Probabilistic–proactive distribution network scheduling against a hurricane as a high impact–low probability event considering chaos theory

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Abstract
High impact–low probability (HILP) incidents, such as hurricanes, usually and gravely damage electric distribution networks. A resilient distribution network must have an ability to recover itself with a fast restoration methodology against the effects of HILP events. Due to improve the electric distribution network resiliency against HILP incidents, this paper suggests a probabilistic–proactive distribution network operation model based upon the chaos theory (P-PDNOMC). Here, a resilience index based upon operational cost and load shedding cost is employed to decrease the effects of a hurricane as an HILP incident. P-PDNOMC is formulated as a framework that consists of a novel hurricane modelling and operation scheduling in normal and emergency conditions with uncertainties considering. It should be noted that a prediction approach based on the chaos theory and the least-squares support vector machine (LS-SVM) is also designed to consider the provisional and spatial behaviour of the hurricane. Furthermore, this paper proposes a novel optimization framework for damaged lines determination based upon the P-PDNOMC (DLs-P-PDNOMC) by considering multi-zone and multi-period damaged equipment budget constraints. Here, the load shedding cost is applied to present the efficiency of the proposed model. The numerical results indicate the resiliency enhancement of the electric distribution network in the face of HILP incidents.

1 INTRODUCTION

Electric distribution networks have been growingly affected by extreme weather phenomena in the world. Due to climate alterations, these phenomena usually arise most frequently and with major intensity in ahead horizon [1, 2]. The universal regard to damaging effects of these high impact–low probability (HILP) events on electric distribution networks has yielded a rising requirement to the electric distribution networks resiliency. The capability of an electric distribution network to predict HILP phenomena, resist over them, dominate their outcomes in a preventive procedure and quickly recover from the damaged condition is defined resilience [3, 4]. Furthermore, resilience is relevant to the HILP phenomena effects on clients and concentrates on how quickly and effectively the equipment is recovered to its proactive operational situation [3]. Due to the high uncertainty of natural phenomena, their anticipation and modelling are complex and difficult. In order to grow the system operator awareness about the natural phenomena, a lot of attempts have been performed in recent years. As explored in [2], the anticipation of a natural phenomenon is mostly in reliance on numeral or simulation models. Pre-determined natural phenomenon cases are supposed in [5] and considered with an identical chance. To improve the system resiliency, a lot of efforts have been proposed and classified as resisting and operation efforts [3]. Resisting efforts seek to consolidate the ingredients and construction of devices to be less fragile against the HILP phenomena. Hardening poles and elements with more robust substances, vegetation modification and moving up substations are mentioned as resisting efforts over the HILP incidents [3]. To site and size candidate sets of distributed generation units and lines in close coordination, Wu et al. [6]...
proposed a two-stage robust optimization framework for microgrid (MG) planning. In [7], capacity allocation of demand–response (DR) and the real-time savings earned from employing DR programs are evaluated based on a mixed-integer nonlinear multi-objective programming structure. Allocation of DR resources in security-constrained preventive maintenance scheduling by a multi-objective decision-making approach is presented in [8]. A resilience-based structure is proposed in [9] for optimal switch location in distribution grids coordinated with the expansion plans of distributed energy resources (DERs). Fanucchi et al. [10] present the evaluation of distribution grids resilience through two probabilistic resilience indexes. Operation efforts illustrate that preventive actions can be employed to empower a system against disastrous situations when they occur [3]. With the appearance of smart power systems, the advanced condition awareness and monitoring technologies of the electric distribution network have been expanded. The operation efforts can be utilized by online visualization systems to be aware of the electric distribution network performance during extreme events. The main aim of the operation efforts is to make the electric network flexible in the condition of an HILP incident [3]. When an HILP disaster unfolds, energy management, network reconfiguration, storage scheduling and precedence-based load shedding are employed as operation efforts to reduce the effects of HILP disasters. Resisting efforts in comparison with operation ones are inactive, long-term and expensive rectification to strengthen the electric network. On the other hand, operation efforts are online, preventive and cheaper actions to keep the electric distribution network more resilient and reliable. In [11], the participation structure of the energy storage system (ESS) in the spinning reserve market develops to both charging and discharging situations. An MG preventive management framework is presented in [12] to cope with the adverse effects of extreme windstorms. According to the receiving alerts for the predicted windstorm, the structure finds a conservative operation scheme of the MG with the minimum number of vulnerable lines in service while total loads are supplied. Liu et al. [13] present an integrated two-stage reconfiguration approach for the resilience improvement of distribution systems. Hafiz et al. [14] illustrate that distribution service restoration can be effectively enhanced by leveraging the flexibility presented by the incorporation of DR. Khodaei [15] addresses a resilience-oriented MG optimal scheduling framework to evaluate the improvement of power system resiliency by the local supply of loads and curtailment decrement. Amirion et al. [16] suggest a quantitative structure for evaluating the MG resilience against HILP windstorms. The presented model jointly implements fragility curves of distribution lines and windstorm profile to evaluate the degradation in the MG operation. Amirion et al. [17] proposed a resilience-oriented preventive model to improve the preparedness of multiple energy carrier MGs against a hurricane. A decentralized outage detection approach is suggested in [18], which evaluates the number of customers and the quantity of disconnected load in the damaged area with local data exchanges among advanced metering infrastructures. Huang et al. [19] suggests an integrated resilience response structure, which not only links the conditional awareness with resilience improvement, but also offers impressive and efficient strategies in both restrictive and emergency cases. In the proposed structure, a two-stage robust mixed-integer optimization model is presented as the main part. A preventive operation methodology is presented in [20] for the resilience improvement of MGs. Just ahead of the flood occurrence, the MG is switched to a stateless impacted by upcoming incidents. To do this, vulnerable elements are first specified. Tripping out all vulnerable elements, preventive measures are applied to optimize the proactive load management. The solution is then applied as the preventive schedule of the MG which is robust in response to the flood event. To preserve the MG resiliency by a two-stage probabilistic programming method, conservation voltage reduction technique and MG facilities are utilized in [21]. A structure is presented in [22] to consider practical challenges, such as the noise of measurements and software requirements. In [23], a recognition and reduction methodology for cyber-attacks and sensor faults is suggested in a direct current MG to satisfy resilient operation in cyber-attack and fault conditions. Gao et al. [24] compare recent efforts on preparation ahead of an HILP incident and then concentrate on resource allocation in electric distribution networks prior to a hurricane. After that, batteries and diesel generator allocation model is employed to restore the distribution network against a hurricane. In [25], a hardware-based and real-time simulation approach is introduced for special cooperation of renewable energy sources (RESs) in active distribution networks with a high concentration on the resiliency. On the other hands, some system variables have uncertainties that should be accurately modelled by an appropriate methodology such as the information gap decision theory [26], possibilistic [27], probabilistic [28] and hybrid probabilistic–possibilistic methods [29]. The mentioned matter is not concentrated in the most reviewed references. Therefore, this paper proposes a three-stage framework to promote the resiliency of a distribution network against a hurricane disaster as an HILP event that is named probabilistic–proactive distribution network operation model based upon the chaos theory (P-PDNOIC5). Stage #1 concentrates on the hurricane modelling and its effects on a distribution network. A combined methodology based upon the least-squares support-vector machine (LS-SVM), chaos theory and associated data is employed to predict the hurricane speed. Then, a novel optimization model is suggested to determine the hurricane effects on the distribution network. The objective function of the proposed hurricane occurrence model considers the lines importance according to its downstream connected loads, lines fragility function and the lines difference angle with the hurricane direction. The multi-zone and multi-period limitations for damaged equipment budget provide the hurricane model constraints. Stage #2 focuses on the P-PDNOIC5 uncertainties modelling consists of solar irradiation (i.e. for photovoltaic units (PVs) output power prediction), wind speed (i.e. for wind turbine (WT) output power anticipation), load and market price. The uncertainties modelling are performed by the associated data, probability distribution function (PDF) and the Monte Carlo (MC) methodology. In stage #3, a distribution network scheduling in a normal and an emergency
| Refs. | ESS  | MT/CHP | PV | EV | WT | DR | Tie-line & switching | Resiliency Index | Fragility curve | Optimization | Event dynamic | Multi-zone, multi-period | Chaos theory | Sensitivity analysis | Uncertainty modelling approach | Wind speed | Solar radiation | Load price |
|-------|------|--------|----|----|----|----|----------------------|------------------|----------------|-------------|--------------|------------------------|------------|------------------|--------------------------------|-----------|----------------|------------|
| [12]  | -    | ✓      | ✓  | ✓  | ✓  | -  | -                    | ✓                | ✓              | ✓           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [13]  | -    | ✓      | -  | -  | -  | -  | -                    | ✓                | ✓              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [14]  | -    | -      | ✓  | -  | -  | -  | ✓                    | ✓                | ✓              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [15]  | ✓    | ✓      | -  | -  | -  | -  | ✓                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [16]  | -    | -      | ✓  | ✓  | ✓  | ✓  | ✓                    | ✓                | ✓              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [17]  | ✓    | ✓      | -  | -  | -  | -  | -                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [19]  | -    | ✓      | -  | -  | -  | -  | ✓                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [20]  | -    | -      | -  | -  | ✓  | ✓  | ✓                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [21]  | ✓    | ✓      | -  | ✓  | ✓  | -  | ✓                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [23]  | ✓    | ✓      | ✓  | -  | ✓  | -  | -                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| [25]  | ✓    | -      | ✓  | -  | -  | -  | ✓                    | ✓                | -              | -           | -            | -                      | -          | -                | -                               | -         | -              | -          |
| This paper | ✓    | ✓      | ✓  | -  | ✓  | -  | ✓                    | ✓                | ✓              | ✓           | ✓            | ✓                      | ✓          | -                | -                               | ✓         | ✓              | ✓          |

**TABLE 1** Taxonomy of the reviewed papers
conditions are formulated and executed as a mixed-integer non-linear program (MINLP) model. In the normal condition, optimization is applied by a cost-based index. Furthermore, a resilience index is considered as the emergency condition objective function. Finally, the optimum micro turbines (MTs), WT, ESS and reserve lines status alternation (i.e. network reconfiguration) profiles will be determined as the outputs of P-PDNOMC. Due to evaluate the effectiveness of P-PDNOMC, load shedding cost (LSC) is implemented. Numerical results for the modified IEEE-33 bus distribution network and a real one indicate the effectiveness of the suggested framework for the improvement of the distribution network resiliency. The innovative contributions of this paper considering the attributes of the works analysed in the literature review which has been shown in Table 1, summarized as follows:

- A novel model is introduced for hurricane based on LS-SVM approach, chaos theory, multi-zone and multi-period of hurricane dynamic. The proposed model considers the hurricane behaviour and effects on a distribution network more accurately than existing approaches.
- A practical structure is proposed to determine the most vulnerable lines against a hurricane that considers lines fragility curve, importance and angle as well as hurricane speed and direction, simultaneously. The existing studies do not employ the above-mentioned factors to specify vulnerable lines, concurrently. Therefore, the proposed preventive scheduling is more effective than other ones.
- A probabilistic–proactive structure for distribution network scheduling is proposed against a HILP event that resilience resources such as WT, MTs, PVs, ESS and reserve lines (i.e. reconfiguration) are simultaneously employed to enhance the resiliency of distribution network coordinated with the HILP event model by implementing a resilience index that is not completely and comprehensively studied in other works.
- The whole problem uncertainties are probabilistically and simultaneously considered in presence of hurricane for preventive scheduling that is either ignored or limitedly concentrated in the existing works.

The residue of this paper is subsumed as follows. Section 2 explains a two-stage natural disaster (i.e. hurricane) modelling based on the combined LS-SVM and chaos theory methodology and optimization framework. Section 3 describes proactive scheduling to improve the resiliency of a distribution network. Section 4 discusses the simulation results and the impression of the proposed model. Finally, the study is concluded in Section 5.

2 | HURRICANE OCCURRENCE MODELLING IN THE PROPOSED P-PDNOMC

HILP disasters uncertainty forecasting is complex and difficult. In this section, a novel and multi-level model is proposed to predict hurricane behaviour and its effects. The HILP model is based on the LS-SVM method, chaos theory, spatial and temporal dynamics and cynical framework. The cynical framework consists of hurricane speed prediction, equipment fragility curve and the importance of lines related to their downstream loads. In the following, more explanations are provided about the hurricane occurrence modelling in the P-PDNOMC.

2.1 | Hurricane provisional and spatial dynamics behaviour

A hurricane route contains several time intervals and various regions as shown in Figure 1 [30]. Regarding Figure 1, the hurricane speed reduces when it goes away from the warm and humidity oceanic areas.

2.2 | Hurricane speed prediction based upon the LS-SVM and chaos theory

Natural phenomena such as hurricanes are usually uncertain incidents that are complex to forecast and model. A lot of studies have been made to promote our awareness of natural events based on historical data and common anticipation methods. The prediction of a natural incident is often based upon simulation models or statistical ones as discussed in [31]. Pre-defined natural phenomena scenarios are supposed in [32] and treated with a similar probability. Due to a miniature mutation in the primary condition of a prediction raises quickly and affects unpredictability by common anticipation methods, hurricane forming is a complex non-linear procedure [33] as a chaotic system. The utilization of chaos theory in many fields has been highly improved by the Lorenz system. The Lorenz system is considered as a classical model to address the essential specification of non-linear systems. The Lorenz disturbance has a great impact on hurricane forecasting, which is revealed by using hurricane data. Different from conventional researches working on
enhancing the numerical approaches for hurricane anticipation, dynamic features of the hurricane system are discussed here. In order to model the non-linear dynamics and chaotic behaviour of hurricanes, this paper employs the Lorenz system as chaos theory combined with the LS-SVM method that is named LS-SVM\textsuperscript{CH} as the hurricane prediction model. Therefore, the proposed model applies the perturbation structure for hurricane prediction by the notion of the Lorenz comprehensive disturbance flow to properly consider the disturbance of the aerial system in the hurricane speed prediction to promote its exactitude. The more explanation for the proposed model is presented as follows:

- Implementation of LS-SVM method

The SVM approach employs a non-linear kernel function to map the input sample space to high-dimension linear feature space due to make the pattern detection and function assessment greatly non-linear possible. The significant preponderance of employing this approach is a model-free description and no requirement of the complete system model. Therefore, the above-mentioned approach is proper for non-linear systems with uncertainties such as hurricane behaviour. LS-SVM is the upgrade form of SVM, which transforms the conventional SVM inequality limitations into equality ones and taking the error squared and the loss function as the training set experience loss. Hence, solving the two programmings is converted into solving a linear problem, which promotes the speed and convergence of the solution [34]. Supposing the training data set as \( \{ t_k, V_k \} \) \( k = 1, 2, \ldots, N \), where \( N \) describes the total number of samples, \( t_k \in \mathbb{R}^n \) depicts input variables, \( V_k \in \mathbb{R} \) indicates output variables, \( n \) is the dimension of \( t_k \). Based on the SVM mapping theory, the samples from the original space \( \mathbb{R}^n \) are transformed to the feature space \( \mathbb{R}^p \) by a non-linear mapping \( \Phi(\cdot) \). The real-valued function \( V(t) \) in a feature space is determined as Equation (1) [35]:

\[
V(t) = \omega^T \Phi(t) + b \quad \omega \in \mathbb{R}^p, \quad b \in \mathbb{R}.
\]

Equation (2) is applied to evaluate the regression error variables for the LS-SVM fitting as follows:

\[
e_k = \omega^T \Phi(t) + b - V_k \quad k = 1, 2, \ldots, N, \quad (2)
\]

\( \{ t_k, V_k \} \) \( k = 1, 2, \ldots, N \) as a training set cooperated with Equation (2) as \( N \) limitations, are employed to construct the following objective function that is considered in the primal weight space:

\[
P : \min_P f_P(\omega, \epsilon)
\]

\[
f_P(\omega, \epsilon) = \frac{1}{2} \omega^T \omega + \frac{1}{2} \sum_{k=1}^{N} \epsilon_k^2. \quad (3)
\]

Equation (3) consists of a compromise between the summation of squared errors and an objective function managed by \( Y \) (i.e. the penalty parameter, which controls the degree of deviation beyond the error of the sample). The \( \frac{1}{2} \omega^T \omega \) term of regression formulation specifies the smoothness of the model instead of hyper-plane separation. Similar to the ridge regression problem formulated in the feature space, the parameter \( Y \) has the same role of smoothing the resultant model in LS-SVM formalism. The dual Lagrangian-based formulation is presented as follows:

\[
D : \max L(\omega, b, \epsilon, a) + a
\]

\[
L(\omega, b, \epsilon, a) = \sum_{k=1}^{N} a_k \left[ (\omega^T \Phi(t_k) + b - V_k)^2 + \epsilon_k \right]. \quad (4)
\]

where \( a_k \) is the Lagrange multiplier. The optimal solutions should satisfy the following equations:

\[
\begin{aligned}
\frac{\partial L}{\partial \omega} &= 0 \Rightarrow \omega = \sum_{k=1}^{N} a_k \Phi(t_k) \quad k = 1, 2, \ldots, N, \\
\frac{\partial L}{\partial b} &= 0 \Rightarrow \sum_{k=1}^{N} a_k = 0 \quad k = 1, 2, \ldots, N, \\
\frac{\partial L}{\partial \epsilon_k} &= 0 \Rightarrow a_k = Y \epsilon_k \quad k = 1, 2, \ldots, N, \\
\frac{\partial L}{\partial a_k} &= 0 \Rightarrow \omega^T \Phi(t_k) + b - V_k = 0 \quad k = 1, 2, \ldots, N.
\end{aligned}
\]

After omission of the variables \( \omega \) and \( \epsilon \), the optimization problem leads to a linear structure as follows:

\[
\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 1^T \\ 1 & K + r^{-1} \end{bmatrix} \begin{bmatrix} \bar{b} \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ V(t) \end{bmatrix}, \quad (6)
\]

where \( V(t) = [V_1(t); V_2(t); \ldots; V_N(t)] \), \( 1 = [1_1; 1_2; \ldots; 1_N] \) and \( a = [a_1; a_2; \ldots; a_N] \). The kernel trick is employed here as Equation (7):

\[
K_{eq} = \Phi(t_k)^T \Phi(t_q) = K(t_k, t_q), \quad k, q = 1, 2, \ldots, N. \quad (7)
\]

Therefore, the LS-SVM model for hurricane speed estimation is obtained as follows [36]:

\[
V_{LS-\text{RM}}(t) = \sum_{k=1}^{N} a_k K(t, t_k) + b. \quad (8)
\]

where \( a_k \) and \( b \) are the solution to the linear system of equation (8). Furthermore, \( b \) and \( K(t, t_k) \) depict the bias parameter, weight factor and kernel mapping function between the training sample \( t \) and support vector \( t_k \), sequentially. The radial
basis function (RBF) networks kernel function utilized for LS-SVM presented as follows [36]:

\[ K(t, t_k) = \exp \left( -\frac{|t - t_k|^2}{2\sigma^2} \right). \]  \hfill (9)

- Implementation of the Lorenz system

The Lorenz system is a three-variable atmospheric convection model that describes the same motion state [37]. Equation (10) illustrates the simplest notation of the chaotic state of a non-linear system as the Lorenz equations:

\[
\begin{align*}
\omega^H_{\lambda, t} &= \omega^H_{\lambda, \text{Min}} - \omega^H_{\lambda, \text{Max}} - x \quad \forall \lambda = x \\
\omega^H_{\omega, t} &= \omega^H_{\omega, \text{Min}} + p \cdot \omega^H_{\omega, \text{Max}} - y \quad \forall \lambda = y \\
\omega^H_{\zeta, t} &= \omega^H_{\zeta, \text{Min}} - \omega^H_{\zeta, \text{Max}} - z \quad \forall \lambda = z.
\end{align*}
\]  \hfill (10)

In this equation, \( \omega^H_{\lambda} \) is attributed to convection severity, \( \omega^H_{\omega} \) is attributed to the warmth degree deviation between rising and declining streams and \( \omega^H_{\zeta} \) is attributed to the warmth degree departure from linearity. \( \sigma \), \( r \) and \( b \) are non-dimensional constants that are defined as the Prandtl number, Rayleigh number and the area of microclimate, sequentially. Since the solution of the Lorenz equations is three-dimensional, to unify the effect of the Lorenz system solution dimensions, the results have been standardized as:

\[
\omega^H_{\lambda, t} = \frac{\omega^H_{\lambda, t} - \omega^H_{\lambda, \text{Min}}}{\omega^H_{\lambda, \text{Max}} - \omega^H_{\lambda, \text{Min}}} \quad \forall \lambda \in \{x, y, z\}. \]  \hfill (11)

The standard form of Lorenz system results are indicated as \( \omega^H_{\lambda, t} \), \( \omega^H_{\omega, t} \) and \( \omega^H_{\zeta, t} \) for \( t = 1, 2, \ldots, n \). Moreover \( \omega^H_{\lambda, \text{Min}}, \omega^H_{\lambda, \text{Max}}, \omega^H_{\omega, \text{Min}}, \omega^H_{\omega, \text{Max}}, \omega^H_{\zeta, \text{Min}}, \omega^H_{\zeta, \text{Max}} \) demonstrate the minimum and maximum amount of \( \omega^H_{x, t}, \omega^H_{\omega, t} \) and \( \omega^H_{z, t} \), sequentially. In order to unify the hurricane speed and three dimensions of the Lorenz system solution, Euclidean distance (ED) is employed to decrease the mentioned dimensions. Therefore, Equation (12) should be utilized as the ED formula [38].

\[
d(C^H_{\lambda, t} - C^H_{\lambda, 0}) = \sqrt{(\omega^H_{\lambda, x, t} - \omega^H_{\lambda, x, 0})^2 + (\omega^H_{\lambda, \omega, t} - \omega^H_{\lambda, \omega, 0})^2 + (\omega^H_{\lambda, \zeta, t} - \omega^H_{\lambda, \zeta, 0})^2}, \]  \hfill (12)

where \( C^H_{\lambda, t} \) signifies \( C^H_{\lambda, t}(\omega^H_{\lambda, x, t}, \omega^H_{\lambda, \omega, t}, \omega^H_{\lambda, \zeta, t}) \) and \( C^H_{\lambda, 0} \) determines \( C^H_{\lambda, 0}(\omega^H_{\lambda, x, 0}, \omega^H_{\lambda, \omega, 0}, \omega^H_{\lambda, \zeta, 0}) \). Moreover, \( L^H_{\lambda, t} \) is set as the length of vectors in phase space based on the perturbative convection, which indicates the deviation from a balanced state \( C^H_{\lambda, 0}(0, 0, 0) \) to an absolute movement situation in the disturbed system as follows [38]:

\[
L^H_{\lambda, t} = \left\| C^H_{\lambda, t} - C^H_{\lambda, 0} \right\| = \sqrt{(\omega^H_{\lambda, x, t} - \omega^H_{\lambda, x, 0})^2 + (\omega^H_{\lambda, \omega, t} - \omega^H_{\lambda, \omega, 0})^2 + (\omega^H_{\lambda, \zeta, t} - \omega^H_{\lambda, \zeta, 0})^2}. \]  \hfill (13)

Due to considering the Lorenz perturbation and hurricane historical data based on the LS-SVM to predict the hurricane speed, Equation (14) is implemented as follows:

\[
S^H_{L,SVM}(t_1, t_2, \ldots, t_j) = V_{L,SVM}(\omega^H_{\lambda, t_1}, \omega^H_{\lambda, t_2}, \ldots, \omega^H_{\lambda, t_j}) + \xi_i L^H_{\lambda, t_1, t_2, \ldots, t_j}. \]  \hfill (14)

In Equation (14), \( S^H_{L,SVM}(t_1, t_2, \ldots, t_j) \) is the hurricane speed anticipation series based on the effect of LS-SVM and Lorenz system solution. The LS-SVM method yields \( V_{L,SVM}(\omega^H_{\lambda, t_1}, \omega^H_{\lambda, t_2}, \ldots, \omega^H_{\lambda, t_j}) \) as the hurricane speed anticipation series. The Lorenz system results \( L^H_{\lambda, t_1, t_2, \ldots, t_j} \) as the atmospheric disturbance series. The effective Lorenz system coefficient is presented by \( \xi_i \), and \( f \) indicates the forecasted specimen number.

In order to verify the effectiveness of the proposed hurricane prediction approach, the performances of different methods such as the RBF networks, support vector regression (SVR) and LS-SVM are compared with the LS-SVM [i.e. proposed approach]. In this way, some prediction error indicators such as mean absolute error (MAE), mean squared error (MSE) and mean average percentage error (MAPE) are employed to show the accuracy of the mentioned prediction approaches and compare them. The above-mentioned prediction error indexes are presented as follows [39]:

\[
MAE = \frac{1}{M} \sum_{t=1}^{M} \left| y(t) - f(t) \right| , \]  \hfill (15)

\[
MSE = \frac{1}{M} \sum_{t=1}^{M} (y(t) - f(t))^2 , \]  \hfill (16)

\[
MAPE = \frac{1}{M} \sum_{t=1}^{M} \left| \frac{y(t) - f(t)}{y(t)} \right| , \]  \hfill (17)

where \( y(t) \) and \( f(t) \) present the observation and forecast of hurricane speed at time \( t \), respectively. Moreover, \( M \) depicts the sample size.

### 2.3 Modelling of hurricane effects on electric distribution networks

In an electric distribution network, overhead lines are the most vulnerable to confront an excessive hurricane. An overhead line fragility curve indicates the failure probability of each line by
the maximum predicted hurricane speed that is performed by the proposed LS-SVM\textsuperscript{11}. The phenomenon occurrence model uses the fragility curve as its input. In order to predict damaged distribution network lines, this paper presents a novel and multi-level model.

It should be noted that the exact prediction of outage lines is impossible similarly to other power system variables anticipations that have errors. In this study, a hurricane prediction and optimization framework are simultaneously employed to anticipate damaged lines against the hurricane. The proposed optimization framework is organized so that the lines with the high vulnerability from the hurricane (i.e. based on the technical issues and hurricane intensity prediction) and line importance (i.e. based on the downstream load of the line), will be determined as the outage lines. Therefore, the proposed damaged lines as the optimal solution, are more probable and more crucial distribution branches. The objective function calculates the deviation angle line with the constructed from three terms. The first term of the proposed objective function calculates the deviation angle line with the maximum deviation angle to make possible the summation of different terms. Moreover, due to considering the relation of the hurricane speed with the line failure probability, the lines fragility curve is employed in the second term. How much the below area of the fragility curve is higher, the line will be more vulnerable. In order to make dimensionless the second term, the evaluated value should be divided into the maximum amount of the below area of the line fragility curve. Line importance is presented as the last term of Equation (18). The quantity and priority of loads in the downstream of each line determine the line importance. Due to normalize the calculated value, it should be divided into the maximum multiplication of loads quantity and priority. This study considers hurricane provisional and spatial dynamics behaviour. When a hurricane arrives into a region, it will descend on the area that is near to the beach. The hurricane strength and intensity will affect the distribution network equipment (i.e. lines) in the mentioned area, while the outlying distribution network lines will remain spotless. In the impressed zone from the hurricane, Equation (19) is utilized to consider the number of destroyed lines limitation based upon the effect of the provisional and spatial behaviour of the hurricane. In Equation (19), $B_\varrho$ is the maximum number of destroyed distribution network lines in the region $\varrho$ that is named fundamental budget. In the suggested hurricane occurrence model, the number of outage lines in each region, as the quantity of optimization problem solution, should not be more than its $B_\varrho$. Hence, different values of $B_\varrho$ leads to a different number of damaged lines in the region $\varrho$. When the hurricane lands in the inward area, it will impress the area from one district to another one and its intensity reduces zone by zone. Therefore, the value of $B_\varrho$ should be determined according to the region $\varrho$ distance from the hurricane source. The $B_\varrho$ value of the farther zones from the hurricane origin should not be more than closer regions. A distribution network operator determines the fundamental budget $B_\varrho$ for the region $\varrho$ based on an event intensity, network restoration equipment and expected resilient level by sensitivity analysis. It means that $B_\varrho$ should not be very much that all nodes be disconnected and not be very low that the significant effects of the hurricane will be ignored.

\[
\sum_{(i,j) \in Z_\varrho} (1 - u'_{ij\varrho}) \leq B_\varrho, \tag{19}\]

In the above equation, the whole damaged lines are defined as the set $\Psi^H$, $\Psi^\varrho$, and $\Psi^\varrho_{ij}$, are sequentially depicted deviation angle of the line $j$ and a hurricane from the north–south direction, $u'_{ij\varrho}$ points to the line $j$ status in the zone $\varrho$ at period $t$ (i.e. 0 is damaged and 1 is not damaged). $P_a$ represents the load of node $n$ in the downstream of line $j$ that whole of these nodes form set $\mathcal{S}_{\bar{y}}$. $\vartheta_j$ is the load importance coefficient of node $n$. $f_{\bar{y}}$ is the fragility function of line $\bar{y}$. Moreover, Equation (18) is constructed from three terms. The first term of the proposed objective function calculates the deviation angle line with the hurricane direction. If the hurricane direction is more perpendicular to a line, the line will be more vulnerable. Furthermore, due to the elimination of the angle unit, the calculated deviation should be divided into $90^\circ$ as the maximum deviation angle to
When the hurricane lands in the zone $\mathcal{G}$ at duration $t$, Equation (20) indicates lines status limitation of this zone. In this condition, the status of the lines in zone $\mathcal{G} - 1$ at duration $t$ is the same with their status at duration $t - 1$ according to Equation (21). Equation (22) determines the situations of the distribution network lines of zone $\mathcal{G} + 1$ that are not affected (i.e. $u_{ij, \mathcal{G}+1} = 1$) while the hurricane arrives in the zone $\mathcal{G}$.

### 3 | P-PDNOM$^C$ STRUCTURE

Figure 2 illustrates the proposed framework for P-PDNOM$^C$. In the first step, hurricane speed should be predicted based on the National Institute of Standards and Technology (NIST) data [40] and LS-SVM method combined with chaos theory (i.e. Lorenz system). Here, the hurricane effects on the electric distribution network are considered based on an optimization model that considers hurricane speed and direction, the fragility of network components and equipment importance. In the second stage, multifarious uncertain variables such as market price, load demand, the output power of WTs and PVs are anticipated by the MC method. The outputs of the above-mentioned steps will be applied as inputs of the third level of the proposed framework that is an optimization problem. In stage #3, the optimization problem will be solved to determine network scheduling to improve resilient conditions against hurricane disasters. Therefore, the optimum and resilient strategy for the reserve lines, charging/discharging and state of charge (SOC) profile of ESS, the output power of controllable and uncontrollable DERs will be determined. More detailed explanations about Figure 2 are provided in the following subsections.

#### 3.1 | Modelling of uncertainties in P-PDNOM$^C$

In this section, the probabilistic manners of RESs output power, market price and load demand are considered by proper PDFs. The parameters of PDFs should be determined by historical data. This study considers PVs and WTs as RESs.

- **WT output power**

  The output power of a WT is related to wind speed. This relation is shown by Equation (23) according to [24].

$$P_{WT} = \begin{cases} 0 & v \leq v_{c1} \text{ or } v \geq v_{c2} \\ \left( \frac{v - v_{c1}}{v_{c2} - v_{c1}} \right) & v_{c1} < v < v_{c2} \\ P_{WT}^R & v_{c2} \leq v < v_{c2}^R \end{cases}$$

(23)
Due to the intermittent wind speed dynamic, the WT output power has a similar manner. Rayleigh PDF is usually employed to model the wind speed [21] as:

\[
f_r(v) = \left(\frac{kr}{\sigma}\right) \cdot \left(\frac{v}{\sigma}\right)^{k-1} \cdot \exp\left(-\frac{v^2}{2\sigma^2}\right) \quad (24)
\]

- **PVs generation**

Solar irradiation, ambient temperature and physical specifications specify a PV output power [41]. Therefore, the PV output power is a function of local irradiation and temperature. Here, the PV output power is evaluated by Equation (25) [42].

\[
P_{pv} = P_{NVC} \cdot \frac{\mathcal{S}}{\mathcal{S}_{NVC}} \cdot [1 + k_{MPPT} \cdot (T_e - T_d)] \quad (25)
\]

where \(\mathcal{S}\) (i.e. area solar irradiation) and \(T_e\) (i.e. area temperature) are probabilistic variables. In order to model these variables, Beta PDF based on historical data is implemented [43]. Beta PDFs of \(\mathcal{S}\) and \(T_e\) are given as:

\[
f_b(x) = \frac{\Gamma(\mu + \beta)}{\Gamma(\mu) \cdot \Gamma(\beta)} \cdot (x)^{\mu-1} \cdot (1-x)^{\beta-1} \quad (26)
\]

\[x = \{
\mathcal{S}, T_e\}
\]

- **Load demand and market price**

In order to model the probabilistic manner of market price and load demand, Normal PDF is applied as Equation (27) [44]. In this equation, the values of \(\sigma_N\) and \(\mu\) are calculated by historical data.

\[
f_N(x) = \frac{1}{\sqrt{2\pi\sigma_N}} \cdot \exp\left[\frac{(x - \mu)^2}{2(\sigma_N)^2}\right] \quad x = \{P_l, U_b\} \quad (27)
\]

### 3.2 Scheduling of ESSs in P-PDONM C

The charging/discharging situation variables of ESSs and their related power scheduling are presented as a part of P-PDONM C. The proposed charging/discharging and SOC or stored energy \(E\) profiles of the ESS should consider the following limitations [45]:

\[
0 \leq P_{dch}^{b,s,h} \leq P_{dch}^{s,h,\text{max}}, \quad \delta_{dch}^{b,s,h} \in \{0, 1\}, \quad \forall s, b \quad (28)
\]

\[
0 \leq P_{rch}^{b,s,h} \leq P_{rch}^{s,h,\text{max}}, \quad \delta_{rch}^{b,s,h} \in \{0, 1\}, \quad \forall s, b \quad (29)
\]

\[
E_{i,s,h}^{\text{min}} \leq E_{i,s,h}^{b} \leq E_{i,s,h}^{\text{max}}, \quad \forall s, b \quad (30)
\]

\[
\delta_{dch}^{b,s,h} + \delta_{rch}^{b,s,h} = 1, \quad \forall s, b \quad (31)
\]

\[
E_{i,b+1} = E_{i,b} + (\delta_{dch}^{b,s,h} \cdot P_{dch}^{b,s,h} \cdot \Delta t - \delta_{rch}^{b,s,h} \cdot P_{rch}^{b,s,h} \cdot \Delta t / \eta_{rch}^{b,s,h}) \quad (32)
\]

\[\forall \ s, b\]

The charging/discharging power constraints are indicated as Equations (28) and (29). Limitation (30) relates to SOC constraints. Concurrent charging/discharging avoidance is considered as (31) and the charging/discharging and SOC relevance are presented in (32). Furthermore, ESSs are presumed that employed just against HILP events. Since HILP events rarely occur in a region, frequent charging/discharging cycles effect on the lifecycle of ESSs can be ignored.

### 3.3 P-PDONM C structure in the normal condition

The P-PDONM C formulation for minimizing the normal operation index \(\text{NOI}\) in the normal operating condition can be presented as Equation (33).

\[
\text{NOI} = \text{Min} \quad \left(\sum_{l=1}^{NL} \frac{\sum_{g=1}^{NG} \sum_{h=1}^{NR} I_{l,g,h} F_x(P_{l,g,h})}{l,g,h} + \sum_{l=1}^{NL} \frac{\sum_{r=1}^{NS} \sum_{l=1}^{NR} C_r + \sum_{l=1}^{NL} D_R \cdot P_{l,g,h}}{l,g,h} + \sum_{l=1}^{NL} \frac{\sum_{h=1}^{NR} \sum_{l=1}^{NS} (\delta_{dch}^{l,g,h} \cdot P_{dch}^{l,g,h} / \eta_{dch}^{l,g,h}) \cdot U_b}{l,g,h} + \sum_{l=1}^{NL} \frac{\sum_{r=1}^{NS} \sum_{l=1}^{NR} (\delta_{rch}^{l,g,h} \cdot P_{rch}^{l,g,h} / \eta_{rch}^{l,g,h}) \cdot U_b}{l,g,h} + \sum_{l=1}^{NL} \frac{\sum_{r=1}^{NS} \sum_{l=1}^{NR} (\delta_{dch}^{l,g,h} \cdot P_{dch}^{l,g,h} / \eta_{dch}^{l,g,h}) \cdot U_b}{l,g,h}ight) \quad (33)
\]

The P-PDONM C constraints in the normal operating condition should be considered as follows:

\[
\sum_{l=1}^{NL} \sum_{r=1}^{NS} I_{l,g,h} = P_{l,g,h} + \sum_{l=1}^{NL} \sum_{r=1}^{NS} P_{l,r,h}
\]

\[
\sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{dch}^{l,g,h} \cdot P_{dch}^{l,g,h} / \eta_{dch}^{l,g,h}) + \sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{rch}^{l,g,h} \cdot P_{rch}^{l,g,h} / \eta_{rch}^{l,g,h}) \quad (34)
\]

\[
\sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{dch}^{l,g,h} \cdot P_{dch}^{l,g,h} / \eta_{dch}^{l,g,h}) + \sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{rch}^{l,g,h} \cdot P_{rch}^{l,g,h} / \eta_{rch}^{l,g,h}) \quad (35)
\]

\[
\sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{dch}^{l,g,h} \cdot P_{dch}^{l,g,h} / \eta_{dch}^{l,g,h}) + \sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{rch}^{l,g,h} \cdot P_{rch}^{l,g,h} / \eta_{rch}^{l,g,h}) \quad (36)
\]

\[
\sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{dch}^{l,g,h} \cdot P_{dch}^{l,g,h} / \eta_{dch}^{l,g,h}) + \sum_{l=1}^{NL} \sum_{r=1}^{NS} (\delta_{rch}^{l,g,h} \cdot P_{rch}^{l,g,h} / \eta_{rch}^{l,g,h}) \quad (37)
\]
Power equilibrium limitation (i.e. 34) should be satisfied at each hour. The output power limitations of MTs are indicated by (35)–(39). The other limitations present injected power limit (35), ramping up/down constraints (36), (37) and startup/shutdown cost limitations (38), (39). The distribution network limitation for the power exchange with the upstream network is presented by (40). Ultimately, the utmost output power of RESs at each hour is considered by (41).

3.4 | Electric distribution network optimum and resilient operation against the hurricane

In this section, a probabilistic scheduling formulation is suggested for P-PDONM C to improve an electric distribution network resiliency in the face of a hurricane. The optimization problem of probabilistic–proactive distribution network operation model based upon chaos theory can be presented as follows:

\[
ROI = \min \sum \sum (C_{loss} \cdot P_{shed}) \text{ Load shedding cost} + \sum \sum \sum (I_{l,g,h} \cdot F_{g}(P_{l,g,h})) \text{ MTs generation cost} + \sum \sum \sum P_{l,r,h} C_r + \sum \sum S_{l,s,h} \cdot U_{l,s,h} \text{ DERS and Upstream network power cost} + \sum \sum \sum (\delta_{l,s,h} \cdot P_{l,s,h} \cdot \eta_{l,s,h}) U_{l,s,h} \text{ ESSs operation cost} + \sum \sum \sum I_{l,g,h} \cdot (SU_{l,g,h} + SD_{l,g,h}) \text{ Start-up and shutdown costs of MTs} \]

(42)

\[
\sum_{l=1}^{NL} \sum_{g=1}^{NG} I_{l,g,h} \cdot p_{l,g,h} + \sum_{r=1}^{NR} \sum_{l=1}^{NL} p_{l,r,h} + \sum_{s=1}^{NS} \sum_{l=1}^{NL} (\delta_{l,s,h} \cdot p_{l,s,h} / \eta_{l,s,h}) - \delta_{l,s,h} \cdot p_{l,s,h} / \eta_{l,s,h} U_{l,s,h} \]

(43)

0 ≤ p_{shed} ≤ p_{shed,max} \text{ ∀ b, l. (44)}

The resilient operation index (ROI) as (42) is proposed to minimize the operation cost and LSC, simultaneously. When a phenomenon appears, ROI minimization leads to promote the distribution system resiliency and provide the most economical solution. In the LSC term of ROI, C_{loss} should be considered as high as that P_{shed} should be equal to zero if the different MG energy resources have available capacity. Moreover, (43) considers the power equilibrium at each bus and the load shedding limitation is presented by Equation (44). Finally, Equations (35)–(41) should be satisfied in this condition.

In order to determine the efficiency of the proposed approach, LSC as a computational cost is calculated as follows:

\[
LSC = \sum_{l=1}^{NL} \sum_{h=1}^{NH} C_{loss} \cdot P_{shed} \text{. (45)}
\]

4 | NUMERICAL STUDY

In this section, the proposed hurricane occurrence model and performance of P-PDONM C are discussed.

It should be noted that all simulations are performed on a personal computer with Intel Core i7 CPU @3.20 GHz and 4 GB RAM in Windows Professional 7 environment. P-PDONM C is formulated as an MINLP problem and solved using the discrete and continuous optimizer (DICOPT) solver under the general algebraic modelling system (i.e. GAMS 24.1.2). Furthermore, the MC simulation for uncertainties and hurricane modelling based on LS-SVM C11 are executed in the multi-paradigm numerical computing environment and proprietary programming language matrix laboratory (i.e. MATLAB R2018b). In this study, LS-SVM Toolbox [46] interfaced with MATLAB is implemented for hurricane speed estimation.
FIGURE 4 The Lorenz attractor

TABLE 2 Error indexes of hurricane prediction methods

| Hurricane speed prediction methods | Error | MSE (m²/s²) | MAE (m/s) | MAPE (%) |
|-----------------------------------|-------|-------------|-----------|----------|
| RBF                               |       | 49.6        | 6.075     | 0.075    |
| SVR                               |       | 42.9        | 6.000     | 0.069    |
| LS-SVM                            |       | 28.1        | 5.084     | 0.066    |
| LS-SVMCH                          |       | 4.0         | 1.877     | 0.021    |

4.1 Hurricane modelling results based on the LS-SVMCH

In order to anticipate the hurricane strength, historical and proper data should be employed. Here, this data is taken from [47] and [48] that are related to the Gulf and East Coasts of the United States as shown in Figure 3. This data consists of hurricane speeds in 16 specified directions, beginning with the north-northeast (NNE) and moving clockwise to the north. As mentioned before, this study employs Lorenz equations to consider hurricane chaotic behaviour as a part of LS-SVMCH. According to [39], the initial Lorenz parameters for the airflow perturbation as $b_L$, $r_R$ and $\sigma_L$ are sequentially chosen equal to 8/3, 10 and 28. The other Lorenz parameters are determined according to [39]. Figure 4 illustrates the Lorenz attractor in the chaotic situation for the above-mentioned initial conditions.

The errors of different methods for the hurricane prediction speed are compared with the proposed approach in Table 2. The most values of the above-mentioned error indexes belong to RBF. $MSE$, $MAE$ and $MAPE$ of SVR method in comparison with RBF, 13.4%, 1.2% and 8.4% are improved, respectively. The reduction of $MSE$, $MAE$ and $MAPE$ indexes by 34.6%, 15.3% and 4.1% sequentially, for LS-SVM in comparison with SVR, shows that LS-SVM is more accurate than SVR and RBF. Finally, the best accuracy happens in the LS-SVMCH approach as the proposed method. The $MSE$, $MAE$ and $MAPE$ indexes for the LS-SVMCH approach are equal to 4, 1.877 and 0.021, respectively. The hurricane speed prediction results for the RBF, SVR, LS-SVM and LS-SVMCH methods are shown in Figure 5. The RBF prediction profile has the most deviation from the expected hurricane speed profile. The SVR prediction result is more accurate than RBF. However, in comparison with LS-SVM and LS-SVMCH, SVR is not closer to the target speed profile. Obviously, although the prediction results of LS-SVM and LS-SVMCH methods are similar to the actual hurricane speed series, the prediction results of the LS-SVMCH method is closer to the actual hurricane speed series in more times.

4.2 Test systems and main assumptions

The suggested model is performed on the IEEE 33-bus distribution network [49] and a real one, that they have been developed by considering multiple DERs, ESS and several reserve lines. It is supposed that the reserve lines are out of service in the normal condition. It should be noted that the reserve lines difference angles from the north due to be underground and not affected by the hurricane will be equal to zero. The specification of ESS and MT units are sequentially presented in Tables 3 and 4 [45]. Other associated constants are considered according
to [50] and [51]. Moreover, the ESS is assumed to be completely discharged at 00:00. The network load and the electric market price are forecasted by the MC method based on the proper PDF and historical data as [45] that is illustrated in Table 5. Furthermore, Table 5 indicates the PV output power profile that is forecasted by the MC method according to the Beta PDF and historical data [52]. The MC method is used to generate 2500 scenarios with even probabilities, and the backward reduction technique is used to reduce the number of scenarios. According to Table 5, the most solar radiation occurs at 12:00 and it continues from 06:00 to 19:00. Moreover, the RESs operation costs are ignored and the LSC is supposed five times as much as the market price. Moreover, Figure 6 demonstrates a distribution network line fragility curve against a hurricane [53]. Furthermore, the maximum load shedding power and the maximum input capacity power from the upstream grid to the distribution network are sequentially assumed 4 and 5 MW.

### 4.3 P-PDNOMC analysis on different case studies

To evaluate the performance of P-PDNOMC, two case studies based on the IEEE 33-node distribution network and a real one are implemented as follows.

#### 4.3.1 Case A

**The IEEE 33-node distribution network:** In this case, due to validate the effectiveness of the proposed structure, several scenarios based on multifarious zones number and hurricane durations are discussed on the modified IEEE 33-node distribution network as shown in Figure 7. The details of the scenarios such as the number of zones, hurricane durations, damaged lines and fundamental budgets are presented in Table 6. Loads of the mentioned system according to their types (e.g. residential, commercial, industrial, military and medical) [45] have multifarious priorities that are presented in Table 7. Furthermore, the lines difference angles from the north are presented in Table 8. Moreover, Figure 7 demonstrates the hurricane speed and direction in different zones. As shown in Figure 7, the main hurricane direction is the north and the hurricane strength steps down by going on each zone. Therefore, the progress procedure of the hurricane on the above-mentioned electric distribution network consists of different periods and zones based upon the route of the hurricane motion and the regions [54]. In this network, zone #1 is supposed close to the beach. Therefore, the distribution network lines of zone #1 are damaged severely from the hurricane during the first period. Then, the hurricane comes to the inland regions and damages the distribution network lines of zone #2. Finally, the hurricane reaches region #3. In this situation,

#### Table 3: Characteristics of the ESS

| $E_{\text{Min}}$ (MWh) | $E_{\text{Max}}$ (MWh) | $P_{\text{ch},\text{Max}}$ (MW) | $P_{\text{dch},\text{Max}}$ (MW) | $\eta_{\text{ch}}$ | $\eta_{\text{dch}}$ |
|------------------------|------------------------|-----------------------------|-----------------------------|----------------|----------------|
| 0                      | 0.7                    | 0.175                       | 0.175                       | 0.88           | 0.88           |

#### Table 4: Characteristics of dispatchable MT units

| Unit # | Operation cost ($/MWh) | Min-Max capacity (MW) | Ramp Up/Down rate (MW/h) |
|--------|------------------------|------------------------|--------------------------|
| 1      | 51.86                  | 0–0.6                  | 0.3                      |
| 2      | 85                     | 0–0.9                  | 0.45                     |

#### Table 5: Forecasted profile for price, load and PV output power

| Time (h) | Price ($/MW) | Load (MW) | PV (MW) | Time (h) | Price ($/MW) | Load (MW) | PV (MW) |
|----------|--------------|-----------|---------|----------|--------------|-----------|---------|
| 1        | 18           | 2.40      | 0       | 13       | 59           | 3.23      | 0.575   |
| 2        | 15           | 2.03      | 0       | 14       | 63           | 3.79      | 0.45    |
| 3        | 13           | 1.62      | 0       | 15       | 76           | 4.18      | 0.3     |
| 4        | 13           | 1.62      | 0       | 16       | 85           | 4.46      | 0.2     |
| 5        | 10           | 1.56      | 0       | 17       | 90           | 4.68      | 0.1     |
| 6        | 25           | 2.51      | 0.025   | 18       | 100          | 5.07      | 0.05    |
| 7        | 20           | 2.23      | 0.1     | 19       | 110          | 5.29      | 0.02    |
| 8        | 22           | 3.05      | 0.2     | 20       | 120          | 5.57      | 0       |
| 9        | 24           | 3.11      | 0.3     | 21       | 105          | 5.13      | 0       |
| 10       | 35           | 3.11      | 0.45    | 22       | 92           | 4.74      | 0       |
| 11       | 40           | 3.18      | 0.575   | 23       | 75           | 4.01      | 0       |
| 12       | 65           | 3.34      | 0.6     | 24       | 60           | 3.68      | 0       |

#### Figure 6: A distribution network line fragility curve against a hurricane
hurricane intensity reduces. Therefore, the number of damaged lines should be less than zones #1 and #2. By executing the proposed hurricane occurrence model on the mentioned system, damaged lines are determined as shown in Figure 8. Moreover, Figure 9 depicts the WT output power in scenarios #1–#10. In scenario #1, the output power of the WT is related to the wind speed in all hours that is forecasted by the MC method, Rayleigh PDF and historical data [55]. In scenarios #2, #5 and #8 during 01:00–02:00, scenarios #3, #6 and #9 in time interval 01:00–05:00 as well as scenarios #4, #7 and #10 during 01:00–08:00, due to the high intensity of the hurricane, the WT protection mechanism has stopped it. Therefore, the WT output power has been equal to zero. In other time intervals, the output power is based on the wind speed fluctuations. At these hours, due to the hurricane conditions, wind speed in scenarios #2–#10 is more than scenario #1 and the WT output power follows its speed. In case A, the charging, discharging and SOC profiles of ESS are shown in Figures 10(a), (b) and (c), respectively.

In scenario #1, due to the lowest market price, the ESS is charged and SOC is grown up during 01:00–05:00. At 06:00, the market price increment leads to the ESS is discharged and the SOC is stepped down. In time interval 08:00–17:00, SOC is preserved on its maximum capacity. After that, due to the great increment of market price, SOC is stepped down during 18:00–21:00. Finally, the ESS is empty at 22:00. In scenarios #5–#7, the distribution network is divided into two zones. Due to the surplus power generation (i.e. increment of solar radiation and PVs output power) as well as damaged lines topology, in the time interval 10:00–13:00, ESS can be charged in addition to the off-peak load time. Therefore, at 06:00, 08:00 and 09:00, the ESS is discharged to balance the lack of power generation and

### Table 6: Scenarios definition for case A

| Scenarios | Zones number | Hurricane duration (Hour) | Damaged lines | $B_P$ |
|-----------|--------------|--------------------------|---------------|-------|
| 1         | –            | –                        | –             | –     |
| 2         | 2            | (2-19), (3-4), (3-23), (26-27), (6-7) | $B_1 = 5$     |
| 3         | 1            | 5                        |               |       |
| 4         | 8            |                          |               |       |
| 5         | 2            | (8-9), (29-30), (12-13), (3-4), (23-3) | $B_1 = 3$     |
| 6         | 2            | 5                        |               |       |
| 7         | 8            | (3-23), (26-27), (6-7), (31-32), (12-13) | $B_2 = 2$     |
| 8         | 2            |                          | $B_1 = 2$     |
| 9         | 3            | 5                        | $B_2 = 2$     |
| 10        | 8            |                          | $B_1 = 1$     |

### Table 7: Loads priority list

| Load no # | Priority | Load no # | Priority | Load no # | Priority |
|-----------|----------|-----------|----------|-----------|----------|
| 2         | 5        | 10        | 1        | 18        | 1        |
| 3         | 5        | 11        | 2        | 19        | 3        |
| 4         | 3        | 12        | 3        | 20        | 4        |
| 5         | 2        | 13        | 1        | 21        | 1        |
| 6         | 4        | 14        | 2        | 22        | 1        |
| 7         | 3        | 15        | 1        | 23        | 2        |
| 8         | 3        | 16        | 3        | 24        | 5        |
| 9         | 1        | 17        | 1        | 25        | 5        |
### Table 8: Lines Difference Angles from the North

| Line No # | Start node # | End node # | Difference angle from the north (°) | Line No # | Start node # | End node # | Difference angle from the north (°) |
|-----------|--------------|------------|------------------------------------|-----------|--------------|------------|------------------------------------|
| 1         | 1            | 2          | 0.9                                | 17        | 17           | 18         | 36                                 |
| 2         | 2            | 3          | 40.5                               | 18        | 2            | 19         | 85.5                               |
| 3         | 3            | 4          | 85.5                               | 19        | 19           | 20         | 85.5                               |
| 4         | 4            | 5          | 45                                 | 20        | 20           | 21         | 85.5                               |
| 5         | 5            | 6          | 27                                 | 21        | 21           | 22         | 85.5                               |
| 6         | 6            | 7          | 85.5                               | 22        | 3            | 23         | 76.5                               |
| 7         | 7            | 8          | 85.5                               | 23        | 24           | 24         | 36                                 |
| 8         | 8            | 9          | 85.5                               | 24        | 24           | 25         | 45                                 |
| 9         | 9            | 10         | 85.5                               | 25        | 6            | 26         | 27                                 |
| 10        | 10           | 11         | 45                                 | 26        | 26           | 27         | 72                                 |
| 11        | 11           | 12         | 40.5                               | 27        | 27           | 28         | 72                                 |
| 12        | 12           | 13         | 72                                 | 28        | 28           | 29         | 45                                 |
| 13        | 13           | 14         | 50                                 | 29        | 29           | 30         | 81                                 |
| 14        | 14           | 15         | 36                                 | 30        | 30           | 31         | 72                                 |
| 15        | 15           | 16         | 45                                 | 31        | 31           | 32         | 18                                 |
| 16        | 16           | 17         | 36                                 | 32        | 32           | 33         | 18                                 |

**Figure 8** The modified 33-bus distribution system and its vulnerability from a hurricane based on different zones. (a) Single-zone, (b) Twin-zone, (c) Tri-zone

**Figure 9** WT output power profile

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 reduces the operation cost. After that, the ESS is charged during 10:00–13:00. Then, SOC is completed and the ESS is discharged at peak load time to have the maximum performance in the distribution network scheduling. In the other scenarios, ESS is charged just in the off-peak load times and discharged at the peak load hours to reduce the operation cost. Figures 11(a) and (b) depict MTs #1 and #2 output power profiles in scenarios #1–#10, respectively. In scenario #1, MTs are employed when the market price is more than the MTs operation cost. However, in scenarios #2–#10, in addition to the difference between the market price and MTs operation cost, the isolation of zones and the hurricane duration affect the optimal performance of MTs. Figure 12(a) illustrates the exchange power of line 14–6 in scenarios #2–#10. The negative value of this line power indicates the surplus power generation of WT than the
WT area load that line 14-6 transforms the surplus power from the WT area to the upstream area of line 14-6. In the scenarios #8, #9 and #10, due to the damaged lines topology, the WT area accesses to the main grid from line 14-6. Therefore, loads of this area are supplied, completely. The exchange power of line 18-33 is presented in Figure 12(b). In scenarios #2–#4, due to the lack of power generation in the upstream area of this line, the mentioned line cannot serve loads of its downstream region in all hours. In scenarios #5–#7, due to the surplus power generation of local resources on the upstream area of line 18-33, in the off-peak load period, this line transforms power from the upstream area to downstream one generally in this period. The damaged lines topology in scenarios #8–#10 leads to connect the downstream isolated loads to the main grid by lines 18-33 and 6-14, simultaneously. Therefore, loads of this area are supplied completely at all hours. Due to the insufficient power generation in both downstream and upstream areas of line 18-33, this line is disconnected in scenarios #2–#4. Figure 12(c) depicts the power transmission from reserve line 24-29 for the whole islanded scenarios. Due to the existence of MT #2 with 0.9 MW generation capacity and proximity to the main grid, the power generally transforms from node 29 (area of MT#2) to node #24 (downstream area of MT#2) that is illustrated as a negative value. The maximum amount of this variable is related to scenario #10 that zones number and hurricane duration are equal to 3 and 8 h, respectively. In this scenario, the zones number and hurricane duration lead to the distribution network is disconnected from the main grid with the longest delay. Finally, the hurricane destroys the access of line 24-29 to the main grid at 16:00 in scenario #10. Therefore, due to the lack of generation, this line does not exchange power between two areas and
be disconnected. The exchange power of reserve line 10–30 is demonstrated in Figure 12(d) for the whole islanded scenarios. Its positive and negative values depict the power transmission direction from node #30 to #10 and node #10 to #30, respectively. During 10:00–13:00, due to the power generation is more than loads, in the isolated area that PVs and MT#1 are placed there, the surplus power injects to other islanded areas by line 10–30 in scenarios 2–10. In this condition, the exchange power of this line is negative. From 16:00 until 24:00, the isolated areas on both sides of line 10–30 have not enough power generation. Therefore, this line is disconnected in this period. In some times that the upstream area of line 10–30 has surplus power generation and downstream region of this line does not have sufficient generation, simultaneously, line 10–30 transfers power to the downstream area. ROI index for hurricane-affected scenarios in case A is compared in Figure 13(a). Increment of zones number leads to failure delay by the hurricane for the vital lines that are placed close to the main grid. Therefore, however, the number of zones is increased the ROI decreased. Moreover, different hurricane durations at each zone does not have a significant effect on the ROI.

To evaluate the effectiveness of the proposed framework, the amount of served loads by the ESS, DERs and reserve lines based upon P-PDNOMC and normal scheduling is compared in a hurricane condition as shown in Figure 13(b). Generally, the suggested scheduling for the whole hurricane-affected scenarios can supply more load than the normal scheduling that is based on the operation cost minimization. Therefore, the proposed preventive scheduling has effective and proper performance in the whole island scenarios based on different zones number and hurricane durations. Due to not simultaneous damaged lines occurrence and failure topology, the maximum effect of the preventive framework happens in the scenarios that their zones number presumed three (i.e. scenarios 8, 9, 10) as shown in Figure 13(b). Furthermore, different hurricane durations have not significant effect on the proposed scheduling results. Moreover, the LSC of normal scheduling against the hurricane is compared with the other scenarios that are scheduled by the proposed preventive scheduling as shown in Figure 13(c). The maximum LSC happens in scenario#1 that is based on the normal scheduling if it is employed in the hurricane condition. Due to employing the proposed preventive scheduling approach, the LSCs of the other scenarios are lower than scenario #1. Furthermore, the most efficient scheduling and the minimum LSC occur in the scenarios that utilize the proposed scheduling method and the number of their hurricane zones presumed more than other ones as same as scenarios #8–#10.

### 4.3.2 Case B

*A real electric distribution system*: In this case, the proposed P-PDNOMC framework is implemented on a real 20 kV distribution network as shown in Figure 14. This network is placed in the Kerman province of Iran. The maximum load demand of this network is equal to 11.15 MW at the peak-load hour. To evaluate the effect of the proposed P-PDNOMC on a practical case study, the mentioned real distribution network is developed...
by the presence of an ESS, different DERs and some reserve lines as same as case A. In this case, the hurricane duration and zones number are presumed 2 h and one, respectively. To anticipate the damaged lines of the real distribution network, the proposed hurricane occurrence model is applied and the outage lines are determined as depicted in Figure 14. The preventive scheduling in a hurricane-affected situation leads to supply 112.65 MWh demand for 24 h. In this condition, ROI index is evaluated as 5,033,764 $. Moreover, in the hurricane-affected situation, 61.47 MWh load demand is not served. Since normal scheduling in this network against the hurricane leads to supply 62.90 MWh load, therefore the proposed P-PDNOMC prompts 28.79% the performance of the real distribution network. Moreover, the proposed preventive scheduling leads to 2767.078 $ reduction for LSC in comparison with normal scheduling in the real case study.

5 | CONCLUSION

This paper proposes a proactive framework (i.e. for scheduling a distribution network so-called P-PDNOMC) when a hurricane disaster as an HILP event occurs. In the proposed P-PDNOMC framework, a hurricane occurrence model is suggested that consists of speed prediction and damaged lines determination. The LS-SVM method coordinated with chaos theory is applied for hurricane speed prediction. The hurricane multi-period, and multi-zone dynamic, as well as a novel optimization model which consists of the DLs P-PDNOMC objective function and the destroyed equipment budget constraints, are employed to specify the damaged lines topology. Executing of the proposed hurricane model determines the most effective and vulnerable topology for damaged lines. P-PDNOMC is formulated in normal and HILP conditions. In a normal condition, P-PDNOMC is employed to minimize the operation cost. In an HILP condition, P-PDNOMC aims to determine a proactive schedule for the electric distribution network tie-lines configuration, DERs output power and ESS charging/discharging to minimize the load shedding and operation cost, simultaneously. Moreover, LSC is employed to present the capability of the proposed model. P-PDNOMC has been executed on the modified IEEE 33-bus distribution network and a real one. The results indicate that the resiliency of the electric distribution network against the hurricane is improved by P-PDNOMC. Finally, from the authors’ point of view, the proposed future work for this paper includes proactive integration to incorporate the uncertainty of other natural incidents into the P-PDNOMC. Future work also includes the lifecycle constraints of ESSs in optimization.
NOMENCLATURE

Indices and Sets

- \( g, NG \): Index and the number of dispatchable DG units.
- \( r, NR \): Index and the number of renewable DG units.
- \( s, NS \): Index and the number of ESSs.
- \( l, NL \): Index and the number of loads.
- \( \{ i, j \} \): Index and set of nodes at the downstream of line \( ij \).
- \( k_{ij} \): Index of training samples.
- \( s, NS \): Index and the number of combined load and RESs output-power scenarios.
- \( t, T \): Index and number of periods according to hurricane progressing.
- \( b, NH \): Index and the number of scheduling hours.
- \( \varphi, N_{\varphi} \): Index and the number of zones.
- \( t_{MC}, T_{MC} \): Index and the number of MC iterations.
- \( N \): The number of training samples.

Parameters and Constants

- \( C_r \): The operation cost of DER \( r \).
- \( C_{ij}, CD_{ij} \): Start-up and shut-down cost constants of unit \( g \).
- \( L_{\ell}^{\ell'} - T_{\ell}^{\ell'} \): Unified Lorenz system solution.
- \( \psi, \beta \): Beta PDF parameters.
- \( k_{\ell, \ell'}, \tau \): Rayleigh PDF parameters.
- \( \varphi \): The region of microclimate.
- \( \sigma_{N}, \mu \): Normal PDF parameters.
- \( \sigma' \): Prandtl number.
- \( a, b \): Weight factor and bias value of training samples.
- \( Y \): Regularization parameter.
- \( B_{\ell, \ell'} \): Fundamental budget for the quantity of destroyed distribution network lines in the region \( \varphi \).
- \( \delta_{ij}^{\ell}, \delta_{ij}^{\ell'} \): Line and hurricane angle differences to the north-south direction.
- \( p_{ij}^{Max} \): The capacity of line \( ij \).
- \( \xi \): Coefficient of Lorenz system effective.
- \( k_{MPF} \): Maximum power temperature coefficient.
- \( S_{SRC} \): Solar irradiance at standard test conditions.
- \( P_{SRC} \): Active power of PV module at standard test conditions.
- \( S \): Solar irradiance.
- \( C_{bas} \): Load shedding cost coefficient.
- \( P_{pe} \): PV output power.
- \( T_{a}, T_{j} \): Ambient and PV cell temperature.
- \( P_{WT}^{R} \): Rated active power of a WT.
- \( \omega_{R}^{R} \): Rated speed of a WT.
- \( \omega \): Weight factor.
- \( \sigma \): Gaussian kernel parameter.
- \( r_{WT}^{W}, r_{WT}^{L} \): Cut-in and cut-out speed of a WT.
- \( P_{WT} \): Active power of a WT.
- \( U_{b} \): Market price.

Functions and Variables

- \( F_{g} \): Cost-function of dispatchable MT \( g \).
- \( E_{c,b} \): The stored energy of ESS at hour \( b \).
- \( UR_{g}, DR_{g} \): Ramp-up/down rates of dispatchable DER unit \( g \).
- \( I_{lb, b} \): On-off-state binary indicator of MT unit \( g \) at hour \( b \) on bus \( l \).
- \( SU_{g}, SD_{g} \): Start-up and shut-down cost variables of MT unit \( g \).
- \( L_{Hi}^{Hi}, P_{VI}^{Hi} \): Euclidean distance and balance state.
- \( H_{s} \): Hurricane speed.
- \( f_{ij} \): The fragility function of line \( ij \).
- \( d_{ij}, \varphi_{ij} \): Status of line \( ij \) in the zone \( \varphi \) at period \( t \).
- \( P_{veh}^{\ell}, P_{veh}^{\ell'} \): The error variables for the fitting problem.
- \( C_{ij}^{\ell} \): Motion state at time \( t \).
- \( \varphi_{n} \): Load importance coefficient of node \( n \).
- \( DL_{s}^{PDNDNOMC} \): Damaged lines function based upon the P-PDNDNOMC.
- \( P_{hi}^{\ell} \): Absolute movement situation.
- \( S_{hi}^{\ell} \): Hurricane speed prediction by LS-SVM and chaos theory.
- \( \omega_{R}^{\ell}, \omega_{h}^{\ell} \): Convection severity.
- \( \omega_{R}^{\ell}, \omega_{h}^{\ell} \): Standardized form of \( \omega_{R}^{\ell}, \omega_{h}^{\ell} \) and \( \omega_{R}^{\ell} \).
- \( P_{veh}^{\ell,b}, P_{veh}^{\ell,b} \): The output power of RES unit \( r \) at hour \( b \) on bus \( l \).
- \( P_{veh}^{\ell,b} \): Charged and discharged power of ESS \( s \) at hour \( b \) on bus \( l \).
- \( P_{veh}^{\ell,b} \): Power transfer with the main grid at hour \( b \).
- \( \eta_{h}^{\ell}, \eta_{h}^{\ell} \): Charging/discharging efficiencies of ESS \( s \) at hour \( b \) on the bus \( l \).
- \( p_{veh}^{\ell} \): Load power of node \( n \).
- \( \psi_{hi}^{\ell} \): Damaged lines set.
- \( f_{c} \): Rayleigh PDF.
- \( f_{N}, f_{b} \): Normal and Beta PDF.
- \( K \): Kernel function.
- \( \emptyset \): Nonlinear mapping function.
- \( L \): Dual Lagrangian-based function.
- \( P_{veh}^{\ell} \): The output power of MT \( g \) at hour \( b \) on the bus \( l \).
- \( P_{veh}^{\ell} \): Power of load / at hour \( b \).
- \( NOI, ROI \): Normal and resilient operation index.
- \( \omega_{R}^{\ell} \): Temperature deviation.
- \( \omega_{R}^{\ell} \): The temperature departure from linearity.
- \( p_{veh}^{\ell,b} \): Active power shedding of bus \( l \) at hour \( b \).
- \( p_{veh}^{\ell,b} \): Active power of line \( ij \) at hour \( b \).

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