noticed that both the combinations lie between the individual values.

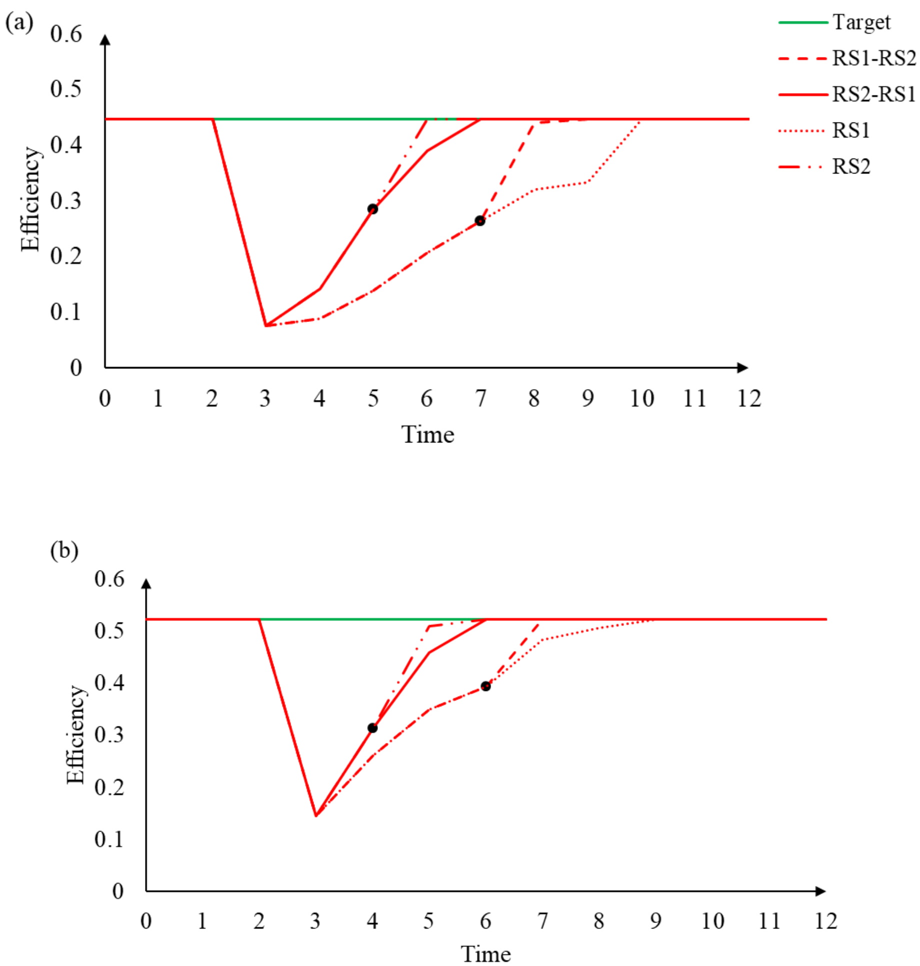

Figure 29: Resilience curve for hybrid recovery

Table 15: Resilience Assessment for hybrid recovery

	RS1		RS1-RS2		RS2-RS1		RS2	
	Gas	**Power**	**Gas**	**Power**	**Gas**	**Power**	**Gas**	**Power**
A_R	3.6503	5.2685	3.8896	5.3252	4.4555	5.6157	4.5114	5.6667
A_T	5.3511	6.2681	5.3511	6.2681	5.3511	6.2681	5.3511	6.2681
R	0.6822	0.8405	0.7269	0.8496	0.8326	0.8959	0.8431	0.9040

The resilience curves for both networks with both combinations and individual strategies are shown in Figure 29. For both networks, the overall recovery time is lowest for RS2 and so, results in the highest resilience value. Among both the combinations, RS2-RS1 requires lesser time and so, results in higher resilience. Although it shows lesser resilience value than RS2, it is more cost-effective. This validates the results found from the proposed algorithm.

5. CONCLUSIONS AND FUTURE WORKS

The focus of this study was to analyze the resilience assessment of recovery strategies against localized attacks and cascading attacks failures and propose a cost-effective resilient recovery method. In this purpose, a general framework for evaluating and assessing the existing recovery strategies was proposed in the first place. This framework was implemented for both localized attacks and cascading failures through two different case studies. For the localized attacks, a lattice network inspired by a water distribution network was considered. The localized attacks followed by three recovery strategies (PR, PRNW, and LR) were simulated and resilience assessment was performed. An optimization model was also developed in order to consider recovery time and cost. The localized recovery (LR) was found to be the most resilient method. Although LR could be expensive if the recovery cost at each time step is considered. On the other hand, PR and PRNW could be cost-effective at individual time steps. The investigation continued with the implementation of the framework on cascading failure. Two interdependent power-water networks were considered in this purpose. The cascading failure with two recovery strategies named probability-based (RS1) and neighboring nodes or boundary recovery (RS2) were simulated. After a resilience assessment, it was found that neighboring nodes recovery method would be more resilient as it is a faster method compared to the probability-based method. Although it could not be cost effective.

Considering the advantages and disadvantages of the existing recovery strategies a time-dependent hybrid recovery method was proposed. Applying a recovery strategy over the total recovery period would not be efficient if other important factors (cost, time, resources, etc.) are to be considered. That is why the hybrid recovery aims to employ a faster strategy until 60% of the performance is not recovered and switch to a cost-effective strategy. An algorithm along with an optimization model was developed in this purpose. In this way, a balance between recovery time and cost as well as the system resilience were maintained. To perform the resilience assessment, an algorithm was also developed so that the right combination of strategies could be selected. The proposed hybrid recovery was implemented on two interdependent power-gas networks after cascading failure. The RS2-RS1 combination was found to be the most resilient.

5.1. Future Works

The present study provides a list of directions towards which the future research could be conducted. The potential research directions include:

(i) One disruptive event was considered in this study. Although multiple disruptions could occur during the study period and so, affect the recovery process. The impact of multiple disruptions on recovery could be analyzed covering the prediction of occurring multiple hazards.

(ii) The hybrid recovery could also be improved in terms of a more efficient search scheme for the resilient combination of strategies. Moreover, finding an optimum switching point could also be a great improvement.

(iii) The variety of different resilience metrics values could be investigated to determine the standard for a sophisticated resilience metric that can be applied in a wide range of infrastructure applications. Further analysis could be conducted for resilience values in using performance metrics with “smaller the better” concept.

(iv) A degradation model based on failure patterns of the networks could be developed in order to prevent the damage of the network from propagating and planning for an optimal recovery strategy.

(v) Finally, the network specific criticality analysis could be performed. Because the criticality of network components could affect network failure as well as the recovery process.

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