Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2019.Doi Number

Optimal Life-Cycle Resilience Enhancement of Aging Power Distribution Systems: A MINLP-Based Preventive Maintenance Planning

Nariman L. Dehghani[1], Yousef Mohammadi Darestani[1&2], and Abdollah Shafieezadeh.[1]

[1]Risk Assessment and Management of Structural and Infrastructure Systems (RAMSIS) lab, Department of Civil, Environmental, and Geodetic Engineering, The Ohio State University, Columbus, OH 43210 USA

[2]Department of Civil and Environmental Engineering, Rice University, Houston, TX 77005 USA

Corresponding author: Abdollah Shafieezadeh (e-mail: Shafieezadeh.1@osu.edu).

This paper is based upon work supported by the National Science Foundation under Grant Nos. CMMI-1333943, 1635569, and 1762918. This support is greatly appreciated.

ABSTRACT Power distribution systems in the US are commonly supported by wood utility poles. These assets require regular maintenance to enhance the reliability of power delivery to support many dependent functions of the society. Limitations in budget, however, warrant efficient allocation of limited resources based on optimal preventive maintenance plans. A few studies have developed risk-based metrics to support risk-informed decision making in preventive maintenance planning for power distribution systems. However, integration of risk-based metrics and optimization for enhancing the life-cycle resilience of distribution systems has not been explored. To address this gap, this paper proposes a mixed-integer nonlinear programming (MINLP) model to maximize the life-cycle resilience of aging power distribution systems subject to multi-occurrences of hurricane events using an optimal risk-based maintenance planning. For this purpose, a risk-based index called the Expected Outages is proposed and integrated into the optimization problem to minimize the total expected number of power outages in the entire planning horizon. Various uncertainties in the performance of poles under stochastic occurrences of hazards are taken into account through advanced fragility models and an efficient recursive formulation that models the uncertainty of precedent pole failures. The proposed approach is applied to a large, realistic power distribution system for long-term maintenance planning given a total budget limit and different levels of periodic budget constraints. The resulting optimization problems are solved through the branch and bound algorithm. Results indicate that applying the presented methodology leads to a significant enhancement of the life-cycle resilience of distribution systems compared to the commonly implemented strength-based maintenance strategy set by National Electric Safety Code.

INDEX TERMS Mixed-integer nonlinear programming, hurricane hazards, power distribution systems, preventive maintenance, resilience enhancement.

I. INTRODUCTION

Electric power supports numerous activities in the modern society. Disruptions in the constant flow of electricity have the potential to incur significant hardship to communities. Over 80% of power outages in the US between 2003 and 2012 have been caused by weather-related hazards such as hurricane events [1], [2]. A large portion of these power outages were caused due to failure of wood poles. Because of the availability and cost-effectiveness of wood poles, they are extensively used for supporting distribution systems. However, wood poles suffer from a significant rate of decay especially in coastal regions with high levels of humidity. Storm-related outages in the US have incurred extensive economic losses that are estimated to be as high as $55 billion every year [3]. For example, in 2005, 12000 poles were damaged in Hurricane Wilma and Hurricane Hugo [4]. Hurricane Irene in 2011 and Hurricane Sandy in 2012 left 6.69 and 8.66 million customers without power, respectively [5]. More recently, in 2017, hurricane Irma damaged over 2900 poles and caused outages for 62% of customers in Florida [6]. The historical evidence along with the high susceptibility of coastal regions to frequent and intense winds from hurricanes highlight the critical need to improve the current and future performance of distribution systems supported by wood poles in coastal regions to mitigate potential direct and indirect socio-economic losses.

A practical strategy to improve the performance of power distribution systems is to apply preventive maintenance during their service life. Unlike the run-to-fail maintenance strategy that is applied after the occurrence of a failure, preventive maintenance is performed prior to a potential failure to decrease the likelihood of disruption in the services provided by the system. For this purpose, utilities perform annual inspection, maintenance, and replacement of wood poles to ensure the safety of distribution systems. The maintenance strategy set by the National Electric Safety Code (NESC) [7] necessitates replacing poles whose strength has fallen below 67% of their initial strength. However, this preventive strategy is not optimal as it only considers the strength reduction and entirely neglects the demand level. Moreover, the importance of the pole in the distribution system is not considered. According to NESC [7] strategy, a pole that serves in the main feeder and provides power for a large number of customers is treated equal to a pole in a side branch of the network and provides power for a small number of customers.

To mitigate these limitations, Salman et al. [8] separated the main feeders from the rest of the distribution system and investigated the performance of the system if the main feeders are only strengthened. For this purpose, an index called Risk Achievement Worth (RAW) was adopted which considers the vulnerability and the consequence of failure for an entire line segment. As this index is not calculated for each individual pole, it does not take into account differences in the properties of adjacent poles. These differences can be significant as distribution systems are often composed of poles with different ages, classes, and span lengths, among others. Subsequently, this index cannot differentiate the importance of individual poles in the distribution system. Second, this index is calculated only one time when the system is assumed to be new and therefore, the evolution of decay, failure, and replacement in the coming years within the service life of the system is not considered. This limitation can potentially lead to a strategy that may not be effective for the future state of the power system when individual poles can experience multiple instances of failure and replacement within the service life of the distribution system. Recently, the authors [9] have proposed an index called Expected Outage Reduction (EOR) for prioritizing maintenance and replacement of wood poles at different time instances within the service life of the distribution system. This index considers the expected reduction in the number of power outages if a decayed pole is replaced by a new pole. Therefore, it not only considers the benefits of replacing a pole with a new pole in terms of damage mitigation, but also considers the benefits in terms of the importance of the pole in the distribution system. Furthermore, this index is capable of considering multiple occurrences of failure and replacement due to multi-occurrences of hurricane hazards that are considerably probable in coastal regions with small hurricane return periods.

Although strategies based on RAW and EOR indices support risk-informed decision making in planning for preventive maintenance, they are still considered as predetermined preventive maintenance strategies and yet to be integrated with optimization procedures to efficiently enhance life-cycle performance of distribution systems. Thus, an optimization problem needs to be solved to efficiently allocate limited budget for enhancing the performance of power distribution systems. It should be noted that performance of infrastructure systems throughout their service life can be estimated based on different metrics, including life-cycle cost (e.g., [10], [11]), life-cycle sustainability (e.g., [12], [13]), and life-cycle resilience (e.g., [9]). Among these metrics, life-cycle resilience is deemed as the most comprehensive measure due to its ability to reflect the damage and recovery performance of systems over their lifetime. A few studies investigated resilience enhancement of distribution systems exposed to an individual occurrence of an extreme hazard event by optimizing repair crew mobilization. For example, Arab et al. [14] formulated a procedure to assign repair crews to damaged components as a mixed-integer linear programming (MILP) model. Van Hentenryck and Coffrin [15] proposed a two-stage deterministic optimization problem for routing repair crews in transmission systems after a significant disruption. Arif et al. [16] proposed a two-stage stochastic MILP model for optimizing repair crew routing in distribution systems after extreme weather events. Recently, Hafiz et al. [17] proposed a framework including three optimization problems to improve the restoration of distribution services in post-outage conditions. The above studies have provided valuable insights on effective hazard restoration strategies. However, optimization of planning strategies taken in advance of hazards to enhance the life-cycle resilience of power distribution systems has not been explored.

In previous studies on optimal maintenance planning of distribution systems, optimization models are generally categorized into three main methods, including (a) minimizing cost given a minimum level of reliability (e.g. [18]–[20]), (b) maximizing reliability subjected to time or budget constraints (e.g. [21]), and (c) minimizing the overall risk (e.g. [22], [23]). Among the proposed methods, category (c) (risk-based maintenance) identifies an optimal level of risk and has been shown as a more realistic and efficient maintenance strategy for distribution networks [22]. Most of previous studies on risk-based optimization assumed that components of distribution networks are only subjected to gradual deterioration and the impacts of extreme hazards such as hurricanes were neglected. For example, Janjic and Popovic [22] used dynamic programing to minimize the total expected maintenance cost of distribution networks without considering impacts of extreme events. Similarly, Abiri-Jahromi et al. [23] solved a MILP problem to identify optimal preventive maintenance actions through minimizing the expected cost of maintenance for a real-size distribution network with no consideration of hurricane hazards. Nonetheless, extreme events such as hurricanes especially in coastal regions incur extensive damage to distribution networks. Subsequently wind-related hazards need to be considered in preventive maintenance strategies.

To address this limitation, Yuan et al. [24] proposed a two-stage robust optimization model to enhance the resilience of distribution networks exposed to natural disasters. However, they represented damage uncertainty via a polyhedral set. Subsequently, unlike most of the studies on risk analysis of infrastructure systems (e.g. [8], [9]) they did not use fragility models to identify performance of components. Recently, Ma et al. [25] performed a two-stage stochastic optimization to select the optimal preventive maintenance of distribution systems subjected to extreme weather events. They investigated resilience enhancement through minimizing the expected cost. In their study, the potential and the associated stochasticity of multiple occurrences of failure and replacement of utility structures due to multiple occurrences of extreme hazards were neglected. Moreover, the same fragility curve was used for all poles of a distribution line. However, fragility of each pole is highly dependent on the properties of that pole. Thus, using the same fragility curve without considering poles' characteristics can result in inaccurate estimate of failure probability of poles.

To address these gaps, this study proposes a mixed-integer nonlinear programming (MINLP) model to enhance the resilience of distribution systems exposed to hurricanes through an optimal preventive maintenance planning. For this purpose, a novel risk-based index called the Expected Outages (EO) is proposed and integrated into this MINLP problem. The EO – a new risk-based performance metric for power distribution systems – estimates the number of power outages in a distribution system when a pole fails. In this MINLP problem, the EO for the entire system over the planning horizon is minimized subjected to total and periodic cost constraints. In fact, minimizing the EO directly enhances resilience of distribution systems. To evaluate this metric, uncertainties in hazard occurrences, pole degradation, and pole performance are incorporated. A state-of-the-art fragility function is adopted to describe the extreme wind performance of each pole based on its characteristics. Subsequently, the proposed MINLP formulation is applied to a realistic power distribution system for a long-term maintenance planning.

The rest of this paper in organized as follows: in Section II, the proposed mathematical formulation of the optimization problem is presented. Section III provides numerical results of this investigation. Finally, in Section IV, concluding remarks are presented.

II. MATHEMATICAL FORMULATION

Identifying the optimal preventive maintenance plan for a system requires solving an optimization problem. The optimization model determines what components require maintenance at each period of the planning horizon. For this purpose, a MINLP problem is proposed to identify the optimal preventive maintenance scheduling for resilience enhancement of power distribution systems. The presented MINLP problem minimizes the total expected number of power outages for the entire planning time horizon subjected to a total budget limit and different levels of periodic budget constraints. Consequently, minimizing the total expected number of power outages directly improves the resilience of the power system subjected to hurricane hazards. Herein, two maintenance actions are considered for each wood pole per period, including (a) do nothing and (b) replace the pole with a new one. When an existing pole is replaced with a new one, deterioration and aging restart. In the following subsections, after introducing the EO index, the mathematical optimization formulation and its solution are elaborated.

A. EXPECTED NUMBER OF POWER OUTAGES

In the proposed MINLP model, the objective function is considered to be the total expected number of power outages throughout the planning horizon. The expected number of power outages caused by a pole, in each period of planning horizon, is estimated as the product of the number of power outages that the system would sustain if the pole fails and the failure probability of the pole in that period. The number of power outages associated with each pole is estimated as the number of nodes (customers) that are not connected to any source of power (substation) assuming that the pole is failed. The failure probability of each pole is estimated through a recursive formula, which is described in the following subsection.

1) ESTIMATING THE FAILURE PROBABILITY OF POLES

As noted earlier, one major objective of this paper is to optimize replacement of wood poles to enhance the current and future resilience of distribution systems. It should be noted that utilities often perform annual inspection, maintenance, and replacement to maintain the reliability of their system. However, this procedure is applied based on the current conditions of the system; therefore, the future performance of distribution systems is often largely neglected. Although some studies investigated the future performance of distribution systems, it is typically assumed that the entire system is aged t years. This is not a realistic assumption as between time 0 and time t, a distribution system may undergo several run-to-fail or preventive maintenance actions. Therefore, it is highly likely that some of the poles at time t have already failed or been replaced at a time before t. To address this issue, the authors [9] proposed a recursive formulation for pole vulnerability that takes into account multiple occurrences of hazards within the service life of distribution systems. This approach is also capable of considering multiple replacements of poles through updating the fragility estimates at the time of replacement in the recursive formulation. Based on this approach, the probability of failure of a pole at time t_i given the wind speed v and wind direction θ can be determined as follows:

$$P\left(F_{v,\theta,t_i}\right) = \sum_{k=-1}^{i-1}\left\{P\left(F_{v,\theta,t_i}\middle|S_{t_{i-1>k+1}},\dots,S_{t_{0\geq k+1}},F_{t_{k\geq 0}}\right) \times\left[\prod_{j=k+1}^{i-1}P\left(S_{t_j}\middle|S_{t_{j-1>k+1}},\dots,S_{t_{0\geq k+1}},F_{t_{k\geq 0}}\right)\right] \times P\left(F_{t_{k\geq 0}}\right)\right\} \tag{1}$$

where $P\left(F_{v,\theta,t_i}\right)$ is the probability of failure calculated using the multi-dimensional fragility model proposed by Darestani and Shafieezadeh [26] (more detail on this fragility model is provided in the next subsection) with the modified age t_i conditioned on a set of failure and replacement events (e.g., surviving at all previous times $S_{t_{i-1}},\dots,S_{t_0}$). $P(F_{t_{i-1}}),\dots,P(F_{t_0})$ are the probabilities of failure at previous periods and $P(S_{t_{i-1}}),\dots,P(S_{t_0})$ are the probabilities of survival at previous time epochs. It should be noted that if a pole is replaced at year t, its age should be changed to zero and subsequently, $P(F_t)$ and $P(S_t)$ should be replaced by $P(F_0)$ and $P(S_0)$, respectively. The present study adopts this recursive model to account for multiple replacement and failure incidents to accurately estimate the failure probability of poles. The adopted multi-dimensional fragility function is elaborated in the following subsection.

2) MULTI-DIMENSIONAL FRAGILITY FUNCTION

Distribution systems normally consist of a large number of poles; a set of components that considerably vary in their properties. For example, span length, class, age, and height of poles as well as number and diameter of conductors may vary from one pole to the adjacent poles. In addition, probabilistic risk and resilience analyses of distribution lines require estimation of the failure probability of poles for many realizations of wind speeds and wind directions. Estimation of failure probabilities for these many scenarios would require a significantly large number of simulations. Fragility models facilitate this process as they provide fast estimates of the failure probability of poles. Recently, Darestani and Shafieezadeh [26] developed a set of multi-dimensional wind fragility models for Class One through Class Seven Southern Yellow Pine wood poles. The fragility model is introduced as the cumulative density function (CDF) of a lognormal distribution with the following form:

$$P[G(X)<0|v,\theta,t,A_C,H] = \Phi\left(\frac{ln(2.23694\times v)-\mu(\theta,t,A_C,H)}{\sigma(\theta,t,A_C,H)}\right) \tag{2}$$

where $G(X)$ is referred to as the limit state function. For the structural failure of poles, this function is defined as:

$$G(X)=M_R(X)-M_S(X) \tag{3}$$

where M_R is the moment capacity of the wood pole at ground line, M_S is the wind induced moment demand on the wood pole at ground line, and X is the set of random variables that define the demand and capacity of the pole. $\Phi(.)$ is the CDF of the standard normal distribution. Moreover, v is the wind speed in m/s, and μ and σ are the parameters of the lognormal distribution estimated through the following response surface model:

$$\begin{aligned}\mu\ or\ \sigma = a_0 + a_1\,\theta + a_2A_C + a_3t + a_4H \\ + a_5\theta^2 + a_6A_C.\theta + a_7A_C^2 \\ + a_8t.\theta + a_9t.A_C + a_{10}t^2 \\ + a_{11}\theta.H + a_{12}A_C.H \\ + a_{13}t.H + a_{14}H^2\end{aligned} \tag{4}$$

where a_i $(i=0,\dots,14)$ are the contribution of each term to the response surface model, t is the modified age of the pole (years) calculated as maximum of the age of the pole and 25 years, and θ is the wind direction (degree). A_C is the conductor area (m^2), which is calculated as the product of the conductor diameter (m), conductor span length (m), and the number of conductors. Moreover, H is the height of the pole (m). This fragility model provides a simple yet accurate pole specific estimate for the probability of failure of wood poles in distribution systems. Detailed information of this fragility model is provided in [26].

3) RISK-BASED INDICES

In resilience enhancement of distribution systems supported by wood poles, inspection and replacement should be prioritized based on the risk that each pole poses to the delivery of power to the customers. For this purpose, a risk based index called Expected Outage Reduction (EOR) has been proposed [9]. This index is adopted here to classify poles into a few groups at the beginning of the planning horizon. More details on grouping poles are provided later in Section II.B.2. The EOR index is determined for each pole as follows:

$$\begin{aligned}EOR_i = N_i\iint[P_i(F_V=v,\Theta=\theta,\Gamma=t) \\ - P_i(F_V=v,\Theta=\theta,\Gamma=0)] \\ \times f_V(v)\times f_\Theta(\theta)\times dv\,d\theta\end{aligned} \tag{5}$$

where N_i is the number of power outages that will occur in the system due to the failure of pole i. P_i is the probability of failure of pole i considering precedent stochastic failure and replacement scenarios. f_V and f_Θ are the probability density functions of wind speed and wind direction, respectively. The EOR_i index denotes the direct expected reduction in the expected outages if pole i is replaced with a new pole. Based on concepts in the EOR index, the EO is introduced here as a new risk-based metric for each pole. The EO index is integrated into the objective function of the MINLP optimization model to estimate the number of power outages in a distribution system when a pole fails. The EO for each pole is estimated as:

$$EO_i = N_i \iint P_i(F_V = v, \Theta = \theta, \Gamma = t) \times f_V(v) \times f_\Theta(\theta) \times dv\, d\theta \tag{6}$$

B. OPTIMIZATION MODEL

As previously mentioned, the current study proposes a MINLP model to efficiently optimize the long-term resilience of distribution systems via maintenance planning. Due to the high complexity of solving MINLP problems, most existing algorithms are not capable of finding optimal solutions for large, complex problems. Thus, to rectify the computational complexity of a long-term optimal preventive maintenance planning for a system with thousands of components, two tactics are employed. First, a risk-based approach is used to group the poles and reduce the dimension of the problem. Second, a surrogate model is developed to estimate the objective function in the optimization problem. In the following subsections, first, the general optimization model is introduced. Second, two tactics for reducing the computational complexity are presented. Finally, the proposed MINLP formulation is explained.

1) GENERAL OPTIMIZATION MODEL

Equation (6) is used to minimize the EO for the entire system over the planning horizon. Using this quantity as the cost function, the general formulation of the optimization problem can be presented as:

$$\min_{r} \sum_{i=1}^{N_C} \sum_{j=1}^{N_T} \left\{ N_i \iint P_i \left(F_V = v, \Theta = \theta, \Gamma = t_{i,j} - \max_{k=1,\ldots,j} \left(t_{i,k} \times r_{i,k} \right) \right) \times f_V(v) \times f_\Theta(\theta) \times dv\, d\theta \right\} \tag{7}$$

$$s.t. \quad r_{i,j} = 0 \; or \; 1, \qquad \begin{matrix} i = 1, \ldots, N_C \\ j = 1, \ldots, N_T \end{matrix} \tag{8}$$

$$\sum_{i=1}^{N_C} \sum_{j=1}^{N_T} r_{i,j} \times cost_i \leq TB \tag{9}$$

$$\sum_{i=1}^{N_C} r_{i,j} \times cost_i \leq PB, \qquad j = 1, \ldots, N_T \tag{10}$$

where N_C and N_T indicate the total number of components and number of planning periods in the planning horizon, respectively. $r_{i,j}$ denotes a binary decision variable for component i in the planning period j. This variable is zero when no preventive maintenance action is applied to component i in the planning period j and it becomes one when the component is replaced with a new one. Equation (9) and (10) are a constraint on the total budget of preventive maintenance actions and a limit on the budget per period, respectively. TB, PB, and $cost_i$ indicate the total budget, budget limit per period, and the replacement cost of component i, respectively. In the optimization formulation, age of component i is defined by $t_{i,j} - \max_{k=1,\ldots,j}(t_{i,k} \times r_{i,k})$ where $t_{i,j}$ denotes the age of component i at planning period j if no replacement is applied to the component. In addition, $\max_{k=1,\ldots,j}(t_{i,k} \times r_{i,k})$ indicates the age of the pole at the most recent replacement.

Solving this optimization model is computationally intractable for a distribution system with a large number of components and an extended planning horizon. Thus, two strategies are developed to reduce the complexity, including first, grouping wood poles and second, developing a surrogate model.

2) GROUPING POLES

Poles are categorized into groups to reduce the dimension of the optimization problem. For this purpose, poles can be classified into several groups based on their properties. In this study, the EOR index is used as the only metric for classification because this index incorporates all characteristics of poles that are significant for the risk of outage into one metric. Based on this index, poles with higher EOR are considered as more important poles in the system because replacing them will result in more reduction in the expected number of power outages of the system. Thus, grouping poles using EOR can categorize poles based on their importance in the system. It is worth noting that the EOR index for each pole varies if the age of the pole changes (i.e. when the pole is replaced with a new one). Thus, EOR is evaluated for all poles in the distribution system at the end of the first period of the planning horizon – referred to as the initial EOR, here. Subsequently, poles are categorized into a few groups and at each time epoch, a similar maintenance action is applied to the poles in the same group. Based on this classification, each component in (7)-(10) represents a group of poles. Grouping poles reduces the dimension and therefore the complexity of the optimization problem. This assumption is also practical as utilities perform maintenance actions on a group of poles rather than maintaining individual poles separately [27], [28].

3) SURROGATE MODEL

Based on (7) for each time that the objective function is evaluated, it is required to quantify the EO for all poles for the entire planning periods. Moreover, the calculation of these expected outages requires quantification of the failure probability of each pole at each time epoch that is based on the recursive model presented in (1). Therefore, using the objective function in the form of (7) is significantly costly for optimization purposes. To overcome this limitation, a machine learning technique called symbolic regression [29] is adopted here to develop a surrogate model for the EO calculation. Symbolic regression generates a mathematical expression for a set of input and output data through combining mathematical building blocks such as arithmetic operators, trigonometric functions, constants, and state variables. Symbolic regression not only searches for appropriate parameters, but also unlike traditional regression techniques, improves the form of equations using an evolutionary process [30].

In this study, Eureqa [31] is used to perform symbolic regression. To develop a surrogate model by performing symbolic regression, first, the EO is estimated using (6) for all components with all possible ages over the planning horizon. Although estimating the EO for all components with all possible ages is a time-consuming process, it is a one-time calculation and avoids these costly computations for every evaluation of the objective function during the optimization process. Then, a model is generated for these data where the inputs are component's age (x'), number of years that passed since the most recent replacement is applied to the component (y'), and the initial EOR of the component (EOR^{int}). The output of the model is the EO for each component. It should be noted that here, each component represents a group of poles. Developing a model based on this assumption requires selection of a single representative value for each group's age. Here, the mean value of all the poles' ages in each group is used as the representative age of the group. EOR^{int} of each group is also determined as the summation of the initial EOR of all the poles in the group. Since the same decision is taken for the entire group, at each period of planning horizon, y' remains the same for all poles in a group. It is worth noting that x' and y' can be the same if the initial age of all components in the system is zero.

4) MINLP FORMULATION

According to the previous section, for each component and period, the generated model using Eureqa returns the EO for that component, which is a function of the component's age at that period, the total number of years passed since the most recent replacement of the component, and the initial EOR of the component. Thus, minimizing the expected number of power outages in the entire system over the planning horizon is modeled as follows:

$$\min_{r} \sum_{i=1}^{N_C} \sum_{j=1}^{N_T} f(x'_{i,j}, y'_{i,j}, EOR_i^{int}) \tag{11}$$

$$s.t. \quad x_{i,1} = Age_i, \qquad i = 1, \dots, N_C \tag{12}$$

$$x'_{i,j} = x_{i,j} + d, \qquad i = 1, \dots, N_C;\ j = 1, \dots, N_T \tag{13}$$

$$y_{i,1} = 0, \qquad i = 1, \dots, N_C \tag{14}$$

$$y'_{i,j} = y_{i,j} + d, \qquad i = 1, \dots, N_C;\ j = 1, \dots, N_T \tag{15}$$

$$x_{i,j} = (1 - r_{i,j-1}) \times x'_{i,j-1}, \qquad i = 1, \dots, N_C;\ j = 2, \dots, N_T \tag{16}$$

$$y_{i,j} = (1 - r_{i,j-1}) \times y'_{i,j-1}, \qquad i = 1, \dots, N_C;\ j = 2, \dots, N_T \tag{17}$$

$$r_{i,j} = 0 \ or \ 1, \qquad i = 1, \dots, N_C;\ j = 1, \dots, N_T \tag{18}$$

$$x_{i,j}, x'_{i,j}, y_{i,j}, y'_{i,j} \geq 0, \qquad i = 1, \dots, N_C;\ j = 2, \dots, N_T \tag{19}$$

$$\sum_{i=1}^{N_C} \sum_{j=1}^{N_T} r_{i,j} \times cost_i \leq TB \tag{20}$$

$$\sum_{i=1}^{N_C} r_{i,j} \times cost_i \leq PB, \qquad j = 1, \dots, N_T \tag{21}$$

where $f(x'_{i,j}, y'_{i,j}, EOR_i^{int})$ in (11) denotes the generated regression model using symbolic regression, which returns the expected number of power outages for each component per period. $x'_{i,j}, y'_{i,j}$ and EOR_i^{int} are the age of component i at the end of period j, the number of years from the most recent replacement of component i to the end of period j, and the initial EOR of component i, respectively. In (12)-(19), $x_{i,j}$, $y_{i,j}$, and d represent the age of component i at the beginning of period j, the total number of years from the most recent replacement of component i to the beginning of period j, and the duration of each period (in years), respectively. The rest of the decision variables and parameters in this optimization problem were described previously.

C. SOLUTION ALGORITHM

As reported by Neumann et al. [32], several global solvers are available to deterministically solve non-convex MINLP problems. These solvers include ANTIGONE [33], BARON [34], Couenne [35], LINDO [36], and SCIP [37]. Considering the successful application of the LINDO solver for MINLP maintenance scheduling problems (e.g. [38], [39]), herein, this solver is selected to tackle the minimization problem in Section II.B. The LINDO solver uses convex relaxations and reformulations within a Branch and Bound (BB) framework to solve non-convex problems [40].

The BB algorithm generally solves MINLP problems by neglecting integer restrictions of the problem. Neglecting these restrictions converts the MINLP to a nonlinear programming problem. Subsequently, the BB algorithm solves the resulting nonlinear programming problem and considers the solution of this new problem as a valid lower bound for the original MINLP problem. If the solution satisfies the integer restrictions, BB takes it as the optimal solution of the original problem. Otherwise, the nonlinear programming problem, which is called a parent node, is branched into two new nonlinear programming sub-problems that are called child nodes. The process of branching continues until two scenarios occur. First, if one of the sub-problems provides a solution that satisfies the integer constraints, BB returns it as a valid upper bound. Second, if one of the nodes becomes infeasible or it returns an optimum solution worse than the upper bound, the node is pruned [40], [41].

III. NUMERICAL RESULTS

The objective of this paper is to present an optimal preventive maintenance planning framework to efficiently enhance the long-term resilience of power distribution systems. To this end, the proposed methodology in Section II is applied to a large, realistic distribution system located in the southern US. Results of the proposed methodology is compared to the common practice (NESC guideline [7]) for the replacement of poles.

A. CASE STUDY

The studied distribution system is assumed to be located in Harris County, Texas, US. The distribution system consists of 7051 wood poles, 115 protective devices and three substations. Height, span length, and class of poles are different, while the age of all poles is considered to be 25 years. Poles' height varies between 7.62 m and 21.34 m and their span length ranges from 4.71 m to 283.76 m. This distribution network includes poles of class one to seven; however, most of the poles are class three and five. A sketch of the distribution system is presented in Fig. 1. More information about this network including its topology can be found in [42].

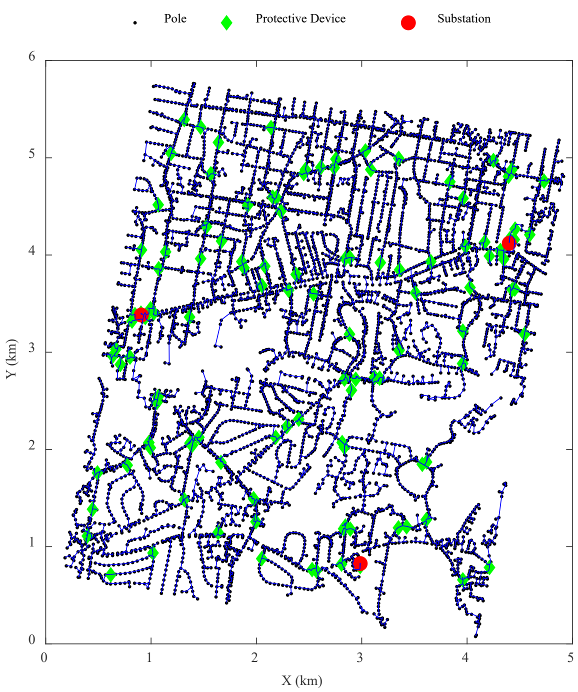


FIGURE 1. The studied distribution system (courtesy of Darestani and Shafieezadeh [42]).

B. DEVELOPED SURROGATE MODEL

As mentioned in Section II.B, poles are categorized into a few groups to reduce the computational cost of the optimization problem. For this purpose, the 7051 poles are categorized into 15 groups with the equal size of 470 (6.7% of the poles in the system), except for one group that includes 471 poles. The groups are classified based on their initial EOR where groups 1 and 15 have the lowest and highest initial EOR, respectively. As mentioned previously, the initial EOR is the EOR of poles at the end of the first period of the planning horizon. This index serves as an objective measure for grouping the poles because it incorporates all characteristics that are key to the risk of outage. The optimization is performed to minimize the total number of expected power outages for a long-term planning horizon. Herein, the total planning horizon is considered to be 60 years, which is divided into 20 periods of three years. This discretization allows for optimal planning for the long horizon of 60 years. The outcome of the optimization specifies the groups that are needed to be replaced in each period. The three-year period also offers the utility the flexibility to perform the replacement of the poles in the specified groups in that period. A second level optimization or prioritization can be applied to the results of this optimization to determine the optimal short-term planning schedule for the replacement of the individual poles in each group per period. However, the second level optimization is out of the scope of this study since here the focus is on long-term optimal scheduling.

As noted earlier in Section II.B, a surrogate model is developed to reduce the complexity of the optimization. Since calculation of the EO as part of the objective function is computationally very demanding during the course of optimization, the surrogate model is trained and constructed prior to the optimization and subsequently replaces the direct calculation of the objective function. For this purpose, the expected outages of all possible replacement scenarios for each group during the entire planning horizon is evaluated. Subsequently, the evaluated expected outages are used to develop the regression model using symbolic regression method. The developed model has the following form:

$$\begin{aligned} f(x', y', EOR^{int}) = {} & 33.7203 \times EOR^{int} \times y' \\ & - \frac{0.05315 \times y' \times (x')^4}{log(EOR^{int}) - 5.3624} \\ & - 32.0835 \times x' \times y' \end{aligned} \quad (22)$$

where x', y' and EOR^{int} are the age of the group, number of years from the most recent replacement of the group, and initial EOR of the group, respectively. This model predicts the expected number of power outages associated with a group given the specific x' and y' of that group.

Fig. 2 shows a comparison between the predicted expected outages based on the generated model in (22) and the true evaluated expected outages based on (6). According to Fig. 2, a point that falls into the lower region of $x = y$ indicates overestimation by the surrogate model compared to the actual EO, while a point in the upper region of $x = y$ represents an underestimated EO by the generated surrogate model. Fig. 2 shows that the developed model is able to properly estimate the expected outages. Noting the logarithmic scale of the plot, it is seen that estimated expected outages by the surrogate model have higher deviations from the true EOs at smaller values. However, the overall trend of the true EO is captured properly for this range and especially for larger expected outages, which contribute considerably to the cost function. More accurate models can be obtained using symbolic regression, but with more complex forms which hinder the application of MINLP solvers.

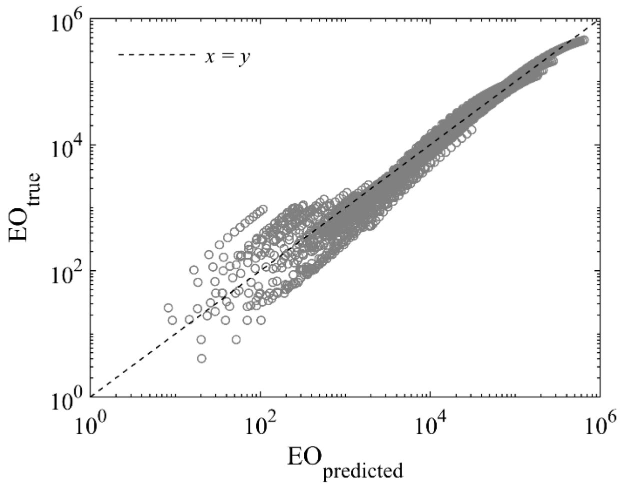
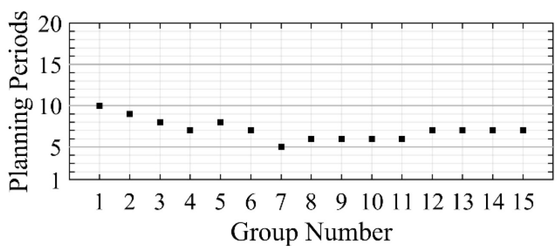


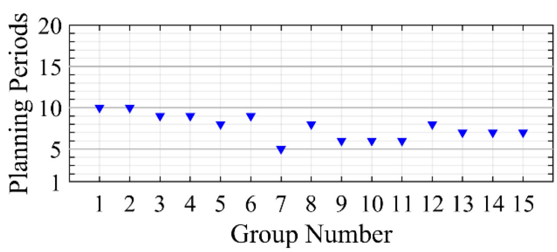
FIGURE 2. Comparison of predicted and true expected number of power outages using symbolic regression (SR).

C. OPTIMAL STRATEGY

The optimal preventive maintenance strategy is obtained after applying the BB algorithm to the presented MINLP model. In this study, the optimal strategy is obtained for three cases that are distinct in terms of limits on budget per period (i.e., PB). In all three cases, the total budget (i.e., TB) constraint is the same and defined to have a maximum of 7051 pole replacements during the entire planning horizon. The considered three cases include: (a) no constraints on PB, (b) maximum of three groups can be replaced in each period, and (c) maximum of two groups can be replaced per period. In the rest of this paper, the optimization problems with the constraints in case (a), (b), and (c) are called Optimization 1, Optimization 2, and Optimization 3, respectively. Results of these optimization problems are presented in Fig. 3. According to this figure, in all three cases, all groups are replaced one time during the planning horizon. Although all groups are allowed to be replaced more than once, none of the groups is replaced twice or more because there is a total budget constraint that allows a total 7051 pole replacements during the entire decision horizon. Thus, if one group is replaced twice, there will be another group that cannot be replaced. This observation shows that the age of the groups plays a more significant role in the total life-cycle resilience of the system compared to the initial EOR of the groups. To elaborate more, the maximum life-cycle resilience will be achieved when all groups are replaced once rather than a case in which groups with high initial EOR are replaced twice and groups with low initial EOR are not replaced. In the latter case, groups that are not replaced will have a high age toward the end of the planning horizon, which consequently leads to a large reduction in the total life-cycle resilience of the system. One important observation in Fig. 3(a) is that 10 groups are replaced at the end of periods 6 and 7, which indicates that many poles need to be replaced between 18 to 21 years after the beginning of the planning horizon. Since the age of all the poles is considered to be the same (i.e. 25 years) at the beginning of the planning horizon, their optimal replacement time is close. Moreover, it is shown in Fig. 3(a) that generally groups with higher initial EOR are replaced before period 8, while the rest of the groups are replaced in subsequent periods. This trend highlights the importance of the EOR index in the order of replacements. However, groups 12 to 15 with higher initial EOR are replaced after groups 4 to 11. Thus, the EOR index cannot be the only criterion for determining the order of replacements. This is because the distribution system is required to be resilient over the entire planning horizon and replacing all the critical components in early periods can result in a large resilience reduction toward the end of the planning horizon. Therefore, there is a trade-off between replacing earlier to enhance the resilience of the system sooner and replacing later to improve the resilience toward the end of the planning horizon. Comparing optimal strategies for all three optimization cases shows that groups 10 to 15 that have the highest initial EOR should be replaced at the end of periods 6 to 8, while groups 1 to 3 with the lowest initial EOR can be replaced after the end of period 10. This observation highlights that more critical poles need to be replaced before the age of 50 to enhance the life-cycle resilience of the distribution system, whereas the replacement of less critical poles can be postponed if there exists a budget limit per period.



(a)



(b)

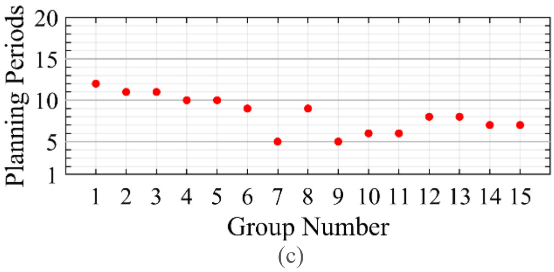


FIGURE 3. Optimal preventive maintenance planning (a) Optimization 1 (b) Optimization 2 (c) Optimization 3

D. RESILIENCE ASSESSMENT

This section evaluates the expected resilience of the distribution system subject to hurricanes. Hurricane resilience for a power distribution system is the capability of the system to absorb the imposed shock from hazard-induced loadings and to recover to a functional state quickly. It is important to assess the hurricane resilience probabilistically since in the life-cycle of the system, both hurricane incidents and pole failures are uncertain. In this study, a probabilistic resilience assessment methodology developed by the authors [9] is adopted. Here, the expected life-cycle resilience of the power distribution system with the optimized preventive maintenance strategies (i.e. results of Optimization 1, 2, and 3) is compared to the system's resilience when the NESC maintenance strategy is applied. To ensure a fair comparison between the NESC strategy and results of optimization, the same budget constraints in the optimization problems are applied to the NESC strategy. The NESC-based preventive maintenance strategies corresponding to Optimization 1, 2, and 3 are called NESC 1, NESC 2, and NESC 3, respectively. As mentioned previously, NESC requires replacing poles when their strength has fallen below 67% of their initial strength [7]. This maintenance strategy is feasible if there is no budget constraint. In this study, in each time epoch, when the total number of required pole replacements by NESC exceeds the permissible number of replacements based on periodic budget constraints, only the permissible number of poles with the highest strength reduction among all the poles are replaced. In order to apply the NESC maintenance strategies, it is necessary to estimate the residual strength of poles to identify the poles that should be replaced per period. For this purpose, the age-dependent probabilistic capacity model of poles proposed by Shafieezadeh et al. [43] is adopted. The adopted model estimates the residual strength of Southern Pine wood poles against extreme wind hazards as a function of age. According to this model, the residual strength of poles at each age follows a lognormal distribution. Using this model, the residual strength of poles as a function of age is generated and the results are presented in Fig. 4.

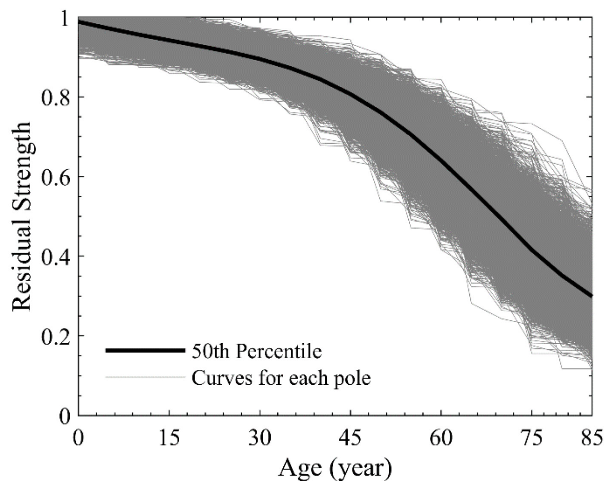


FIGURE 4. Residual strength of the poles as a function of age.

Fig. 5 shows the cumulative number of pole replacements by each strategy and Fig. 6 presents the resilience of the power distribution system during the planning horizon. As it can be seen in Fig. 5, the total number of replacements is equal for all strategies because the same constraint for the total budget is applied to all cases. It is shown in Fig. 5 that all strategies require performing replacements in a short period of time. As previously explained, this trend happens because of the assumption that all the poles have the same age at the beginning of the planning horizon. The proposed optimization-based maintenance strategies replace poles earlier than the NESC strategies. Observing the long-term resilience (Fig. 6), the optimization-based strategies considerably outperform the NESC strategies. This result highlights the significance of minimizing the expected number of power outages in optimal preventive maintenance scheduling for increasing the life-cycle resilience. When no periodic budget constraint is considered, the applied NESC strategy (i.e., NESC 1) results in a minimum resilience of 98.23%, however, applying the proposed optimization-based strategy (i.e., Optimization 1) increases the minimum resilience to 99.39%. The achieved 1.16% enhancement in the minimum resilience of the distribution systems is significant. According to previous studies on economic loss of engineered systems (e.g., [44]–[46]), such improvements in the annual expected resilience of power grid systems can save millions of dollars per year. For example, Ouyang and Dueñas-Osorio [45] showed that for the power system in Harris County, Texas, US, a 0.038% decrease in the annual resilience can incur economic losses as high as $83 million dollar per year. These loss estimates and the observed differences in the life-cycle resilience of considered cases highlight the significance of the proposed optimization model for power distribution systems. According to Fig. 6, considering optimization-based strategies, there is a noticeable increase in the resilience over the most of the planning horizon. However, in a few years toward the end of the planning horizon, applying the NESC strategies to the system leads to a slightly higher annual resilience. This is because in the NESC maintenance strategies, the poles are replaced toward the end of the time horizon, whereas in the optimization-based maintenance strategies, these poles are replaced earlier. Subsequently, following the optimization-based strategies, the poles will be much older than the poles in the NESC strategies at the end of the planning horizon, thus, it is expected to observe lower resilience. However, in the optimization-based strategies, the resilience enhancement in all years of the service life is taken into consideration, thus, following the optimization process, the system remains more resilient over most of the service life. Furthermore, if the minimum or average value of life-cycle resilience is considered, the optimization-based strategies significantly outperform the NESC strategies.

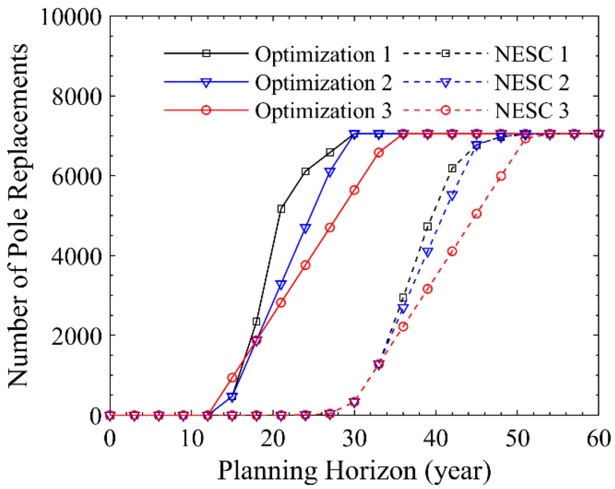


FIGURE 5. **Impacts of maintenance strategies on the cumulative number of pole replacements throughout the planning horizon.**

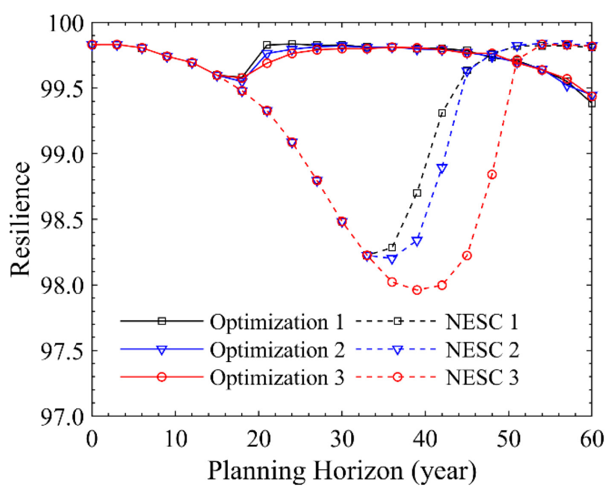


FIGURE 6. **Impacts of maintenance strategies on the resilience of the power distribution system throughout the planning horizon.**

VII. CONCLUSION

In this study, a mixed-integer nonlinear programming (MINLP) model is proposed to enhance the long-term resilience of power distribution systems based on an optimal preventive maintenance planning. Distribution systems are subjected to probabilistic multi-occurrence hurricane events during their service life. To determine the optimal maintenance strategy, a novel risk-based objective function is integrated into the MINLP problem. This risk-based measure is the total expected number of power outages in a distribution system throughout the entire planning horizon. The expected outage of a pole is computed as the product of the probability of failure of that pole and the number of power outages that the system would sustain if the pole fails. The proposed MINLP model is applied to a realistic power distribution system for determining an optimal preventive maintenance planning for the system.

To investigate the effectiveness of the developed methodology for resilience enhancement, the MINLP-based preventive maintenance strategies are determined and applied to the system. Then, the hurricane resilience of the system is estimated throughout the long planning horizon. The results are compared to the hurricane resilience of the system when the common maintenance practice set by the National Electric Safety Code (NESC) is applied to the system. The results reveal that the optimization-based preventive maintenance strategies significantly improve system resilience compared to the NESC preventive maintenance strategies. Applying the NESC strategies can only increase the resilience at the beginning and end of the planning horizon; however, when the preventive maintenance planning is determined by optimization, the system remains resilient over most of its service lifetime. Therefore, the proposed approach can significantly enhance the resilience of distribution systems, and consequently prevent considerable direct and indirect socio-economic losses.

REFERENCES

[1] A. Kenward and U. Raja, "Blackout: Extreme weather, climate change and power outages," *Climate central*, vol. 10, 2014.

[2] M. Panteli and P. Mancarella, "Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies," *Electric Power Systems Research*, vol. 127, pp. 259–270, 2015.

[3] R. J. Campbell, "Weather-related power outages and electric system resiliency." [Online]. Available: https://www.ourenergypolicy.org/wp-content/uploads/2016/02/R42696.pdf. [Accessed: 20-Oct-2019].

[4] R. E. Brown, "Hurricane Wilma and FPL," 2006. [Online]. Available: http://grouper.ieee.org/groups/td/dist/sd/doc/2006-06-Hurricane-Wilma.pdf. [Accessed: 05-Nov-2019].

[5] P. Hoffman and W. Bryan, "Comparing the impacts of northeast hurricanes on energy infrastructure," *Office of Electricity Delivery and Energy Reliability, US Dept. of Energy, Washington, DC*, 2013.

[6] Florida Public Service Commission, "Review of Florida's Electric Utility Hurricane Preparedness and Restoration Actions 2018," Florida Public Service Commission, 2018.

[7] National Electrical Safety Code® (NESC®), "ANSI/IEEE Standard," 2017.

[8] A. M. Salman, Y. Li, and M. G. Stewart, "Evaluating system reliability and targeted hardening strategies of power distribution

systems subjected to hurricanes," *Reliability Engineering & System Safety*, vol. 144, pp. 319–333, 2015.

[9] Y. M. Darestani, "Hurricane Resilience Quantification and Enhancement of Overhead Power Electric," The Ohio State University, Columbus, OH, USA, 2019.

[10] E. Fereshtehnejad and A. Shafieezadeh, "Multiple hazard incidents lifecycle cost assessment of structural systems considering state-dependent repair times and fragility curves," *Earthquake Engineering & Structural Dynamics*, vol. 45, no. 14, pp. 2327–2347, 2016.

[11] M. Rahimi, N. L. Dehghani, and A. Shafieezadeh, "Probabilistic Lifecycle Cost Analysis of Levees against Backward Erosion," in *International Conference on Sustainable Infrastructure 2019: Leading Resilient Communities through the 21st Century*, Los Angeles, CA, 2019, pp. 566–574.

[12] N. L. Dehghani and A. Shafieezadeh, "Probabilistic Sustainability Assessment of Bridges Subjected to Multi-Occurrence Hazards," in *International Conference on Sustainable Infrastructure 2019: Leading Resilient Communities through the 21st Century*, Los Angeles, CA, 2019, pp. 555–565.

[13] J. E. Padgett and C. Tapia, "Sustainability of natural hazard risk mitigation: Life cycle analysis of environmental indicators for bridge infrastructure," *Journal of Infrastructure Systems*, vol. 19, no. 4, pp. 395–408, 2013.

[14] A. Arab, A. Khodaei, Z. Han, and S. K. Khator, "Proactive recovery of electric power assets for resiliency enhancement," *IEEE Access*, vol. 3, pp. 99–109, 2015.

[15] P. Van Hentenryck and C. Coffrin, "Transmission system repair and restoration," *Mathematical Programming*, vol. 151, no. 1, pp. 347–373, 2015.

[16] A. Arif, S. Ma, Z. Wang, J. Wang, S. M. Ryan, and C. Chen, "Optimizing service restoration in distribution systems with uncertain repair time and demand," *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 6828–6838, 2018.

[17] F. Hafiz, B. Chen, C. Chen, A. R. de Queiroz, and I. Husain, "Utilising demand response for distribution service restoration to achieve grid resiliency against natural disasters," *IET Generation, Transmission & Distribution*, vol. 13, no. 14, pp. 2942–2950, 2019.

[18] P. A. Kuntz, R. D. Christie, and S. S. Venkata, "Optimal vegetation maintenance scheduling of overhead electric power distribution systems," *IEEE Transactions on Power Delivery*, vol. 17, no. 4, pp. 1164–1169, 2002.

[19] M. Shahidehpour and M. Marwali, *Maintenance scheduling in restructured power systems*. Springer Science & Business Media, 2012.

[20] E. T. Bacalhau, F. L. Usberti, and C. Lyra, "A dynamic programming approach for optimal allocation of maintenance resources on power distribution networks," in *2013 IEEE Power & Energy Society General Meeting*, 2013, pp. 1–5.

[21] A. F. Shahraki and O. P. Yadav, "Selective Maintenance Optimization for Multi-State Systems Operating in Dynamic Environments," in *2018 Annual Reliability and Maintainability Symposium (RAMS)*, 2018, pp. 1–6.

[22] A. D. Janjic and D. S. Popovic, "Selective maintenance schedule of distribution networks based on risk management approach," *IEEE transactions on power systems*, vol. 22, no. 2, pp. 597–604, 2007.

[23] A. Abiri-Jahromi, M. Fotuhi-Firuzabad, and E. Abbasi, "An efficient mixed-integer linear formulation for long-term overhead lines maintenance scheduling in power distribution systems," *IEEE transactions on Power Delivery*, vol. 24, no. 4, pp. 2043–2053, 2009.

[24] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang, and B. Zeng, "Robust optimization-based resilient distribution network planning against natural disasters," *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2817–2826, 2016.

[25] S. Ma, L. Su, Z. Wang, F. Qiu, and G. Guo, "Resilience enhancement of distribution grids against extreme weather events," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 4842–4853, 2018.

[26] Y. M. Darestani and A. Shafieezadeh, "Multi-dimensional wind fragility functions for wood utility poles," *Engineering Structures*, vol. 183, pp. 937–948, 2019.

[27] US department of agriculture, "Wood Pole Inspection and Maintenance," 13-Aug-2013.

[28] H. Lee Willis, Julio Romero-Aguero, and William Hammett, "Distribution Wood Pole Management Practices in the electric utility," Jan-2012. .

[29] J. R. Koza and J. R. Koza, *Genetic programming: on the programming of computers by means of natural selection*, vol. 1. MIT press, 1992.

[30] J.-S. Jeon, A. Shafieezadeh, and R. DesRoches, "Statistical models for shear strength of RC beam-column joints using machine-learning techniques," *Earthquake engineering & structural dynamics*, vol. 43, no. 14, pp. 2075–2095, 2014.

[31] M. Schmidt and H. Lipson, "Distilling free-form natural laws from experimental data," *science*, vol. 324, no. 5923, pp. 81–85, 2009.

[32] P. Neumann, L. Cao, D. Russo, V. S. Vassiliadis, and A. A. Lapkin, "A new formulation for symbolic regression to identify physico-chemical laws from experimental data," *Chemical Engineering Journal*, p. 123412, 2019.

[33] R. Misener and C. A. Floudas, "ANTIGONE: algorithms for continuous/integer global optimization of nonlinear equations," *Journal of Global Optimization*, vol. 59, no. 2–3, pp. 503–526, 2014.

[34] M. Tawarmalani and N. V. Sahinidis, "A polyhedral branch-and-cut approach to global optimization," *Mathematical Programming*, vol. 103, no. 2, pp. 225–249, 2005.

[35] P. Belotti, J. Lee, L. Liberti, F. Margot, and A. Wächter, "Branching and bounds tighteningtechniques for non-convex MINLP," *Optimization Methods & Software*, vol. 24, no. 4–5, pp. 597–634, 2009.

[36] Y. Lin and L. Schrage, "The global solver in the LINDO API," *Optimization Methods & Software*, vol. 24, no. 4–5, pp. 657–668, 2009.

[37] S. Vigerske and A. Gleixner, "SCIP: Global optimization of mixed-integer nonlinear programs in a branch-and-cut framework," *Optimization Methods and Software*, vol. 33, no. 3, pp. 563–593, 2018.

[38] K. S. Moghaddam, "Preventive maintenance and replacement scheduling: models and algorithms." University of Louisville, Louisville, KY, USA, 2010.

[39] A. Khatab, C. Diallo, U. Venkatadri, Z. Liu, and E.-H. Aghezzaf, "Optimization of the joint selective maintenance and repairperson assignment problem under imperfect maintenance," *Computers & Industrial Engineering*, vol. 125, pp. 413–422, 2018.

[40] J. Kronqvist, D. E. Bernal, A. Lundell, and I. E. Grossmann, "A review and comparison of solvers for convex MINLP," *Optimization and Engineering*, vol. 20, no. 2, pp. 397–455, 2019.

[41] P. Belotti, C. Kirches, S. Leyffer, J. Linderoth, J. Luedtke, and A. Mahajan, "Mixed-integer nonlinear optimization," *Acta Numerica*, vol. 22, pp. 1–131, 2013.

[42] Y. M. Darestani and A. Shafieezadeh, "A framework for hurricane resilience assessment of power distribution systems," in *13th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP13), Seoul, South Korea*, 2019.

[43] A. Shafieezadeh, U. P. Onyewuchi, M. M. Begovic, and R. DesRoches, "Age-dependent fragility models of utility wood poles in power distribution networks against extreme wind hazards," *IEEE Transactions on Power Delivery*, vol. 29, no. 1, pp. 131–139, 2013.

[44] M. Ouyang, L. Dueñas-Osorio, and X. Min, "A three-stage resilience analysis framework for urban infrastructure systems," *Structural safety*, vol. 36, pp. 23–31, 2012.

[45] M. Ouyang and L. Duenas-Osorio, "Multi-dimensional hurricane resilience assessment of electric power systems," *Structural Safety*, vol. 48, pp. 15–24, 2014.

[46] National Institute of Standards and Technology. "White paper: energy-technologies to enable a smart grid."

NARIMAN L. DEHGHANI received the B.S. degree in civil engineering from Iran University of Science and Technology, Tehran, Iran, in 2013. He received the M.S. degree in earthquake engineering from Amirkabir University of Technology, Tehran, Iran, in 2016. He is currently pursuing the Ph.D. degree in structural engineering at The Ohio State University, OH, USA.

He is a Graduate Research Associate in the Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, Columbus, OH, USA. His primary research interests include sustainability and resilience quantification, reliability assessment of civil infrastructure systems, and optimal decision making for multi-state systems.

YOUSEF MOHAMMADI DARESTANI received the B.S. in civil engineering from The University of Tehran, Tehran, Iran, in 2011, the M.S. in structural engineering from Sharif University of Technology, Tehran, Iran, in 2014, and PhD in civil engineering from The Ohio State University in 2019.

He is currently a Postdoctoral Researcher in the department of Civil and Environmental Engineering at Rice University, TX, USA. His research focuses on reliability, risk, and resilience quantification and enhancement of infrastructure systems against wind and flood hazards.

ABDOLLAH SHAFIEEZADEH received the B.S. and M.S. degrees in civil engineering from the University of Tehran, Tehran, Iran, in 2002 and 2006, respectively. He received the M.S. degree in structural engineering from the Utah State University, Provo, UT, USA, in 2008 and the Ph.D. degree in structural engineering with a minor in mathematics from the Georgia Institute of Technology, Atlanta, GA, USA, in 2011.

He is an Associate Professor in the Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, Columbus, OH, USA. His primary research and teaching interests are in resilience quantification and improvement of civil infrastructure, probabilistic optimal performance-based design and retrofit of geostructures, and multihazard performance and reliability assessment of infrastructure systems.

Dr. Shafieezadeh is a member of American Society of Civil Engineers (ASCE), Earthquake Engineering Research Institute (EERI), Network for Earthquake Engineering Simulation (NEES), and Structural Engineering Association of Southern California (SEAOSC). He is a Sam Nunn Security Fellow awarded by the Sam Nunn School of International Affairs at Georgia Institute of Technology.