Transmission-Distribution Coordination for Enhancing Grid Resiliency Against Flood Hazards

Mohadese Movahednia, *Student Member, IEEE*, Reza Mahroo, *Student Member, IEEE*, Amin Kargarian, *Senior Member, IEEE*

***Abstract*—Flooding poses a significant threat to power system infrastructures, especially substations, causing widespread outages. Prior preventive actions can avert significant financial losses and prolonged disruptions. Protecting electrical substations by Tiger Dams before flooding is a temporary yet effective solution to improve power grid resiliency. Nonetheless, resource constraints prevent the protection of all substations. This paper proposes a two-stage stochastic optimization problem for proactive substation protection within both transmission and distribution systems, aiming to optimize grid resilience with a set of short-term operational actions. Transmission and distribution substation protection actions are coordinated to obtain a more effective protection scheme against flooding. A flood-aware optimal power flow is incorporated into the optimization model taking into account flood-related constraints coupling transmission and distribution systems. The possibility of transferring load through normally open switches of distribution systems is added to the model. The optimization problem is linearized and cast as a mixed-integer linear program. The efficiency of the proposed model is tested on a 24-bus system containing 24 transmission substations and 40 distribution substations.**

***Index Terms*—Flood hazards, proactive substation protection, Tiger Dam, two-stage stochastic approach, power system resiliency.**

I. Introduction

According to the US Department of Energy, extreme weather events are the leading cause of power outages in the United States [1]. Infrastructure damages and energy not supplied caused by extreme weather events impose millions of dollars of loss to the power grid. Between 2003 and 2012, approximately 679 power outages, each affecting at least 50,000 customers, occurred due to hazardous weather events in the US [1]. Hurricane Sandy in 2012, for instance, knocked out power for 8.5 million customers. The estimated cost of weather-related outages in 2012 alone is $27-$52 billion [1]. More recently, Hurricane Harvey in 2017 left nearly 300,000 customers in Louisiana and Texas without power. One substation was substantially damaged and six were reconfigured or bypassed due to flood [2]. Due to power outages, crude oil and natural gas production was reduced by more than 80% [3]. Hurricane Irma, as another example, brought record flooding to Jacksonville, FL, in 2017, and more than 7 million customers were left without power with total damages exceeding $1 billion [4]. Such events have demonstrated power grid vulnerability to hazardous weather. Moreover, the number and intensity of extreme weather events are expected to increase due to climate change and sea level rise [5]–[7]. Therefore, enhancing power grid resilience and its capacity to endure, recover, and adapt to such inevitable extreme events is crucial. Diverse approaches are available to manage and mitigate the consequences of different extreme events [8], [9]. For example, addressing earthquakes often involves post-event recovery efforts due to limited pre-incident preparations [10]. Handling hurricanes that disrupt transmission lines often centers on employing stochastic unit commitment methods to minimize load shedding and devising effective recovery strategies [11]. The impacts of flooding can be mitigated through the adoption of protective actions prior to the occurrence, as well as through restorative actions. [12], [13].

In the pursuit of improving power grid resiliency, long-term infrastructure hardening is a viable option [13]–[18]. However, recent events have proved that long-term hardening is not sufficient and needs to be augmented by short-term operational actions. Identifying vulnerable components and tripping them out before an incident would reduce load shedding [19], [20]. Network reconfiguration is also an effective solution to reduce energy not supplied [21]. Optimal pre-positioning of mobile generators and crew teams is another effective short-term operational strategy for load shedding reduction [22]. Demand response and energy storage scheduling can be used to reduce load curtailment [23]. Cascading outages can be mitigated by islanding [24]. Optimal restoration actions are critical for effectively restoring the power system to its pre-event state. Allocating crew teams in the restoration stage and scheduling generators and energy storage to quickly restore the power system while minimizing load shedding is another effective short-term operational action [25], [26].

Flooding is the primary hazard to the power system in terms of cost and loss of life [16]. Flooding can cause severe damage to electrical components, particularly substations, resulting in prolonged power outages. Elevating electrical substations and long-term power system hardening have proven to be effective, but they cannot be relied upon as standalone solutions. Long-term planning for substation hardening is presented in [13]. A resiliency index to assess the impact of flooding in levee-protected areas under a changing climate is presented in [27], [28]. [29] presents a strategy to redirect floodwaters from flood-prone utility poles which frequently result in power outages during flood events. In [30], a two-stage optimization model is introduced to effectively establish multiple islands

This work was supported by the National Science Foundation under Grants ECCS-1944752 and CMMI-2242643.

The authors are with the Department of Electrical and Computer Engineering, Louisiana State University, Baton Rouge, LA 70803 USA (e-mail: mmovah4@lsu.edu, rmahro1@lsu.edu, kargarian@lsu.edu).

within the system following flooding and serve loads through mobile generation units. [31] presents a scenario-based two-stage stochastic optimization approach to determine the optimal investment budget to enhance grid resiliency and minimize the total costs across a multi-year planning period.

Abstracting flood data, substation failure rate and expected costs of the system from historical data is an important preliminary step in developing a model. Flood data abstraction and its impact on individual substations are presented in [12], [32]–[34]. Installing temporary barriers such as sandbags and Tiger Dams prior to a flood incident is an effective yet practical solution to mitigate substations' vulnerability and enhance power grid resilience [12]. Crew team allocation for installing Tiger Dams one day prior to flooding is presented in [12], [35]. A two-stage stochastic approach is presented in [36], [37] to perform proactive protection actions. Authors of [36], [37] assume that varying levels of resiliency can be achieved for substations by installing different numbers of layers of Tiger Dams. However, it is important to note that installing layers of Tiger Dams less than the expected flood level will not protect substations while installing more layers than necessary will not enhance resiliency beyond an expected level.

Nevertheless, limited studies are available on system-level analysis of flood-induced hazards on power systems and systematic protection of substations against flooding. The lack of understanding and modeling of the impact of floods on power systems has hindered the development of effective mitigation strategies to protect critical infrastructure. In addition, the lack of coordination between transmission and distribution substations protection may yield inefficient management of resources to protect the grid and, thus, resilience degradation. A systematic decision-making approach is needed to proactively protect transmission and distribution substations in a coordinated manner.

To address this gap, this paper presents a resource allocation optimization problem to protect power transmission and distribution substations against flood-induced hazards using Tiger Dams. The proposed approach focuses on short-term operational actions. Installing Tiger Dams around substations reduces the vulnerability of substations, resulting in fewer failures during a flood event and a more resilient system that can return to its normal state more quickly. The installation of Tiger Dams occurs a few days prior to anticipated flooding, ensuring that the entire process is completed before the flood event commences. As a result, the challenges faced during the grid restoration phase following flooding, such as road closures and travel disruptions, do not apply to this specific problem. The proposed optimization model serves as a guide, aiding operators in resource allocation decisions in the days prior to a flood while also allowing them to make real-time adjustments during the flood event. By conducting a system-level analysis of flood-induced hazards and strategically distributing resources, our model aims to maximize the resilience of transmission and distribution systems. By system-level analysis, we mean a decision-making model that takes the entire power system into account and finds the best set of proactive actions for substation protection. The main contributions of the paper are summarized as follows:

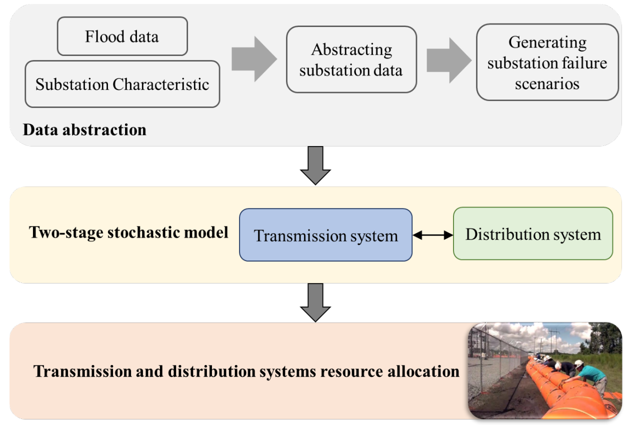

Fig. 1: Flowchart of the proposed framework.

- A two-stage stochastic optimization model, customized to coordinate proactive protection of transmission and distribution systems a day before anticipated flood occurrences, is formulated. This model integrates a flood-aware optimal power flow by taking substation availability into account. Flood-related constraints within the transmission and distribution (T&D) systems, in addition to coupling constraints between the two, as well as limitations of crew team resources are developed. This comprehensive model, to the best of our knowledge, represents a novel advancement absent from prior literature.
- Power transfer capability through normally open switches located within the distribution system is formulated. This aspect is incorporated into our decision-making processes to optimize the utilization of available resources within the power system.
- To facilitate efficient execution, a set of linearization techniques is proposed to cast the resource allocation optimization as a mixed-integer linear problem.

The simulation results show the effectiveness of the proposed approach to enhance grid resilience against flooding. The adaptable nature of the proposed model extends beyond flood events. With minor adjustments, it holds the potential to identify critical substations in different applications, such as cyber-attacks, thereby showcasing its versatility and broader applicability. Table I provides a comprehensive comparison between this paper and existing literature.

The rest of this paper is organized as follows. The proposed two-stage optimization problem is formulated in Section II. Grid resilience improvement by normally open switches is included in the model in Section III. The model is linearized in Section IV. Numerical simulations are discussed in Section V. Concluding remarks and future work are provided in Sections VI and VII.

II. Proposed Optimization Model

An overview of the proposed day-ahead substation protection framework is shown in Fig. 1. In the middle block, transmission and distribution decisions are coordinated. As shown in Fig. 2, transmission substations feed distribution substations. Uncoordinated protection of transmission and

TABLE I: Comparison of the proposed model with relevant literature

Ref.	Model	Flood impact on substation	Long term plans	Short term plans	Switching	T&D co-ordination
[13]	It minimizes the expected cost of transmission system across a multi-year time frame to enhance substations resiliency through long-term hardening.	✗	✓	✗	✗	✗
[23]	It presents a strategy to use demand response, energy storage scheduling, and network reconfiguration during flooding to reduce load curtailment.	✗	✗	✓	✓	✗
[27], [28]	It presents a resiliency index to assess the impact of flooding in levee-protected areas under a changing climate.	✓	✗	✗	✗	✗
[29]	It presents a strategy to redirect floodwaters from flood-prone utility poles which frequently result in power outages during flood events.	✗	✗	✓	✗	✗
[30]	It introduces a two-stage optimization model to effectively establish multiple islands within the system following flooding and serve loads through mobile generation units.	✗	✗	✓	✓	✗
[32], [33]	It evaluates flood impacts on individual substations and outlines the process of abstracting substation data using a probabilistic approach.	✓	✗	✗	✗	✗
[31], [34]	It assesses the financial aspects of long-term hardening strategies.	✗	✓	✗	✗	✗
[12]	It presents a stochastic approach to minimize the expected cost and allocate resources for substations protection with Tiger Dam, without considering network connections.	✓	✗	✓	✗	✗
[36], [37]	It presents a two-stage stochastic approach to minimize load shedding through the installation of Tiger Dams around substations. Different levels of resiliency are considered and determined by the number of Tiger Dam's layers that are installed.	✗	✗	✓	✗	✗
This study	It presents a two-stage stochastic optimization approach to protect substations in transmission and distribution systems in a coordinated manner by Tiger Dam. Normally open switches are incorporated in the model to improve power grid resiliency. A set of linearization techniques is proposed to cast the resource allocation optimization as mixed-integer linear programming.	✗	✗	✓	✓	✓

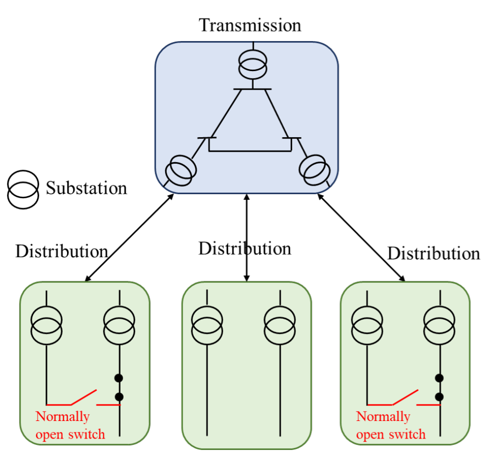

Fig. 2: Transmission and distribution systems interconnections.

distribution substations may lead to ineffective decisions and overall system resilience degradation. Assume protecting a distribution substation j whose upstream transmission substation k has failed. Although protecting distribution substation j reduces the structural damage cost, it does not prevent the outage of loads connected to this substation.

We consider protection, structural damage, and load-shedding costs as indicators of the criticality of a substation. The proposed framework is formulated as a two-stage stochastic optimization problem. Stage one refers to the time before a flood event, and stage two refers to the time after the realization of the flood scenario. Decisions corresponding to protecting substations with Tiger Dams are the first-stage variables, known as here-and-now decisions. These decisions are made by the system operator a day before an incident, based on the available resources and taking into account flood uncertainty. Given the first-stage protection decisions, the second-stage wait-and-see decisions are adjustments of generating unit production and load curtailment to mitigate damages after the realization of a flood scenario. A compact formulation of the proposed two-stage stochastic model is presented in (1a)-(1b):

$$\begin{aligned} \min_x \; & f(x) + E_s[z_s] \\ s.t. \quad & h(x) \le 0 \\ & x \in \{0,1\} \end{aligned} \tag{1a}$$

$$\begin{aligned} z_s = \{ & \min_{y_s} f(y_s) \\ s.t. \quad & g_s(x, y_s) \le 0 \\ & y_s \in \mathbb{R}\}, \forall s \end{aligned} \tag{1b}$$

$f(x)$ is the first stage cost. $E_s[z_s]$ is the second-stage expected costs. (1b), which constraints problem (1a), represents operational decisions per scenario s. x are binary variables representing protection decisions of transmission and distribution substations and the status of normally open switches. y are flood scenario-dependent variables, such as thermal unit generations, availability of substations, and load shedding. $h(x)$ are the first-stage equality and inequality constraints, such as crew team constraints. $g_s(x, y_s)$ are the second-stage scenario-dependent operational constraints, such as nodal power balance and generation boundaries.

We generate a set of substation failure scenarios and reformulate (1) as follows:

$$\begin{aligned} \min_x f(x) + & \sum_{\forall s} \pi_s f(y_s) \\ s.t. \quad & h(x) \le 0 \\ & x \in \{0,1\} \\ & g_s(x, y_s) \le 0, \forall s \\ & y_s \in \mathbb{R}, \forall s \end{aligned} \tag{2}$$

We explain uncertainty modeling, objective function, and constraints in the next sections.

A. Uncertainty Modeling

The level of flood severity in substation locations may vary considerably as transmission and distribution substations cover a large geographic area. Assuming that all substations are subject to the same flooding conditions simplifies the model but makes it unrealistic. The vulnerability of a substation to flooding depends on its structure and elevation as well as flood depth and duration. Knowing substations that would fail due to a flood allows system operators to plan preventive operational actions effectively for the upcoming day. However, this information is unavailable due to the unpredictable nature of flooding.

We employ a stochastic approach and generate a set of substation failure scenarios. In each failure scenario, we consider two mutually exclusive conditions for each substation, "fail" and "survive." The fail condition is labeled with “1” and the survive condition with “0”. We use index k for transmission and j for distribution. F_{js} refers to the condition of distribution substation j in scenario s, and F_{ks} refers to the condition of transmission substation k in scenario s. 2^{J+K} scenarios can be generated for $J + K$ substations, where J and K are the total numbers of distribution and transmission substations in the flooded region. Generating all possible scenarios makes the problem computationally expensive and is unnecessary due to the low probability of many of these scenarios. Generating a smaller set of scenarios that represent all possible scenarios is more efficient. We generate a set of representative scenarios using a scenario reduction method presented in [12]. First, required data for the scenario reduction method, including substation failure rates, expected damage, damage cost, and repair time, are abstracted from flood depth and substation characteristics such as fragility, damage curve, and price. The substation importance level for the grid is defined and evaluated by substation load, repair time, and damage cost. A two-dimensional space is created by placing the importance level of substations on the y-axis and the failure rate on the x-axis as shown in Fig. 3. By defining multiple horizontal and vertical thresholds, the 2-D space is divided into smaller regions. The intersections of thresholds are called scenario points. A substation failure scenario can be generated for each scenario point. To do so, substations located on the right and above a scenario point are considered failed and the rest survived. Using this method, substations with higher failure rates and importance levels are considered "failed" in more scenarios. The proposed two-stage stochastic optimization is designed to protect substations considered "failed" in multiple scenarios. Therefore, the proposed approach selects substations with high failure rates and importance levels as critical substations to be protected.

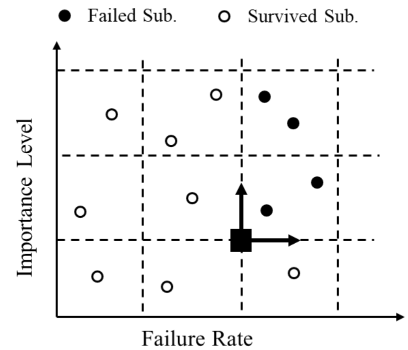

Fig. 3: Scenario reduction method based on substations failure rates and importance levels.

We use the substation outage modeling of [12] to calculate substation failure rates. The probability of each scenario s is calculated based on the substation failure rate.

$$\begin{aligned} \pi_s = & \prod_{\forall j} \left(F_{js}\pi_j + (1 - F_{js})(1 - \pi_j)\right) \\ & \times \prod_{\forall k} \left(F_{ks}\pi_k + (1 - F_{ks})(1 - \pi_k)\right) \end{aligned} \tag{3}$$

where π_s is the probability of scenario s. π_j and π_k are the failure rate of distribution substation j and transmission substation k, respectively. $(1 - \pi_j)$ and $(1 - \pi_k)$ are the survival probabilities of substations j and k, respectively. The first term of (3) is the product of distribution substation condition rates. If the condition of substation j is fail, $F_{js} = 1$, with a probability of π_j. If the condition of substation j is survive,

$F_{js}=0$, with a probability of $(1-\pi_j)$. The second term of (3) is the product of transmission substation condition rates. In this study, the correlation between substation failure rates is neglected. This serves as a limitation of our work and offers an opportunity for future research improvement.

B. Objective function

The proposed model is designed to minimize the overall expected cost, which includes both transmission and distribution systems costs. To achieve this, we have adopted a flood-aware optimal power flow analysis approach specifically for the transmission network. Within this framework, distribution substations function as loads for the transmission substations. It is important to highlight that while our model embraces the power flow of the transmission network, we have deliberately excluded power flow considerations at the distribution level. This approach enhances the pragmatic utility of our model for real-world power utility operations.

The objective function of (2) is formulated by (4), which includes costs related to distribution and transmission substations. The first-stage cost $f(x)$ is negligible, and (4) is the second-stage cost. The first term is the expected costs imposed on the distribution system due to flooding, and the second and third terms model the expected costs imposed on the transmission system.

$$\begin{aligned}\min \sum_{\forall j}\sum_{\forall s}\pi_s F_{js}\beta_j+\sum_{\forall k}\sum_{\forall s}\pi_s F_{ks}\beta_k\\+\sum_{\forall s}\pi_s\sum_{\forall i}\sum_{\forall t} VOLL\times\mathcal{L}_{ist}\end{aligned}\tag{4}$$

where $VOLL$ is the monetary value of load shedding. $\mathcal{L}_{ist}$ is the load shedding on bus i in scenario s at time t. β_j and β_k are respectively costs associated with distribution and transmission substations. β_j is calculated as follows:

$$\beta_j=\theta_j\mathcal{C}_j+(1-\theta_j)\,\bar{\mathcal{C}}_j \tag{5}$$

where the binary variable θ_j is 1 if substation j is protected, and 0 otherwise. The system cost varies depending on whether the substation is protected or not. If substation j is protected, the cost is equal to $\mathcal{C}_j$, which is the cost of protecting the substation including Tiger Dam expenses and crew team salaries. $\mathcal{C}_j$ is negligible compared with other costs. $\bar{\mathcal{C}}_j$ is the distribution system cost due to failure to protect substation j against flooding.

$$\bar{\mathcal{C}}_j=\mathcal{D}_j+\Gamma_j \tag{6}$$

where $\mathcal{D}_j$ is the damage cost to the structure of distribution substation j and is assumed a given input. Γ_j is the energy not supplied cost of substation j and is calculated by (7).

$$\Gamma_j=\sum_{t}^{T_j^{out}}\omega_j P_{jt}^{load}\Lambda_j \tag{7}$$

where ω_j is a weighting coefficient to model the importance level of load connected to substation j. P_{jt}^{load} is load of substation j at time t. Λ_j is the price of load connected to substation j. T_j^{out} is the duration of the substation outage.

The cost associated with transmission substation k is calculated by (8).

$$\beta_k=\theta_k\mathcal{C}_k+(1-\theta_k)\,\mathcal{D}_k \tag{8}$$

where β_k represents the cost related to transmission substation k. The binary variable θ_k is the protection decision of substation k, which is 1 if it is protected, and 0 otherwise. $\mathcal{C}_k$ is the protection cost of substation k, which is negligible as compared to other costs. $\mathcal{D}_k$ shows the structural damage cost of substation k. Since load shedding due to transmission substation failures depends on network connections, load shedding cost is considered separately in the objective function.

C. Distribution System Constraints

The availability of distribution substation j in scenario s, represented by $\mathfrak{h}_{js}$ in (9), depends on its failure condition and protection decision. $\mathfrak{h}_{js}$ is 1 if substation j is available and 0 otherwise. For instance, if substation j is considered failed in scenario s and not protected, it is unavailable and $\mathfrak{h}_{js}=0$.

$$\mathfrak{h}_{js}=1-F_{js}\,(1-\theta_j)\,,\ \forall j \tag{9}$$

The availability of distribution substation j in scenario s impacts the load on transmission buses, which makes distribution and transmission systems correlated, as explained in Section II-E.

D. Transmission System Constraints

The availability of transmission substations impacts distribution system protection decisions. Also, the generation of thermal units and the availability of transmission lines connected to them depend on the availability of transmission substations. Expression (10) shows the availability of transmission substation k in scenario s.

$$\mathfrak{h}_{ks}=1-F_{ks}\,(1-\theta_k)\,,\ \forall k,\forall s \tag{10}$$

If transmission substation k is unavailable, the generation output of the thermal unit connected to this substation must be zero. This is modeled by multiplying the thermal unit generation boundaries by substation availability, as shown in (11). The ramp limitations of thermal units are enforced by (12) and (13).

$$\mathfrak{h}_{ks}P_g^{min}\le p_{gst}\le \mathfrak{h}_{ks}P_g^{max},\ \forall g,\forall s,\forall t \tag{11}$$

$$p_{gst}-p_{gst-1}\le\mathcal{RU}_g,\ \forall g,\forall s,\forall t \tag{12}$$

$$p_{gst-1}-p_{gst}\le\mathcal{RD}_g,\ \forall g,\forall s,\forall t \tag{13}$$

where p_{gst} is the power generation of unit g in scenario s at time t. P_g^{min} and P_g^{max} are generation boundaries. $\mathcal{RU}_g$ and $\mathcal{RD}_g$ are the ramp up and ramp down capabilities.

The availability of line l in scenario s, represented by $\mathfrak{h}_{ls}$, depends on the availability of its origin and destination substations. The line will be unavailable if at least one terminal is unavailable. $\mathfrak{h}_{ls}$ is modeled by (14) as the product of the availability of origin and destination substations. If line l is not available, its power flow must be zero, and the voltage angles of origin and destination nodes need to be independent as enforced by (15)-(17). The nodal power balance is enforced by (18). The load shedding on node i must be limited by (19).

$$\mathfrak{h}_{ls} = \mathfrak{h}_{k_o s}\mathfrak{h}_{k_d s},\ \forall l, \forall s \tag{14}$$

$$-\mathfrak{h}_{ls} f_l^{max} \leq f_{lst} \leq \mathfrak{h}_{ls} f_l^{max},\ \forall l, \forall s, \forall t \tag{15}$$

$$f_{lst} + M\left(1 - \mathfrak{h}_{ls}\right) \geq B_l\left(\triangle\delta_{st}\right),\ \forall l, \forall s, \forall t \tag{16}$$

$$f_{lst} \leq M\left(1 - \mathfrak{h}_{ls}\right) + B_l\left(\triangle\delta_{st}\right),\ \forall l, \forall s, \forall t \tag{17}$$

$$\sum_{\forall g \in \Omega^i} p_{gst} + \mathcal{L}_{ist} - p_{ist}^d = \sum_{\forall l \in \Omega^i} f_{lst},\ \forall i, \forall s, \forall t \tag{18}$$

$$0 \leq \mathcal{L}_{ist} \leq p_{ist}^d,\ \forall i, \forall s, \forall t \tag{19}$$

where $\mathfrak{h}_{k_o s}$ and $\mathfrak{h}_{k_d s}$ are respectively the origin and destination substation availability. f_{lst} is power flow in line l in scenario s at time t. f_l^{max} is the capacity of line l. B_l is line susceptance. $\triangle\delta_{st}$ is the difference between ending terminal voltage angles in scenario s. M is a big constant, making voltage angles independent if line l is unavailable, i.e., $\mathfrak{h}_{ls} = 0$. p_{ist}^d is the total load connected to node i in scenario s at time t. Nonlinear constraint (14) is linearized in Section IV.

E. Transmission and Distribution Systems Coupling Constraints

The protection decisions of transmission and distribution substations are interdependent. The load on a transmission substation k is affected by the availability of downstream distribution substations, and vice versa. The interdependency between the transmission and distribution systems becomes apparent through their operational status. In simpler terms, the availability of distribution substations directly affects the amount of load carried by transmission substations. Additionally, the availability of transmission substations determines whether the load can be successfully delivered. We formulate constraints (20) and (21) to model interconnections between distribution and transmission systems.

$$p_{ist}^d \leq \sum_{j \in \Omega^k} \mathfrak{h}_{js} P_{jt}^{load},\ \forall i, \forall s, \forall t \tag{20}$$

$$\left(1 - \mathfrak{h}_{ks}\right) \sum_{j \in \Omega^k} \mathfrak{h}_{js} P_{jt}^{load} \leq p_{ist}^d,\ \forall i, \forall s, \forall t \tag{21}$$

If transmission substation k is available, $\mathfrak{h}_{ks} = 1$ and we have $0 \leq p_{ist}^d \leq \sum_{j \in \Omega^k} \mathfrak{h}_{js} P_{jt}^{load}$, meaning that the demand of substation k can vary between zero and the summation of load of available downstream distribution substations connected to substation k. If substation k is not available, $\mathfrak{h}_{ks} = 0$ and we have $P_{ist}^d = \sum_{j \in \Omega^k} \mathfrak{h}_{js} P_{jt}^{load}$. According to (11), (15) and (18), if substation k is not available, we have $p_{gst} = 0$, $f_{lst} = 0$ and $\mathcal{L}_{ist} = p_{ist}^d$. Therefore, the load of substation k is equal to $\sum_{j \in \Omega^k} \mathfrak{h}_{js} P_{jt}^{load}$ all of which will be shed given that substation k is not available.

F. Transmission and Distribution Systems Common Constraints

The number of substations that can be protected depends on available crew teams, Tiger Dam installation time, and available protection window before flooding. We assume that transmission and distribution systems have their own resources, such as crew teams, and separately determine the optimal crew schedule. The constraints pertaining to crew team scheduling are similar for transmission and distribution systems. We explain these constraints for transmission substations using index k. The same set of constraints must be incorporated into the optimization model for the distribution system. We assume a single distribution company that consolidates resources for all distribution-level substations.

The time required to install Tiger Dams, τ, is determined based on the average flood depth at the substation location and crew team availability.

$$\tau_k = \frac{4 + 10\left(\mathcal{FD}_k - 0.45\right)}{\mathcal{M}_n},\ 0.45 \leq \mathcal{FD}_k \leq 1.5 \tag{22}$$

where τ_k is the time to install Tiger Dams at substation k. $\mathcal{FD}_k$ is the average flood depth at substation k. $\mathcal{M}_n$ is the number of team members in crew n.

Allocation of crew teams a day before a flood event depends on the total hours available for performing protection actions and the number of crew teams. Only one crew team performs protection actions at a substation. Each crew team would finish installing Tiger Dams at a substation before moving on to the next one. After spending the required time to install the Tiger Dam, each crew team would complete the installation actions. Traveling time between substations is neglected. The limitations described above are modeled by (23)-(28).

$$\sum_{\forall n} \sum_{\forall k} \sum_{\forall \tilde{t}} u_{nk\tilde{t}} \leq \mathcal{N}^{team} \mathcal{T} \tag{23}$$

$$\sum_{\forall n} \sum_{\forall \tilde{t}} u_{nk\tilde{t}} = \theta_k \tau_k,\ \forall k \tag{24}$$

$$\sum_{\forall k} u_{nk\tilde{t}} \leq 1,\ \forall n, \forall \tilde{t} \tag{25}$$

$$\frac{u_{nk\tilde{t}} - u_{nk\tilde{t}-1}}{2} - \epsilon \leq o_{nk\tilde{t}},\ \forall n, \forall k, \forall \tilde{t} \tag{26}$$

$$o_{nk\tilde{t}} \leq \frac{1 + u_{nk\tilde{t}} - u_{nk\tilde{t}-1}}{2} + \epsilon,\ \forall n, \forall k, \forall \tilde{t} \tag{27}$$

$$\sum_{\forall n} \sum_{\forall \tilde{t}} o_{nk\tilde{t}} \leq 1,\ \forall k \tag{28}$$

where index $\tilde{t}$ is the time intervals showing crew scheduling. n is the index for crew teams. $\mathcal{T}$ is the total available time to perform protection actions. $\mathcal{N}^{team}$ is the number of available crew teams. $u_{nk\tilde{t}}$ is a binary variable for crew team dispatch. For instance, if $u_{nk\tilde{t}} = 1$, crew team n is scheduled to perform protection action at substation k at time $\tilde{t}$. ϵ is a small positive number. $o_{nk\tilde{t}}$ is an auxiliary binary variable enforcing the number of teams dispatched to a substation location to be at most one.

III. Resiliency Improvement Through Switching

Transferring loads between neighboring distribution substations using normally open points can reduce energy not supplied. We model load transfer capability in the proposed two-stage substation protection approach. Leveraging such resources enhances grid resilience against flooding. A normally open switch between two distribution substations $\tilde{j}$ and j can transfer a portion of the load from substation $\tilde{j}$ to substation j if the switch is closed. We modify (7) by replacing the load of substation j, P_{jt}^{load}, with p_{jt}^{load}:

$$p_{jt}^{load} = P_{jt}^{load} + A\gamma P_{\tilde{j}t}^{load},\ \forall j, \tilde{j} \tag{29}$$

where A is a constant representing the percentage of the load from substation $\tilde{j}$ that can be transferred to substation j. γ is a binary variable that indicates the status of the normally open switch and is equal to 1 if the switch is closed. $P_{\tilde{j}t}^{load}$ is the load of neighboring substation $\tilde{j}$. The load of substation $\tilde{j}$ also changes as follows:

$$p_{\tilde{j}t}^{load} = (1-A)P_{\tilde{j}t}^{load} + A(1-\gamma)P_{\tilde{j}t}^{load},\ \forall \tilde{j} \tag{30}$$

If the switch is open, $\gamma = 0$ and the load of substation $\tilde{j}$ is equal to $P_{\tilde{j}t}^{load}$. If the normally open switch is closed, the load of substation $\tilde{j}$ will reduce by $AP_{\tilde{j}t}^{load}$. When the normally open switch is closed, another switch will open, disconnecting the transferred load from substation $\tilde{j}$.

According to (29) and (30), the load of distribution substations depends on binary variables γ and thus are variables. This makes $\bar{\mathcal{C}}_j$ and Γ_j calculated in (6) and (7), variables and thus the model nonlinear.

IV. Model Linearization

Several nonlinear terms appear in the proposed two-stage model making it a mixed-integer nonlinear program that is hard to solve. We linearize the model to make it a mixed-integer linear program solvable by standard solvers.

A. Linearization Without Switching

Constraint (14): The availability of line l in scenario s is calculated as the product of two binary variables. We linearize (14) by replacing it with (31)-(33).

$$\mathfrak{h}_{ls} \leq \mathfrak{h}_{k_o s},\ \forall l, \forall s \tag{31}$$

$$\mathfrak{h}_{ls} \leq \mathfrak{h}_{k_d s},\ \forall l, \forall s \tag{32}$$

$$\mathfrak{h}_{ls} \geq \mathfrak{h}_{k_o s} + \mathfrak{h}_{k_d s} - 1,\ \forall l, \forall s \tag{33}$$

Constraint (21): The term $\mathfrak{h}_{ks} \sum_{j\in\Omega^k} \mathfrak{h}_{js} P_{jt}^{load}$ is nonlinear as it includes the product of two binary variables $\mathfrak{h}_{ks}$ and $\mathfrak{h}_{js}$. We introduce an auxiliary variable as $\lambda_{ist} = \mathfrak{h}_{ks} \sum_{j\in\Omega^k} \mathfrak{h}_{js} P_{jt}^{load}$ and linearize the nonlinear term as follows:

$$\lambda_{ist} \leq \mathfrak{h}_{ks} M,\ \forall i, \forall s, \forall t \tag{34}$$

$$\lambda_{ist} \leq \sum_{j\in\Omega^k} \mathfrak{h}_{js} P_{jt}^{load},\ \forall i, \forall s, \forall t \tag{35}$$

$$\lambda_{ist} \geq \sum_{j\in\Omega^k} \mathfrak{h}_{js} P_{jt}^{load} - (1-\mathfrak{h}_{ks})M,\ \forall i, \forall s, \forall t \tag{36}$$

$$\lambda_{ist} \geq 0,\ \forall i, \forall s, \forall t \tag{37}$$

Substituting auxiliary variable λ_{ist}, we rewrite (21) by (38).

$$\sum_{j\in\Omega^k} \mathfrak{h}_{js} P_{jt}^{load} - \lambda_{ist} \leq p_{ist}^{d},\ \forall i, \forall s, \forall t \tag{38}$$

Model Summary: The proposed mixed-integer linear program is summarized as follows:

$$\min_{x, y_s} (4) \tag{39}$$

$$\text{s.t. } (3), (5)\text{-}(13), (15)\text{-}(20), (22)\text{-}(28), (31)\text{-}(38)$$
$$x = \{\theta_j, \beta_j, \theta_k, \beta_k, \tau_k, u_{nk\tilde{t}}, o_{nk\tilde{t}}\}$$
$$y_s = \{\mathfrak{h}_{js}, \mathfrak{h}_{ks}, p_{gst}, \mathfrak{h}_{ls}, f_{lst}, \triangle\delta_{st}, \mathcal{L}_{ist}, p_{ist}^{d}, \lambda_{ist}\}$$

where x are the first-stage here-and-now decision variables, and y_s are the second-stage wait-and-see variables.

B. Linearization With Switching

Expression (5): $\bar{\mathcal{C}}_j$ is a variable if load transfer is considered. We introduce a continuous auxiliary variable $\mathcal{C}_j'$, replace (5) by (40), and linearize the nonlinear product term $\bar{\mathcal{C}}_j \theta_j$ by (41)-(44).

$$\beta_j = \theta_j \mathcal{C}_j + \bar{\mathcal{C}}_j - \mathcal{C}_j',\ \forall j \tag{40}$$

$$\mathcal{C}_j' \leq \theta_j M,\ \forall j \tag{41}$$

$$\mathcal{C}_j' \leq \bar{\mathcal{C}}_j,\ \forall j \tag{42}$$

$$\mathcal{C}_j' \geq \bar{\mathcal{C}}_j - (1-\theta_j)M,\ \forall j \tag{43}$$

$$\mathcal{C}_j' \geq 0,\ \forall j \tag{44}$$

Constraints (20) and (21): Constant P_{jt}^{load} is replaced by variable p_{jt}^{load} if normally open switches are considered. We define $\mu_{jst} = \mathfrak{h}_{js} p_{jt}^{load}$ and $\alpha_{st} = \sum_{j\in\Omega^k} \mu_{jst}$ and formulate (45)-(48).

$$\mu_{jst} \leq \mathfrak{h}_{js} M,\ \forall j, \forall s, \forall t \tag{45}$$

$$\mu_{jst} \leq p_{jt}^{load},\ \forall j, \forall s, \forall t \tag{46}$$

$$\mu_{jst} \geq p_{jt}^{load} - (1-\mathfrak{h}_{js})M,\ \forall j, \forall s, \forall t \tag{47}$$

$$\mu_{jst} \geq 0,\ \forall j, \forall s, \forall t \tag{48}$$

The term $\mathfrak{h}_{ks} \sum_{j\in\Omega^k} \mathfrak{h}_{js} p_{jt}^{load}$ in (21) is now $\mathfrak{h}_{ks}\alpha_{st}$, which is nonlinear as it includes the product of a binary variable $\mathfrak{h}_{ks}$ and a continuous variable α_{st}. We introduce an auxiliary variable $\eta_{kst} = \mathfrak{h}_{ks}\alpha_{st}$ and linearize it as follows:

$$\eta_{kst} \leq \mathfrak{h}_{ks} M,\ \forall k, \forall s, \forall t \tag{49}$$

$$\eta_{kst} \leq \alpha_{st},\ \forall k, \forall s, \forall t \tag{50}$$

$$\eta_{kst} \geq \alpha_{st} - (1-\mathfrak{h}_{ks})M,\ \forall k, \forall s, \forall t \tag{51}$$

$$\eta_{kst} \geq 0,\ \forall k, \forall s, \forall t \tag{52}$$

Using (45)-(52), we rewrite (20) and (21) with (53) and (54).

$$p_{ist}^{d} \leq \alpha_{st},\ \forall i, \forall s, \forall t \tag{53}$$

$$\alpha_{st} - \eta_{kst} \leq p_{ist}^{d},\ \forall i, \forall s, \forall t \tag{54}$$

Model Summary: The linearized model considering normally open points is summarized as follows:

$$\min_{x,y_s} (4) \tag{55}$$

$$\text{s.t. } (3), (6)\text{-}(13), (15)\text{-}(19), (22)\text{-}(33),(40)\text{-}(54)$$
$$x = \{\theta_j, \beta_j, \theta_k, \beta_k, \tau_k, u_{nk\tilde{t}}, o_{nk\tilde{t}}, \gamma, p^{load}_{jt}, \mathcal{C}'_j\}$$
$$y_s = \{\mathfrak{h}_{js}, \mathfrak{h}_{ks}, p_{gst}, \mathfrak{h}_{ls}, f_{lst}, \triangle\delta_{st}, \mathcal{L}_{ist}, p^d_{ist}, \lambda_{ist}, \mu_{jst}, \alpha_{st}, \eta_{kst}\}$$

V. Numerical Simulations

The proposed methodology is put to the test using the IEEE 24-bus system [38]. This network includes 24 transmission substations and 40 distribution substations, their interconnections elaborated in Table II. The protection of transmission and distribution substations is performed by three and five teams, respectively, each team comprising four crew members. This proactive approach is executed within a ten-hour window the day prior to a potential incident. The process of substation data abstraction and failure scenario generation are thoroughly presented in our prior work [12]. For the sake of brevity, we assume that these data have been supplied as inputs for this study. Substation data, encompassing failure probabilities, expected damage percentages, expected damage costs, and repair times, are extrapolated from flood data and substation-specific fragility curves, damage curves, repair time curves, and cost considerations. Due to the unavailability of real-world data, we made assumptions regarding average flood data in substation locations [12]. Using the scenarios generation and reduction explained in Section II-A, eleven substation failure scenarios are generated and tabulated in Table III. These scenarios, which offer a nuanced outlook, are harnessed to formulate the foundation of our two-stage stochastic model.

A. Crew Team Dispatch Schedule

The model identifies critical transmission and distribution substations and allocates crew teams over the 10-hour protection horizon, taking into account the required time for Tiger Dam installation. Figures 4 and 5 show the crew team scheduling. Each team completes the protection action at one substation and moves on to another location. For the sake of simplicity, the travel time between substations is ignored. Nine transmissions and 17 distribution substations are protected over the 10-hour horizon. No crew team is dispatched to more than one substation at a time. Also, at most one crew team is assigned to a substation.

B. Stochastic Model vs. No Protection

The proposed two-stage stochastic approach is compared with a case without protective action. Expected power outage, outage duration, and costs are reported in Table IV. Power outage is evaluated by aggregating the load shedding across both transmission and distribution substations. Similarly, outage duration is computed through the summation of outage time, assumed to equate to their respective repair times, for both the transmission and distribution substations. Moreover, the expected cost corresponds to the value of the objective function as detailed in (4).

The proposed approach leads to a substantial enhancement in power system resilience as compared to taking no protective action. The power outage is reduced by 61.93%, and the outage duration and system cost are lowered by 84.63% and 87.81%, respectively. These results highlight the significance of the proposed model in mitigating the negative impacts of flooding and reducing power system vulnerability to such events.

The resilience curves are depicted in Fig. 6. The area under the curve, denoted as R, is an indicator of system resiliency against the flood event. A smaller R means a more resilient system and better preparation for flooding. The area under the resilience curve is the product of power outage time outage duration, meaning R is energy. The proposed two-stage stochastic approach leads to a much smaller outage magnitude and duration than the no-protection strategy. In other words, less load curtailment occurs, and the system returns to pre-flood normal status faster.

C. Coordinated T&D vs. Uncoordinated Protection

Two cases are studied. In case 1, transmission and distribution systems are protected independently, with no awareness of each other's substation availability. The uncoordinated strategy is two stochastic optimization problems, one corresponding to the transmission system and another to the distribution system. In transmission system optimization, we assume all connected distribution substations are fully operational. Similarly, in distribution system optimization, all transmission substations are assumed to be intact and functioning. Case 2 is the proposed coordinated T&D substation protection. We assume that the same transmission substation failure scenarios of the T&D approach occur for the transmission system optimization problem of the uncoordinated approach. The same assumption is made for the uncoordinated distribution system problem as well. The failure scenario rates, as presented in (3), are modified to only consider either transmission or distribution substations for each optimization problem. However, for a fair comparison between cases 1 and 2, results calculations such as power outage and cost utilize the scenario rates obtained from the coordinated T&D approach.

The simulation results are reported in Table V. The coordinated approach leads to a 9.17% reduction in power outage magnitude. However, the total outage duration increases by 15.37%. Despite this trade-off, the coordinated strategy results in an overall cost reduction of 24.07%, which is the primary objective of the proposed model. The improved performance of the coordinated model over the uncoordinated approach can be attributed to the enhanced information-sharing and coordination between the transmission and distribution systems. This leads to better utilization of available resources and more effective decision-making. For example, in the coordinated strategy, both j40 and k20, which are interconnected substations, are protected, whereas only j40 is protected in the uncoordinated strategy. Substation k20 has a failure rate of 0.36, and protecting j40, while the supplying transmission substation k20 may fail, is an inefficient allocation of resources. Given

TABLE II: Transmission and Distribution Substations Connections

Transmission	Distribution	Transmission	Distribution	Transmission	Distribution
k1	j1-j2	k7	j13-j14	k15	j27-j28-j29
k2	j3-j4	k8	j15-j16	k16	j30-j31
k3	j5-j6	k9	j17-j18	k18	j32-j33-j34
k4	j7-j8	k10	j19-j20	k19	j35-j36-j37
k5	j9-j10	k13	j21-j22-j23	k20	j38-j39-j40
k6	j11-j12	k14	j24-j25-j26	-	-

TABLE III: Substation Failure Scenarios

Scenario	Failed substations	Rates
S1	k24	0.323
S2	k22-k23-k24	0.254
S3	k24-j15-j30	0.379
S4	k6-k7-k8-k9-k10-k21-k22-k23-k24-j12-j13-j14-j15-j27-j28-j29-j30	0.034
S5	k6-k7-k8-k9-k10-k18-k19-k20-k21-k22-k23-k24-j12-j13-j14-j15-j27-j28-j29-j30	0.005
S6	k6-k7-k8-k9-k10-k21-k22-k23-k24-j10-j11-j12-j13-j14-j15-j25-j26-j27-j28-j29-j30	0.004
S7	k3-k4-k5-k6-k7-k8-k9-k10-k18-k19-k20-k21-k22-k23-k24-j7-j8-j9-j10-j11-j12-j13-j14-j15-j22-j23-j24-j25-j26-j27-j28-j29-j30-j37-j38-j39-j40	3e-7
S8	k1-k2-k3-k4-k5-k6-k7-k8-k9-k10-k15-k16-k17-k18-k19-k20-k21-k22-k23-k24-j7-j8-j9-j10-j11-j12-j13-j14-j15-j22-j23-j24-j25-j26-j27-j28-j29-j30-j37-j38-j39-j40	2e-9
S9	k1-k2-k3-k4-k5-k6-k7-k8-k9-k10-k15-k16-k17-k18-k19-k20-k21-k22-k23-k24-j4-j5-j6-j7-j8-j9-j10-j11-j12-j13-j14-j15-j19-j20-j21-j22-j23-j24-j25-j26-j27-j28-j29-j30-j33-j34-j35-j36-j37-j38-j39-j40	2e-13
S10	k12-k13-k14-j2-j3-j4-j5-j6-j7-j8-j9-j10-j11-j12-j13-j14-j15-j17-j18-j19-j20-j21-j22-j23-j24-j25-j26-j27-j28-j29-j30-j32-j33-j34-j35-j36-j37-j38-j39-j40	3e-15
S11	All	2e-22

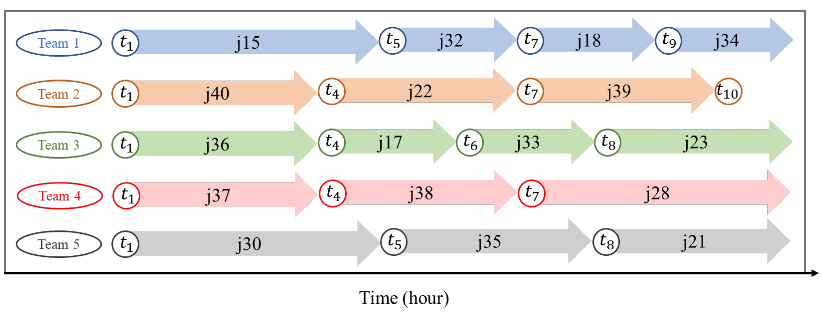

Fig. 4: Distribution system crew team schedule.

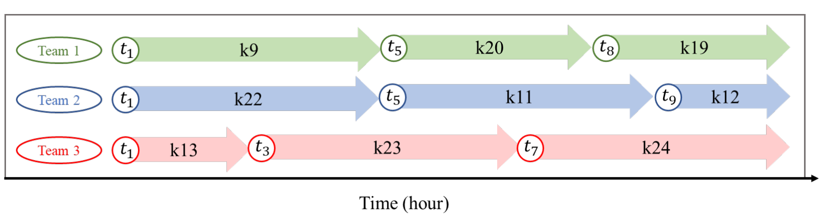

Fig. 5: Transmission system crew team schedule.

TABLE IV: Results of the Stochastic vs. No Protection Case

Model	Power outage (MW)	Outage duration (h)	Cost ($)
Stochastic	23.97	13.66	239,236
No protection	62.97	88.88	1,961,855
Improvement	61.93%	84.63%	87.81%

TABLE V: Results of the Coordinated T&D vs. Uncoordinated Approach

Model	Power outage (MW)	Outage duration (h)	Cost ($)
Coordinated T&D	23.97	13.66	239,286
Uncoordinated	26.39	11.84	315,147
Improvement	9.17%	-15.37%	24.07%

that transmission and distribution systems are not sharing information in the uncoordinated strategy, they might not make well-informed decisions, resulting in suboptimal outcomes.

D. Resiliency Improvement Via Switching

To evaluate the impact of load transfer between neighboring distribution substations, we compare the expected power

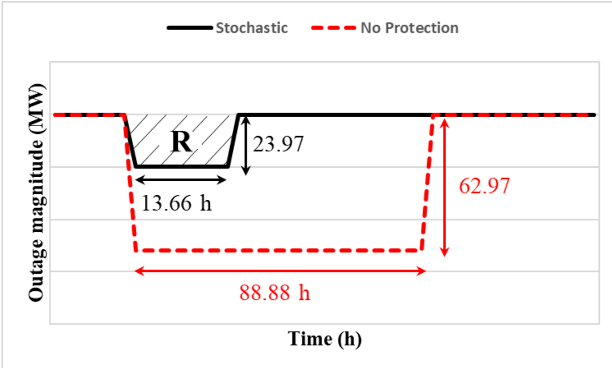

Fig. 6: Resilience curve of the two-stage stochastic approach vs. no protection case.

outage magnitude and cost with and without normally open switches. Four cases are studied: the two-stage approach without power transfer modeling, incorporating power transfer into proactive protection with two normally open switches, three switches, and four switches. In the two-switch case, one switch is considered between each substation pair (j16, j15) and (j30, j31). These switches enable transferring 30% of power from the second substation to the first substation in each pair during a flood event. The optimal solution is to close the switch connecting (j16, j15) and leave the switch linking (j30, j31) open. Table VI shows the expected power outage magnitude and cost improvement as compared to the case without power transfer. Leveraging normally open switches reduces the outage magnitude and cost by 1.83% and 0.35% as compared to the case without power transfer. These resilience improvements are due to more flexibility in load management and being able to serve demand by operational substations.

In the three-switch case, switches are located between each substation pair (j16, j15), (j27, j28), and (j30, j31). The optimal solution is to close the switches connecting (j16, j15) and (j27, j28) and leave the switch linking (j30, j31) open. The expected power outage magnitude and cost reduce by 3.13% and 0.55%. In the four-switch case, the expected power outage magnitude and cost reduce by 5.63% and 1.34%. Having more normally open switches and load transfer capability are expected to enhance resilience.

TABLE VI: Resilience Improvement with Load Transfer

Model	Power outage (MW)	Cost ($)
Two Switches	23.53 (-1.83%)	238,458 (-0.35%)
Three Switches	23.22 (-3.13%)	237,978 (-0.55%)
Four Switches	22.62 (-5.63%)	236,017 (-1.34%)

VI. Conclusion

Protecting critical substations with Tiger Dam a day before the incident enhances power system resilience significantly. A two-stage stochastic resource allocation optimization problem is formulated to identify critical substations and protect them against flood hazards. Flood uncertainty is included in the decision-making in the form of substation failure scenarios. The probability of protecting substations located in more severely flooded regions is higher. Also, substations supplying a significant amount of demand or with expensive structures whose damage would cause substantial losses are given a higher priority for protection. The model incorporates both transmission and distribution substations and takes into account their interdependency. This accounts for the potential impact of one substation on decisions made for other interconnected substations. Substation protection decisions are considered first-stage decision variables, whereas power flow-related variables, such as the amount of power transmitted through transmission lines, are regarded as second-stage variables.

A 24-bus system with 24 transmission and 40 distribution substations is used to evaluate the model's effectiveness. Optimal crew team scheduling is determined to install Tiger Dam for transmission and distribution systems protection. The proposed approach significantly improves power system resilience, as demonstrated by a 61.93% reduction in the power outage magnitude, 84.63% reduction in outage duration, and 87.81% reduction in cost as compared to the no-protective action scenario. The impact of coordinating transmission and distribution systems is evaluated by comparing the results with an uncoordinated approach. The coordinated approach leads to a reduction of 9.17% in power outage magnitude and 24.07% in cost. The resiliency improvement through switching is tested considering two, three, and four normally open switches. Load curtailment and cost are reduced by 1.83% and 0.35% in the two-switch case, 3.23% and 0.55% in the three-switch case, and 5.63% and 1.34% in the four-switch case. Integrating normally open switches into the model provides more flexibility in load management and enhances grid resilience. This allows transfer load between neighboring substations and enables demand to be served by safer substations.

VII. Future Work

As the frequency and intensity of weather events continue to increase due to climate change, it is crucial to consider the potential compounding effects of multiple weather events, particularly in vulnerable regions such as coastal areas, low-lying regions, and areas prone to natural disasters. For instance, compound flood and wind events would be more hazardous, and various proactive operational actions may be needed to enhance grid resilience.

References

[1] Executive Office of the President, "Economic benefits of increasing electric grid resilience to weather outages," tech. rep., The Council, 2013 [Online].

[2] NERC, "Hurricane harvey event analysis report," tech. rep., 2018 [Online].

[3] US department of energy, "Hurricane harvey event analysis report," tech. rep., 2017 [Online].

[4] CBSNEWS, "Irma leaves widespread devastation, flooding in florida," Sep., 2017 [Online].

[5] L. H. Erikson, A. Espejo, P. L. Barnard, K. A. Serafin, C. A. Hegermiller, A. O'Neill, P. Ruggiero, P. W. Limber, and F. J. Mendez, "Identification of storm events and contiguous coastal sections for deterministic modeling of extreme coastal flood events in response to climate change," *Coastal Engineering*, vol. 140, pp. 316–330, 2018.

[6] S. Brown, S. Hanson, and R. J. Nicholls, "Implications of sea-level rise and extreme events around europe: a review of coastal energy infrastructure," *Climatic Change*, vol. 122, no. 1-2, pp. 81–95, 2014.

[7] K. E. Trenberth, J. T. Fasullo, and T. G. Shepherd, “Attribution of climate extreme events,” *Nature Climate Change*, vol. 5, no. 8, pp. 725–730, 2015.

[8] F. H. Jufri, V. Widiputra, and J. Jung, “State-of-the-art review on power grid resilience to extreme weather events: Definitions, frameworks, quantitative assessment methodologies, and enhancement strategies,” *Applied energy*, vol. 239, pp. 1049–1065, 2019.

[9] E. Hossain, S. Roy, N. Mohammad, N. Nawar, and D. R. Dipta, “Metrics and enhancement strategies for grid resilience and reliability during natural disasters,” *Applied energy*, vol. 290, p. 116709, 2021.

[10] M. Nazemi, M. Moeini-Aghtaie, M. Fotuhi-Firuzabad, and P. Dehghanian, “Energy storage planning for enhanced resilience of power distribution networks against earthquakes,” *IEEE Transactions on Sustainable Energy*, vol. 11, no. 2, pp. 795–806, 2019.

[11] E. B. Watson and A. H. Etemadi, “Modeling electrical grid resilience under hurricane wind conditions with increased solar and wind power generation,” *IEEE Transactions on Power Systems*, vol. 35, no. 2, pp. 929–937, 2019.

[12] M. Movahednia, A. Kargarian, C. E. Ozdemir, and S. Hagen, “Power grid resilience enhancement via protecting electrical substations against flood hazards: A stochastic framework,” *IEEE Transactions on Industrial Informatics*, 2021.

[13] L. Souto, J. Yip, W.-Y. Wu, B. Austgen, E. Kutanoglu, J. Hasenbein, Z.-L. Yang, C. W. King, and S. Santoso, “Power system resilience to floods: Modeling, impact assessment, and mid-term mitigation strategies,” *International Journal of Electrical Power & Energy Systems*, vol. 135, p. 107545, 2022.

[14] M. Panteli and P. Mancarella, “The grid: Stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience,” *IEEE Power and Energy Magazine*, vol. 13, no. 3, pp. 58–66, 2015.

[15] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, “Power systems resilience assessment: Hardening and smart operational enhancement strategies,” *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1202–1213, 2017.

[16] R. E. Costa and G. R. McAllister, “Substation flood program and flood hardening case study,” in *2017 IEEE Power & Energy Society General Meeting*, pp. 1–5, IEEE, 2017.

[17] J. Boggess, G. Becker, and M. Mitchell, “Storm & flood hardening of electrical substations,” in *2014 IEEE PES T&D Conference and Exposition*, pp. 1–5, IEEE, 2014.

[18] M. Ahmadi, M. Bahrami, M. Vakilian, and M. Lehtonen, “Application of hardening strategies and dg placement to improve distribution network resilience against earthquakes,” in *2020 IEEE PES Transmission & Distribution Conference and Exhibition-Latin America (T&D LA)*, pp. 1–6, IEEE, 2021.

[19] M. Amirioun, F. Aminifar, and H. Lesani, “Resilience-oriented proactive management of microgrids against windstorms,” *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4275–4284, 2017.

[20] B. Taheri, A. Safdarian, M. Moeini-Aghtaie, and M. Lehtonen, “Distribution systems resilience enhancement via pre-and post-event actions,” *IET Smart Grid*, vol. 2, no. 4, pp. 549–556, 2019.

[21] G. Huang, J. Wang, C. Chen, J. Qi, and C. Guo, “Integration of preventive and emergency responses for power grid resilience enhancement,” *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4451–4463, 2017.

[22] S. Lei, J. Wang, C. Chen, and Y. Hou, “Mobile emergency generator pre-positioning and real-time allocation for resilient response to natural disasters,” *IEEE Transactions on Smart Grid*, vol. 9, no. 3, pp. 2030–2041, 2016.

[23] M. H. Amirioun, F. Aminifar, and H. Lesani, “Towards proactive scheduling of microgrids against extreme floods,” *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3900–3902, 2017.

[24] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, “Boosting the power grid resilience to extreme weather events using defensive islanding,” *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2913–2922, 2016.

[25] G. H. Reddy, P. Chakrapani, A. K. Goswami, and N. B. D. Choudhury, “Fuzzy based approach for restoration of distribution system during post natural disasters,” *IEEE Access*, vol. 6, pp. 3448–3458, 2017.

[26] H. Gao, Y. Chen, S. Mei, S. Huang, and Y. Xu, “Resilience-oriented pre-hurricane resource allocation in distribution systems considering electric buses,” *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1214–1233, 2017.

[27] S. Miraee Ashtiani, F. Vahedifard, M. Karimi-Ghartemani, I. Mallakpour, and A. AghaKouchak, “A resiliency study of electric power network to flooding in a levee-protected area under climate change,” in *Geo-Extreme 2021*, pp. 445–455.

[28] S. Miraee-Ashtiani, F. Vahedifard, M. Karimi-Ghartemani, J. Zhao, I. Mallakpour, and A. AghaKouchak, “Performance degradation of levee-protected electric power network due to flooding in a changing climate,” *IEEE Transactions on Power Systems*, vol. 37, no. 6, pp. 4651–4660, 2022.

[29] M. Violante, H. Davani, and S. D. Manshadi, “A decision support system to enhance electricity grid resilience against flooding disasters,” *Water*, vol. 14, no. 16, p. 2483, 2022.

[30] C. Liu, P. Zhou, Y. Zhou, Q. Liao, L. Tang, A. Tao, and Q. Wang, “Two-stage optimization model of emergency power supply for improving resilience of the distribution network under flood disaster,” in *2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST)*, pp. 1865–1868, IEEE, 2021.

[31] A. Shukla, J. Hasenbein, and E. Kutanoglu, “A scenario-based optimization approach for electric grid substation hardening against storm surge flooding,” in *IIE Annual Conference. Proceedings*, pp. 1004–1009, Institute of Industrial and Systems Engineers (IISE), 2021.

[32] D. Sánchez-Muñoz, J. L. Domínguez-García, E. Martínez-Gomariz, B. Russo, J. Stevens, and M. Pardo, “Electrical grid risk assessment against flooding in barcelona and bristol cities,” *Sustainability*, vol. 12, no. 4, p. 1527, 2020.

[33] J. Stevens, R. Henderson, J. Webber, B. Evans, A. Chen, S. Djordjević, D. Sanchez-Munoz, and J. Dominguez-Garcia, “Interlinking bristol based models to build resilience to climate change,” *Sustainability*, vol. 12, no. 8, p. 3233, 2020.

[34] J. C. Aerts, W. W. Botzen, K. Emanuel, N. Lin, H. De Moel, and E. O. Michel-Kerjan, “Evaluating flood resilience strategies for coastal megacities,” *Science*, vol. 344, no. 6183, pp. 473–475, 2014.

[35] M. Movahednia and A. Kargarian, “Flood-aware optimal power flow for proactive day-ahead transmission substation hardening,” *arXiv preprint arXiv:2201.03162*, 2022.

[36] B. Austgen, E. Kutanoglu, and J. J. Hasenbein, “A two-stage stochastic programming model for electric substation flood mitigation prior to an imminent hurricane,” *arXiv e-prints*, pp. arXiv–2302, 2023.

[37] B. Austgen, E. Kutanoglu, and J. J. Hasenbein, “Comparison of two-stage models for electrical substation flood mitigation under uncertainty,” *arXiv e-prints*, pp. arXiv–2302, 2023.

[38] C. Ordoudis, P. Pinson, J. M. Morales, and M. Zugno, “An updated version of the ieee rts 24-bus system for electricity market and power system operation studies,” *Technical University of Denmark*, vol. 13, 2016.

Mohadese Movahednia (Student Member, IEEE) received her B.Sc. and M.Sc. degrees from the Iran University of Science and Technology, Tehran, Iran, in 2016 and 2018, respectively. She is currently working toward a Ph.D. degree within the Department of Electrical and Computer Engineering at Louisiana State University, Baton Rouge, LA, USA. Her research interests include optimization theory, machine learning, power system resiliency, and power system equity.

Reza Mahroo (Student Member, IEEE) received his B.Sc. degree from the Iran University of Science and Technology, Tehran, Iran, in 2016, and his M.Sc. degree from the Sharif University of Technology, Tehran, Iran, in 2019. He is currently working toward a Ph.D. degree within the Department of Electrical and Computer Engineering at Louisiana State University, Baton Rouge, LA, USA. His research interests include optimization theory, quantum computing applications, and improving power systems analysis using artificial intelligence.

Amin Kargarian (Senior Member, IEEE) is an Associate Professor within the Electrical and Computer Engineering Department at Louisiana State University, Baton Rouge, LA, USA. His research interests include optimization, machine learning, quantum computing, and their applications to power systems.