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RESEARCH ARTICLE

Data-Driven Approach for Generator Rejection Prediction to Prevent Transient Instability in Power System Using Wide-Area Measurements

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ABSTRACT This paper presents a novel data-driven approach to predict generator rejection/tripping for preventing transient instability in power systems. Since calculating the total amount of generator rejection and assigning the optimal amount of tripping to each generating facility is a time-consuming process, the optimal generator tripping calculation might be impractical for a real-life interconnected power system. In addition, communication delays deteriorate the efficiency of any wide-area remedial control action (RCA) in response to fault events which quickly evolve into transient instability. The presented framework predicts the optimal generator rejection for critical generators based on voltage data of generator terminals before and after the occurrence of the contingency. To simplify the problem and enhance the prediction accuracy, the framework is designed for each transmission line independently. The proposed framework is comprised of two stages: offline optimization which involves calculating proper RCAs using a full dynamic model of the power system for training the machine learning engine, and online prediction. In the offline stage, bulk scenarios are generated for individual transmission lines, the unstable cases are determined, then the critical generator patterns and generator rejection patterns are extracted for each unstable scenario. In the online stage, the proposed framework predicts the stability status, critical generators, and the optimal amount of generator tripping for each critical generator in real-time. The performance of the proposed framework is tested on the IEEE 9-bus system and the Nordic test system. The obtained results show the effectiveness of the proposed framework in responding to critical fault events in real-time.

INDEX TERMS Critical generator prediction, generator rejection, machine learning, remedial control action, transient stability.

I. INTRODUCTION

A. MOTIVATION

Preventing transient instabilities and blackouts in power network have drawn the attention of engineers and researchers for decades; however, there are still major challenges and unresolved technical issues which have caused the protection schemes unable to efficiently prevent blackouts occurred in different areas [1], [2], [3]. In addition, growing demand, economic and environmental issues, and growing uncertainty related to renewable energy sources and new technologies cause power networks to operate close to their stability limits. Consequently, modern power networks are more prone to lose synchronism. Therefore, designing proper remedial control action (RCA) schemes or special protection schemes (SPS) is of great importance in saving power networks from blackouts [1], [3].

RCAs are a set of corrective actions taken when emergency conditions are detected to maintain the stability and integrity of the system [4]. Generally, RCAs including

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controlled islanding [5], [6], [7], [8], load shedding [9], [10], and generator rejection/tripping [11], [12], [13], [14], can be classified into two main groups: event-based and response-based. Event-based methods are designed based on offline simulations [15]. Although the event-based methods are very fast, they are only triggered for specific scenarios. On the contrary, response-based methods are developed based on collected data from phasor measurement units (PMUs) and are able to determine proper RCAs for each scenario. However, the available time to maintain the stability of the system might be very short for some events since receiving the PMU data, calculating the proper RCAs, and sending back the commands take a relatively considerable amount of time. Therefore, considering the very fast nature of transient instability, and due to the communication delays, the existing response-based methods may not be practical for those scenarios quickly evolving into transient instability [16]. In this regard, designing an effective and fast RCA scheme capable of preventing fast transient instability for severe fault events is a necessity for a power network.

B. BACKGROUND AND LITERATURE REVIEW

One of the most commonly used RCAs to prevent transient instability is generator rejection [12], [13]. Three important factors need to be considered while designing a generator rejection framework: 1) determining the accurate amount of generator rejection to stabilize the network, 2) identifying the critical generators, and 3) assigning the optimal amount of generator rejection to each critical generator. Several research studies have been conducted in the literature for online generator tripping to improve transient stability and prevent blackouts while the power network is encountering a large disturbance. Generally speaking, the previous studies can be categorized into two groups, including energy function-based and optimization-based methods.

The energy-based methods reduce the complexity of the power network enabling the protection scheme to calculate the amount of generator rejection quickly. In [17], a combination of load shedding and generator tripping calculation is proposed which is based on relay setting limited EAC for single machine infinite bus (SMIB) system representation using PMU data. To do so, an SMIB equivalent model is formed following the instability detection. Then, the parameters of the SMIB system are estimated using real-time PMU data, and the amount of generator tripping and load shedding are calculated based on power-angle (P–δ) curve estimation. In [12], the virtual load concept is defined as a safety margin for the generator tripping scheme, and an offline look-up table is designed to trip generators for a number of scenarios and calculate the amount of virtual load at the generation side. In [18], the amount of generator tripping and load shedding has been calculated based on EAC and a STATCOM has been designed on the generation side to reduce the amount of generation tripping and improve the transient stability. In addition, an energy function-based method is proposed in [19] to quickly identify the critical and non-critical generators and compute the required generation rejection using the relative energy of the equivalent post-fault system. In [11], a combination of load shedding and generator tripping is designed to prevent relay mal-operation and loss of synchronism, respectively. In this scheme, the amount of load shedding and generator tripping are calculated based on critical equivalent acceleration at the clearing time for stable and unstable swings, respectively. In [20], a new index is proposed to determine the stability status of the power system using a two-layer SMIB framework. This method reduces the communicational burden, identifies the critical generators using the largest angle gap, and finally, calculates the amount of generator rejection to prevent instability. In [21], a method is proposed to predict transient instability and determine the number of tripped generators using local measurements. This method predicts the stability status by predicting the magnitude of the P–δ curve and determines the number of generators needed to be tripped. Although the aforementioned methods based on energy functions and EAC are fast and can be employed for online applications, approximated models are used in these approaches to reduce the computational burden which affects the accuracy of calculated generator rejection and the obtained solution might be far from the optimal solution.

Another drawback of the energy function-based methods is that they do not consider the optimal location of generator shedding. Assigning the amount of generator rejection and optimally dividing this amount between critical generators is another important issue that needs to be addressed [19]. The existing methods usually select the sequence of generator tripping based on out-of-step order [11] or energy index [19], [22], [23]. Numerous methods such as angular separation, generator frequency, kinetic energy, etc. are proposed in the literature to determine critical generators [22], [23], [24]. In [19], relative kinetic energy and absorption capacity of the network are used to identify the critical generators and assign the amount of generator rejection based on their criticality order. In [12], the sequence of generator tripping is determined based on the acceleration energy index of generators.

On the contrary, the optimization-based approaches attempt to calculate the amount of generator rejection accurately, because an excessive amount of generator tripping is too costly and it can also lead to an excessive amount of load shedding and a costly restoration process [12], [18]. In addition, a lower amount of generator rejection might lead to instability and blackout. Therefore, one of the most important research directions in transient stability studies is generator rejection optimization. In [25], [26], and [27], finding the proper RCAs (i.e., a combination of generator tripping and load shedding) is modeled as a large-scale optimization problem to prevent transient instability. These methods solve a non-linear optimization problem using methods such as direct discretization [25] and a sequential approach known as control vector parameterization [26], [27] which are time-consuming. Although optimization-based methods are accurate and find the optimal solutions, their relatively high computational time may cause the framework to fail to prevent transient instability, particularly for those cases evolving into transient instability very fast.

C. CONTRIBUTIONS

To overcome the shortcomings of the previous schemes, RCA prediction has been proposed instead of RCA calculation. Although a combination of controlled islanding and load shedding prediction is proposed in our previous work [28], in this paper a novel generator rejection prediction, which is another common RCA is proposed to avoid transient instability based on pre-contingency and post-contingency samples of voltage data of generator terminals. For each transmission line, the proposed method predicts the stability status, critical generators, and the amount of optimal generator rejection for each critical generator to stabilize the network for unstable scenarios and increase the stability margin before the loss of synchronism. The proposed method uses the full dynamic model of the power system in the offline optimization problems without using approximated models that simplify the dynamic response model of the power system elements. Also, thanks to the machine learning applicability, the proposed framework can be fast enough for real-time applications. Reducing the computational time and using the optimization models to improve the accuracy in an offline fashion solve a big challenge in power system stability and control and is a significant improvement on the existing methods. The main contributions of the proposed framework are summarized as follows:

a) A new RCA scheme based on generator rejection prediction is proposed to prevent fast transient instabilities after the occurrence of fault events. The proposed method eliminates the need for performing computationally expensive calculations and therefore, is suitable for real-time applications.

b) In the offline stage of the proposed framework, a heuristic optimization model considering the full dynamic model of the power network is proposed to assign the optimal amount of generator rejection to critical generators and maximize the stability margin with high accuracy for training the machine learning models.

D. PAPER ORGANIZATION

The rest of this paper is organized as follows. Section II describes the mathematical formulation for generator rejection calculation based on the extended equal area criterion (EEAC). Section III presents the optimization model of the problem. The comprehensive framework is explained in detail in section IV. Simulation results and discussions are expressed in section V. Finally, Section VI gives the conclusions of the paper.

II. GENERATOR REJECTION CALCULATION BASED ON EEAC

In this paper, EEAC has been used to determine the stability status and calculate the needed amount of generator rejection for each unstable scenario. Contrary to the previous methods all the calculations are performed in an offline fashion to build the dataset. Therefore, the P-δ curve is calculated using accurate full dynamic simulations.

The EEAC is used to convert the multi-machine power system to a single-machine infinite bus system (SMIB) [29]. EEAC is a powerful graphical tool in the transient stability study. It can assess the stability status, stability margin, and amount of required generator rejection to stabilize an unstable scenario by calculating the accelerating and decelerating areas in $P - \delta$ curve. To do so, the generators are grouped into two classes including critical machines (CMs) and non-critical machines (NMs). CMs consist of all generators that have lost their synchronism. Therefore, the system can be converted to a two-machine representation with CMs and NMs. Next, the system can be reduced to SMIB using the equations (1) - (6) [29]:

$$M_{CM} = \sum_{i\in CM} M_i, M_{NM} = \sum_{j\in NM} M_j \tag{1}$$

$$M_T = M_{CM} + M_{NM}, M = \frac{M_{CM} \cdot M_{NM}}{M_T} \tag{2}$$

$$\delta_{CM} = \frac{1}{M_{CM}} \cdot \sum_{i\in CM} M_i \cdot \delta_i, \delta_{NM} = \frac{1}{M_{NM}} \cdot \sum_{j\in NM} M_j \cdot \delta_j \tag{3}$$

$$P_m = \frac{1}{M_T} \cdot \left(M_{NM} \cdot \sum_{i\in CM} P_{mi} - M_{CM} \sum_{j\in NM} P_{mj} \right) \tag{4}$$

$$P_e = \frac{1}{M_T} \cdot \left(M_{NM} \cdot \sum_{i\in CM} P_{ei} - M_{CM} \cdot \sum_{j\in NM} P_{ej} \right) \tag{5}$$

$$\delta = \delta_{CM} - \delta_{NM}, M \cdot \frac{d^2\delta}{dt^2} = P_m - P_e \tag{6}$$

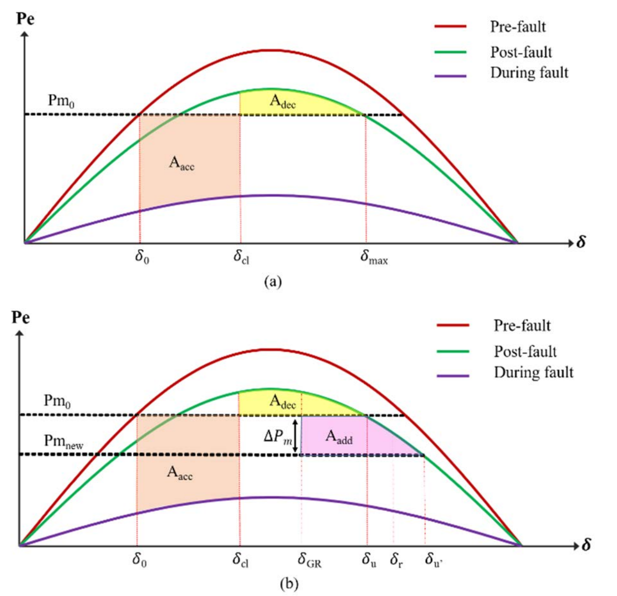


FIGURE 1. Schematic of the EEAC methods to (a) determine the stability status of the power network, (b) determine the amount of required generator rejection to prevent transient instability.

where δ, M, P_m, and P_e represent rotor angle, inertia, mechanical power, and electrical power related to the equivalent SMIB system, respectively. In addition, indices CM and NM are used for critical and non-critical machines, respectively. The process of determining stability status and amount of generator rejection based on EEAC is explained in detail.

As shown in Figure 1(a), A_{acc} is the amount of energy of generators that increases during the fault and A_{dec} is the maximum energy that the power system can dissipate in the post-fault condition. The stability status of the power system can be determined by calculating the difference between A_{acc} and A_{dcc} as follows:

$$A_{acc} = \int_{\delta_0}^{\delta_{cl}} (P_{m_0} - Pe_{DF}(\delta))d\delta \tag{7}$$

$$A_{dcc} = \int_{\delta_{cl}}^{\delta_u} (Pe_{PF}(\delta) - P_{m_0})d\delta \tag{8}$$

$$\eta = A_{dec} - A_{acc} \tag{9}$$

where η represents the stability margin. According to this criterion, if $\eta< 0$, the system is unstable, otherwise the system remains stable. In Figure 1, δ_0, δ_{cl}, δ_{GR}, δ_u, and $\delta_{u'}$ are rotor angels at fault moment, fault clearing time, moment of applying generator rejection, the moment system reaches the unstable equilibrium point before applying RCA, and the instant of unstable equilibrium point after applying RCA, respectively. Also, Pe_{DF}, and Pe_{PF} indicate the electrical power during the fault and after clearing the fault, respectively. In addition, the required amount of generator rejection can be obtained using the procedure shown in Figure 1(b). As shown in Figure 1(b), generator rejection can increase the deceleration area and preserve the stability of the system. Previous methods simplify the problem by considering $\delta_u = \delta_{u'}$ [12]. However, in this paper, the amount of generator rejection based on a new stability margin model is calculated using (10) for each unstable scenario.

$$A_{acc} \leq A_{dec_{new}} = \int_{\delta_{cl}}^{\delta_{GR}} \left(Pe_{PF}(\delta) - P_{m_0}\right) d\delta + \int_{\delta_{GR}}^{\delta_{u'}} \left(Pe_{PF}(\delta) - P_{m_{new}}\right) d\delta \tag{10}$$

where $P_{m_{new}}$ and $\delta_{u'}$ are unknown variables to be determined. To calculate the amount of generator shedding ($\Delta P_m = Pm_0 - Pm_{new}$), a repetitive algorithm is developed as shown in Figure 2. First, an arbitrary value for $Pm_{new}^{(0)}$ necessarily lower than Pm_0 is chosen and using the SMIB $P-\delta$ curve, $\delta_{u'}$ is determined. Then, $A_{dec_{new}}$ is calculated and compared with A_{acc}. If $A_{dec_{new}}^{(i)} = A_{acc} + \varepsilon$, where ε is a small positive constant. The process continues and the Pm_{new} will be updated until a stop criterion is satisfied.

The amount of generator shedding for each unstable scenario can be obtained using the explained strategy.

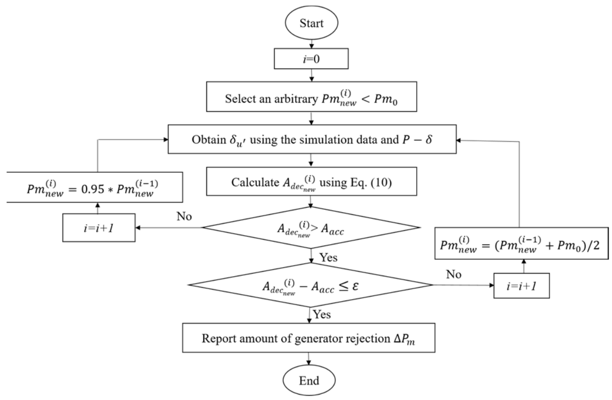


FIGURE 2. Flowchart of generator rejection calculation for an unstable scenario.

III. HEURISTIC OPTIMIZATION TO EXTRACT GENERATOR REJECTION PATTERNS

In this section, the critical generator identification model is explained. In addition, a heuristic optimization algorithm is employed to distribute the total calculated amount of generator rejection among the critical generators to maximize the stability margin and minimize the amount of generator rejection.

A. CRITICAL GENERATOR IDENTIFICATION

The critical generators are identified for each unstable scenario using the offline simulations. When an out-of-step event occurs, the related generators are labeled as CM as expressed in (11).

$$CM_i = \begin{cases} 1 & out\ of\ step = 1 \\ 0 & otherwise \end{cases} \quad i = 1, 2, .., N_G \tag{11}$$

The criticality of the generators depends on the fault location. In addition, there are $2^{N_G} - 1$ possible patterns for critical generators in a network with N_G number of generators. Therefore, it is hard to identify critical generators following a disturbance. To reduce the complexity of the critical generator prediction problem, transmission lines are classified into three groups and evaluated separately. Since there are a limited number of patterns for critical generators related to each transmission line, predicting critical generator patterns for individual lines is much easier than the prediction of critical generators for the whole network in one module. In this regard, the transmission lines are categorized into three groups as follows:

$$L_{ij}^{C} = \begin{cases} Neutral & N_{ij}^{CGP} = 0 \\ Non-critical & N_{ij}^{CGP} = 1 \\ Critical & N_{ij}^{CGP} \geq 2 \end{cases} \quad i, j = 1, 2, .., N_b, i \neq j \tag{12}$$

where L_{ij}^{C} and N_{ij}^{CGP} represents the transmission line ij classes and the number of critical generator patterns for line ij, respectively. The set of neutral lines does not have any unstable cases in the scenario generation process. Therefore, if a fault occurs on these lines, no RCA action is required. In addition, sets of non-critical lines have only one pattern for critical generators. Therefore, critical generator prediction is not required for non-critical lines. For critical lines, the patterns are extracted for each unstable scenario using (11). Since the number of patterns is limited, critical generator identification is a multi-class classification problem. Therefore, using pre-contingency and post-contingency voltage data and the generated dataset, the critical generator patterns for each critical line can be predicted by a classification module.

B. HEURISTIC OPTIMIZATION ALGORITHM TO ASSIGN GENERATOR REJECTION TO CRITICAL GENERATORS

Several methods have been proposed to assign the amount of generator tripping to different critical generators based on the amount of kinetic energy that each generator gained during the fault [19], [22], [23], [26]. Also, some papers only assign the amount of generator shedding based on the sequence of out-of-step [25]. In this study, an optimization-based algorithm is proposed to divide the amount of calculated generator shedding between critical generators by maximizing the stability margin of the system. Note that every power plant consists of a number of parallel generating units. Reducing the mechanical power of generators is a slow process. Therefore, to perform generator shedding, a number of generation units should be selected from critical generators to be switched off immediately following a transient instability detection. Also, the total amount of generator rejection should be equal to or greater than the amount of generator rejection calculated in the previous section. Since the amount of generator shedding is a discrete variable in real-life and may not be exactly equal to the amount, the optimization algorithm tries to assign generation rejection to generators so that the summation of the assigned values is close to the calculated total generation rejection. The goal of the optimization problem is to minimize the amount of generation rejection and maximize the stability margin. The objective function along with the operational constraints can be expressed as follows.

$$min \sum_{i \in \Omega^{G}} \Delta P_{G_i} - \beta(A_{dec} - A_{Acc}) \tag{13}$$

$$\sum_{i \in \Omega^{G}} \Delta P_{G_i} \geq \Delta P_m \tag{14}$$

Note that the full dynamic model of the power system is considered. As shown in Figure 3, a repetitive algorithm is employed to find the minimum amount of generator shedding considering (14). Then, among the considered RCA cases, the RCA with the highest stability margin is selected as the optimal RCA for each unstable scenario.

IV. GENERATOR REJECTION PREDICTION FRAMEWORK

In this paper, the details of the proposed generator rejection prediction are presented. The proposed framework has three main stages: 1) transient stability status prediction, 2) critical generator prediction, and 3) optimal generator shedding prediction.

Heuristic optimization Algorithm

Step1. Collect the data including ΔP_m, Critical generators, and amount of generation units steps for critical generators

Step2. Divide the ΔP_m between critical generators and form a set consist of all possible options $S^{(1)} = \left\{s_1^{(1)}, s_2^{(1)}, \dots, s_k^{(1)}\right\}$

Step3. $\forall s_j^{(1)} \in S^{(1)}$, if $\sum_{i=1}^{N_{CM}} \Delta P_{G_i}^{trip} \geq \Delta P_m$, form new $S^{(2)}$ icluding all cases satisfy this condition, $S^{(2)} = \left\{s_1^{(2)}, s_2^{(2)}, \dots, s_z^{(2)}\right\}$

Step4. Run the full dynamic simulation for those cases in $S^{(2)}$

Step5. Check stability status of all cases in *step4*, form $S^{(3)}$ including all cases stabilize the system, $S^{(3)} = \left\{s_1^{(3)}, s_2^{(3)}, \dots, s_x^{(3)}\right\}$

Step6. Calculate the stability margin for all cases in $S^{(3)}$

Step7. Report the best solution as optimize generator rejection scheme

FIGURE 3. Algorithm for finding the optimal generator rejection amount for each critical generators.

A. BULK SCENARIO GENERATION

To train the machine learning models, a bulk scenario dataset is generated for individual transmission lines. The dynamic behavior of the power network is closely related to fault location, fault duration, network configuration, and loading condition. Therefore, the random variation of these parameters is considered in the data generation process to generate a comprehensive dataset. Also, the data are generated for each line independently to reduce the complexities of the prediction models and increase the prediction accuracy of the modules. Moreover, a large number of scenarios are generated for each line to cover credible scenarios.

B. OPTIMIZED RANDOM FOREST CLASSIFIER

Since all the three modules predict specific patterns among a limited number of patterns, an optimized random forest classifier is trained for each module for individual lines. Random forest is an ensemble method that is a combination of different tree-structured classifiers. Assume a training dataset as follows:

$$T_i = \{(X_i, Y_i)_{i=1}^{N} | X_i \in R^M, Y_i \in R\} \tag{15}$$

where N, and M indicate the number of samples and number of features in the original dataset, respectively. The X_i, and Y_i represent the i^{th} row of samples and its target. Each tree is trained using a randomly selected dataset and a random subset of features. The number of trees is an important parameter that should be optimized. A higher number of classifiers increases the accuracy, however, it also increases the complexity of the model. Each tree can be shown as $\{h(x, \theta_k), k = 1, 2, \dots, l$. where l is the number of trees. Moreover, $\{\theta_k\}$ is a random parameter vector that determines how the k^{th} tree is grown. Every two of these random variables θ_k are independent and identically distributed. Depending on the problem the optimal number of classifiers is determined and after k iterations, the sequence of classifiers is obtained as follows.

$$\{h_1(x), h_2(x), \dots, h_k(x)\} \tag{16}$$

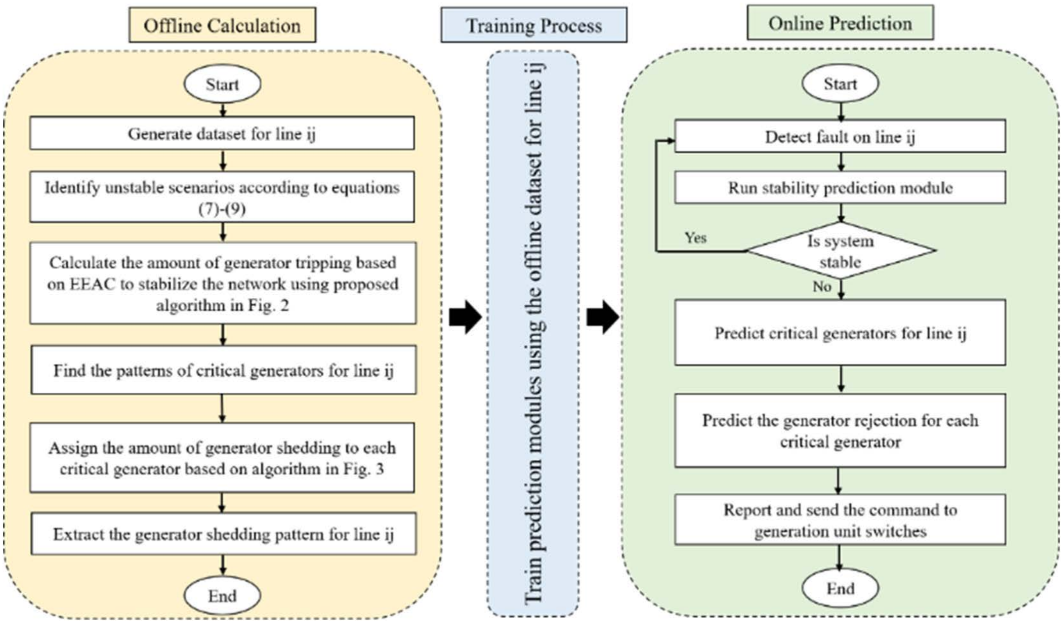


FIGURE 4. A comprehensive diagram of the proposed framework to predict optimal generator rejection for line ij.

The final result of the random forest is determined by an ordinary majority vote based on the decision function expressed as follows:

$$H(x) = argmax_y \sum_{i=1}^{k} I(h_i(x) = Y) \tag{17}$$

where the $H(x)$, h_i, I, and Y are the combination of the classification model, i^{th} decision tree, the indicator function, and the output variable respectively. There are different hyper-parameters for a random forest that need to be tuned according to the problem. For each module and for each line, the optimal number of trees, the random subsets of features to find the best split, and the maximum depth of the trees are determined to improve the performance of the random forest [31].

C. STABILITY STATUS PREDICTION MODULE

In normal operation conditions, the system is operated at a stable point and there is a balance between electrical power and the mechanical power of generators. When a disturbance occurs in a power network, generators start fluctuating and gain kinetic energy. If the generators can absorb the released energy, the system goes to another stable point and remains stable. Bulk scenarios are generated for each line, and using EEAC, A_{dec} and A_{acc} are calculated for all scenarios using (7)-(8). Scenarios with $\eta < 0$ are labeled as unstable (i.e., 1), and scenarios with $\eta \geq 0$ are labeled as stable (i.e., 0). Based on the generated dataset with two target classes, the stability prediction is a binary classification problem. Using the pre-contingency and post-contingency samples of generators' voltage data, the machine learning engine is trained to predict the stability status of the power network. Following instability detection, a signal will be sent to the next modules to finally determine the proper RCA for maintaining the transient stability of the system.

D. CRITICAL GENERATOR PREDICTION MODULE

Instead of identifying the critical generators or predicting the critical generators for the whole power network, in this paper, the critical generators are predicted for individual lines separately. If a scenario is predicted as unstable for those lines with only one critical generator pattern, the generator rejection will be predicted immediately for the critical generators in that pattern. Moreover, these lines have 100% accuracy for the critical generator prediction module and therefore, they increase the average accuracy of this module significantly. In addition, the lines with more than one critical generator pattern have a limited number of patterns which makes it easier for the classifier to predict the right pattern.

Since each line has a limited number of patterns for critical generators, predicting critical generators is a multi-class classification problem. The pre-contingency and post-contingency of generators' terminal voltage data are input data and patterns of critical generators represent the targets. The machine learning model of this module is trained using the generated dataset and critical generators are predicted for individual lines. Therefore, if a fault scenario is predicted as unstable by the transient stability prediction module, the critical generator prediction module will predict the related critical generators and send the predicted critical generators pattern to the final module to predict the optimal amount of generator shedding as RCA.

E. GENERATOR REJECTION PREDICTION MODULE

Practically, a generation facility consists of multiple machines. In this paper, 10 parallel machines are considered for each power plant. It is assumed that parallel machines have the same characteristics in each power plant. Therefore, the generator rejection variable for critical generators is practically a discrete variable. Therefore, it is not possible to shed the exact calculated amount of generator rejection based on EEAC. However, using the heuristic optimization, the amount of generator rejection (i.e. number of units to be tripped) that needs to be done for each critical generator is the possible closest amount to the calculated amount of generator rejection. For each unstable scenario, the number of units for critical generators is extracted which is an integer number between 0 (i.e. in case no generator shedding is required for that critical generator) and 10 (i.e., in case the whole power plant is required to be tripped). Therefore, the generator shedding prediction is converted to a multi-class classification with N_{CG} (number of critical generators) targets. If generator shedding is implemented for the whole network in one module, the generator shedding should be implemented for all generators. However, only specific generators need generator shedding prediction when each line is evaluated separately. It significantly reduces the solution space and increases the overall accuracy of this module.

$$\Delta P_{G_i}^{trip} \in \{K|0 \leq k \leq 10, k \in z\}, \mathrm{i} = 1, 2, .., N_{CM} \quad (18)$$

In the training stage, the steps of generator rejection for each critical generator and individual line are extracted offline using the optimization model presented in section III. Then for each transmission line, the dataset is built using the generator rejection patterns as targets and $V_G^{pre-fault}$ and $V_G^{post-fault}$ values along with critical generator patterns as inputs. The comprehensive diagram of the proposed framework is illustrated in Figure 4.

V. TESTS AND RESULTS

To validate the performance of the proposed framework, the IEEE 9-bus and 74-bus Nordic test systems are used. Bulk scenarios are generated using DIgSILENT programming language (DPL) commands. Full dynamic simulations are performed using DIgSILENT PowerFactory to derive the rotor angle curves of the generators before and after applying RCA. All the calculations, optimizations, and machine learning model training are coded and run using MATLAB. In addition, DIgSILENT and MATLAB are linked in order to apply possible solutions in each step of the optimization. The simulations are performed on an Intel 3.4 GHz CPU with 16 GB of RAM.

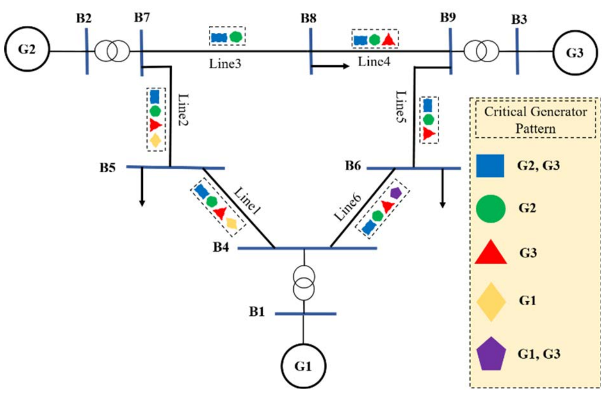


FIGURE 5. Schematic of single line diagram of the IEEE 9-bus system along with critical generator patterns for each line.

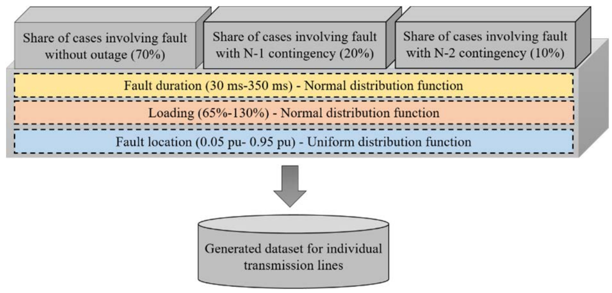


FIGURE 6. Scenario generation process for individual transmission lines.

In this paper, randomly selected 80% and the remaining 20% of the dataset samples are used for training and testing the machine learning engine, respectively.

A. IEEE 9-BUS SYSTEM

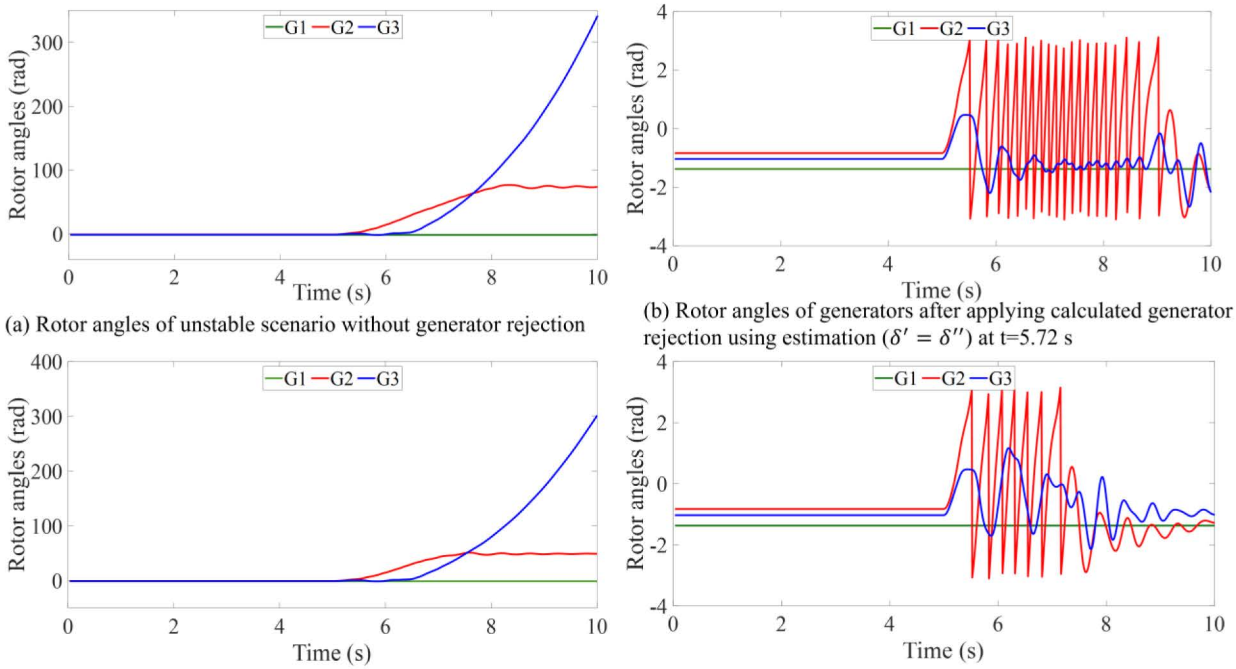
The IEEE 9-bus system has 3 generators, 6 transmission lines, 9 buses, and 3 loads. The single-line diagram of this network is shown in Figure 5. Since there is no parallel transmission line in this network, six frameworks are designed for this system. In the following sub-sections, different parts of the proposed framework are implemented on this network.

1) BULK SCENARIO GENERATION

To generate bulk scenarios for each line, different fault locations, fault durations, and system loadings are randomly chosen. For the IEEE 9-bus system, 2000 scenarios are generated for each line independently. Moreover, fault duration is randomly set in the range of 30 ms up to 350 ms based on the normal distribution function. In addition, the system's loading is varied randomly between 65% and 130%. Finally, the fault locations are randomly chosen using a uniform distribution function in the range of 0.05 to 0.95 of line length. In addition, N-1 and N-2 contingencies are considered in the scenario generation process to cover credible outage events for each

TABLE 1. Accuracy of transient stability prediction module in the IEEE 9-bus test system.

Set of transmission lines	Number of unstable cases	Prediction accuracy (%)
{5-4}	361/2000 (18.05%)	99.16%
{5-7}	875/2000 (43.75%)	99.48%
{7-8}	302/2000 (15.1%)	98.84%
{8-9}	484/2000 (24.2%)	99.05%
{9-6}	467/2000 (23.35%)	98.76%
{4-6}	469/2000 (23.45%)	99.11%



(a) Rotor angles of unstable scenario without generator rejection

(b) Rotor angles of generators after applying calculated generator rejection using estimation ($\delta' = \delta''$) at t=5.72 s

(c) Rotor angles of generators after applying calculated generator rejection using optimization at t=6.197 s

(d) Rotor angles of generators after applying predicted optimize generator rejection at t=5.72

FIGURE 7. **The rotor angles of generators after applying different generator rejection strategies for a specific case study in the IEEE 9-bus system, (a) the scenario without RCA, (b) scenario after applying RCA based on estimation methods, (c) Scenario after applying optimization-based RCA, (d) Scenario after applying proposed RCA.**

transmission line. Figure 6 shows the process of scenario generation for each line.

2) STABILITY STATUS PREDICTION

The stability status of power system is predicted for each fault event in this module. First, using (7)-(9), the stability status of each scenario is investigated in an offline fashion. The terminal voltage of the generators including one pre-fault data and 10 post-fault cycles (PFCs) as inputs and the stability status of the power network (0 or 1) as output are fed into the machine learning engine for training. The accuracy of the transient stability prediction module for each line is presented in Table 1.

As shown in Table 1, the prediction accuracy of the stability status prediction module related to the IEEE 9-bus system is more than 98.76% following a large disturbance. When the stability status of the system following the occurrence of a new fault event is predicted as unstable, the critical generator prediction module will be run to identify the critical generators for finding a proper RCA.

3) CRITICAL GENERATOR PREDICTION

In this part, critical generator patterns for each line are extracted to train the machine learning model in an offline process. The critical generator patterns for each line of the IEEE 9-bus test system are demonstrated in Figure 5. Next, using the input data (i.e., the pre-contingency and post-contingency voltage values) and the output data (i.e., the critical generator patterns), the critical generators can be predicted using the multi-class classifier. The accuracy of the critical generator prediction module for all lines is shown in Table 2.

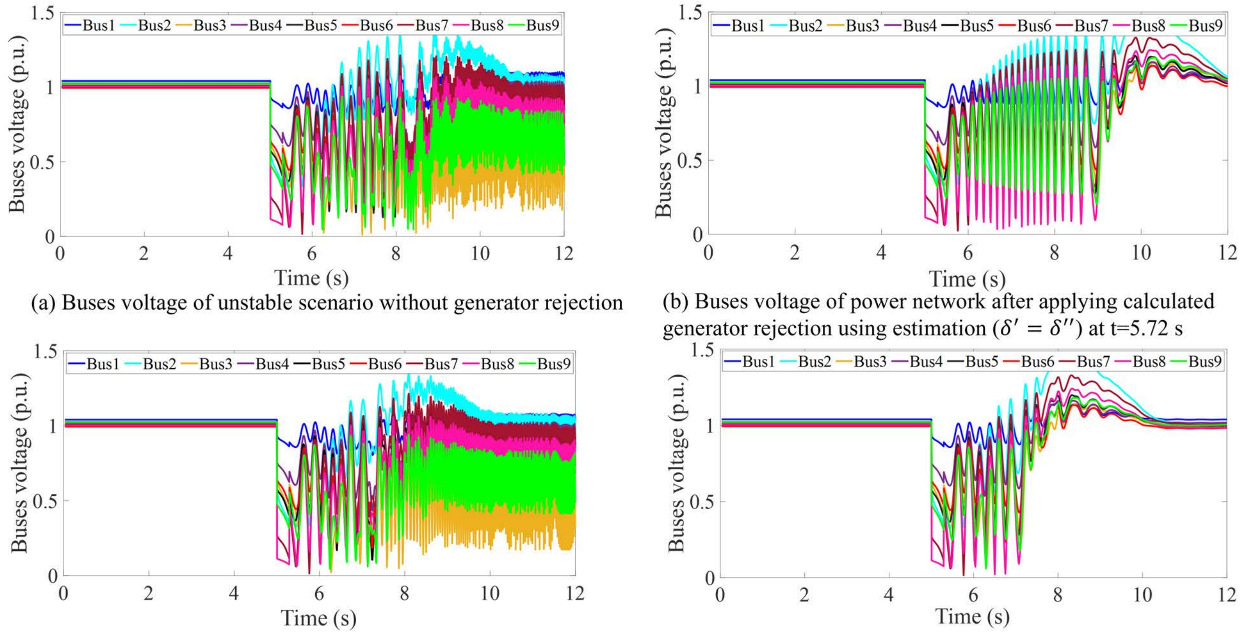
TABLE 2. **Accuracy of critical generator prediction module in the IEEE 9-bus test system.**

Set of transmission lines	Number of critical generator patterns	Prediction accuracy (%)	Average accuracy using MMS (%)	Accuracy without using MMS strategy (%)
{5-4}	4	96.39	96.77	94.89
{5-7}	4	97.06		
{7-8}	2	97.22		
{8-9}	3	96.87		
{9-6}	3	96.68		
{4-6}	4	96.44		

According to Table 2, the average accuracy of critical generator prediction modules using the proposed strategy (i.e., building a framework for each line independently) is approximately 2% higher than that of the existing methods which predict the critical generators for the whole network using a single integrated module. Therefore, the proposed strategy enhances the accuracy of critical generator prediction.

4) GENERATOR REJECTION PREDICTION

In this part, the patterns of generator rejection as RCA for all critical generators are identified using the heuristic



(a) Buses voltage of unstable scenario without generator rejection

(b) Buses voltage of power network after applying calculated generator rejection using estimation ($\delta' = \delta''$) at t=5.72 s

(c) Buses voltage of power network after applying calculated generator rejection using optimization at t=6.197 s

(d) Buses voltage of power network after applying predicted optimize generator rejection at t=5.72

FIGURE 8. Voltage magnitudes after applying different generator rejection strategies for a specific case study in the IEEE 9-bus system.

TABLE 3. Accuracy of generator rejection prediction module for individual lines in the IEEE 9-bus test system.

Set of transmission lines	Accuracy of generator rejection prediction (%)			Average accuracy of generator shedding prediction (%)
	G1	G2	G3	
{5-4}	89.11	93.27	94.66	92.34
{5-7}	91.85	94.38	94.07	93.44
{7-8}	-	95.23	94.62	94.92
{8-9}	-	93.79	94.16	93.97
{9-6}	-	93.18	95.06	94.12
{4-6}	90.57	94.30	94.68	93.18

optimization in an offline mode. Using the generated dataset and depending on the number of critical generators for each line, one, two, or three classifiers are trained for each line and the amount of generator shedding for each critical generator is predicted. The prediction accuracy of the generator rejection prediction module for the IEEE 9-bus system is shown in Table 3. Note that G1 does not exist in the critical generator patterns for 3 lines including {7-8}, {8-9}, and {9-6}. Therefore, there is no need to predict the number of generation units of G1 for these lines in the generator shedding prediction module. It can be seen that the obtained average accuracies are high for this system.

5) PERFORMANCE COMPARISON BETWEEN THE PROPOSED AND EXISTING METHODS

In this part, a comparison is performed to show the functionality of the proposed framework. A 3-phase fault is applied on line 7-8 at t=5 s and is cleared after 297 ms. The first module (i.e., the stability prediction module) predicts that the system becomes unstable following this contingency. Figure 7 shows the rotor angle oscillations of all generators. The rotor angle instability for this scenario is shown in Figure 7(a). The proposed optimization model is run and the needed amount of generator shedding is 15.87 MW in this case. Also, the amount of generation shedding is calculated based on approximation $\delta_u = \delta_{u'}$ and the calculated amount is 26.81 MW using the existing energy function-based methods. First, generator shedding is applied based on an energy function-based method [11] using an approximated model to calculate the generator rejection quickly. The generator shedding value of 26.81 MW requires 3.16 generator units to be tripped. Since these methods trip the generators based on the sequence of out-of-step or energy index, the calculated amount is tipped from G3. Therefore, four units of G3 are tripped at t=5.72 s. As shown in Figure 7(b), these methods are fast enough to effectively stabilize the network. Moreover, based on another approach, generator shedding is performed by running an optimization model with a computational time of about 500 ms. Using this method, the optimal RCA decision is tripping one unit of G2. The optimal generator shedding is applied at t=6.197 s. The rotor angles of the generators after applying the calculated generator shedding are shown in Figure 7(c). Since the generator rejection is applied relatively late, the system loses the synchronism. Finally, the proposed framework predicts that one unit of G2 and one unit of G3 (totally 24.8 MW) need to be tripped to stabilize the network. The predicted generator rejection is applied at t=5.72 s and the rotor angles of the generators

TABLE 4. Performance comparison of the proposed framework and existing methods for a specific case study in the IEEE 9-bus system.

Generator rejection strategy	Execution time		Amount of generator shedding		Location of generator shedding	Stability of the network
	Considering communication delays	practicality	$\sum_{i=1}^{N_{CM}} \Delta P_{G_i}^{trip}$	practicality		
Estimation	~ 450 ms	✓	34 MW	X	G3	stable
Optimization	~ 1-2 s	X	16.3 MW	✓	G2	unstable
Proposed framework	~ 450 ms	✓	24.8 MW	✓	G2, G3	stable

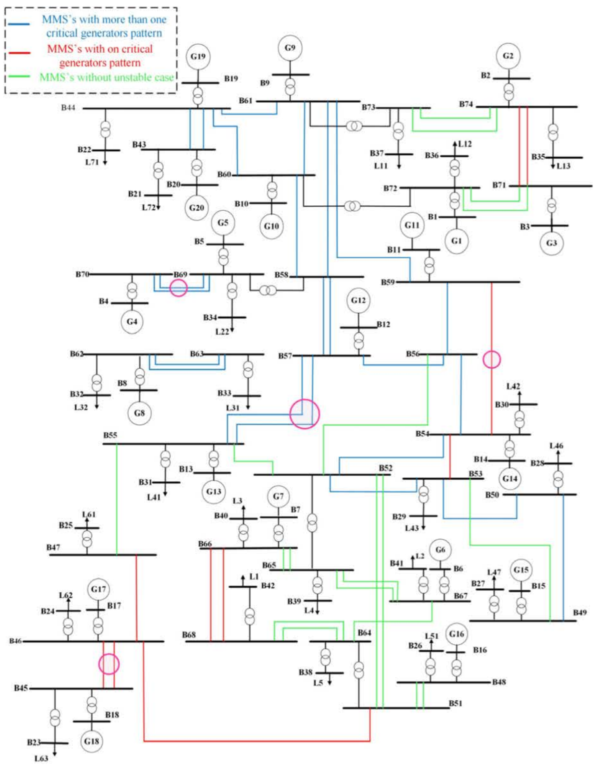


FIGURE 9. Single line diagram of the Nordic test system.

for this case are shown in Figure 7(d). This comparative analysis shows the effectiveness of the proposed framework. Although the generator rejection based on estimation can stabilize the network, it tripped around 9 MW higher than the proposed framework. Figures 7(b) and 7(d) show the importance of choosing the right candidate generators for generator shedding. The obtained bus voltages are also illustrated in Figure 8 for all methods. Comparing Figures 8(b) and 8(d), the proposed framework is able to recover voltage faster and with fewer fluctuations.

In this regard, the performance of the existing methods and the proposed method are summarized in Table 4. It is clear that the optimization-based methods might be impractical for unstable fault scenarios quickly evolving into transient instability due to their relatively high computational time. According to Table 4, the proposed framework benefits from the merits of estimation-based methods in terms of low computational time and optimization-based methods in terms of the capability of maintaining the stability of the system.

TABLE 5. Accuracy of two first modules of the proposed framework in the Nordic test system.

Set of transmission lines	Accuracy of stability prediction module (%)	Number of critical generator patterns	Accuracy of critical generator prediction (%)
{43-44, 43-44*}	98.96	11	94.57
{46-45, 46-45*}	99.49	1	100
{46-47}	99.05	1	100
{50-49}	98.85	4	95.84
{51-46}	98.88	1	100
{50-53}	99.04	3	95.31
{53-52}	99.15	10	94.17
{54-52}	99.02	8	94.31
{53-54}	98.90	1	100
{54-56}	99.12	2	96.54
{55-57, 55-57*}	99.25	8	94.23
{56-57}	99.49	11	94.78
{58-57, 58-57*}	99.25	17	93.84
{54-59}	99.06	1	100
{56-59}	99.21	4	94.96
{44-60}	98.69	6	94.72
{58-60}	99.02	16	93.73
{44-61}	98.98	9	95.41
{61-58}	99.23	14	93.96
{59-61}	99.13	10	94.75
{60-61}	99.04	16	93.82
{62-63, 62-63*}	99.27	2	95.48
{66-68, 66-68*}	99.06	1	100
{69-70,69-70*}	99.22	2	95.38
{74-71, 74-71*}	98.85	1	100

B. NORDIC TEST SYSTEM

To generalize the proposed methodology, the Nordic system as a larger power network is used to evaluate the performance of the proposed framework. The Nordic test system consists of 74 buses, 20 generators, and 52 transmission lines. According to the presence of parallel lines in this system, 37 sets of distinct lines exist in this network. For each set of lines, 6000 scenarios are generated. The single-line diagram of the Nordic system is shown in Figure 9. As shown in Figure 9, the Nordic test system has three groups of lines, 1) lines with more than one pattern for critical generators (blue lines), 2) lines with only one pattern for critical generators (red lines), and 3) lines with no unstable scenarios (green lines). The effectiveness of individual evaluation of lines is more noticeable in the Nordic test system. For example, the sets of lines without any unstable cases do not need any RCA prediction. According to Figure 9, there are 12 sets of lines that do not have unstable cases in the scenario

TABLE 6. Details of the generator rejection prediction for the selected sets of transmission lines in the Nordic test system.

Set of transmission lines	Critical power plant	Accuracy of generator rejection prediction (%)											
		G4	G6	G7	G8	G11	G12	G13	G14	G15	G16	G17	G18
{59-54}	G11	-	-	-	-	96.5	-	-	-	-	-	-	-
{46-45, 46-45*}	G17, G18	-	-	-	-	-	-	-	-	-	-	94.3	95.7
{69-70, 69-70*}	G4	97.3	-	-	-	-	-	-	-	-	-	-	-
	G6-G8, G11-G18	-	91.5	100	93.8	93.2	90.1	100	100	100	100	93.8	93.1
{55-57, 55-57*}	G8	-	-	-	96.2	-	-	-	-	-	-	-	-
	G6-G8, G11-G18	-	92.2	100	93.8	93.9	89.9	100	100	100	100	94.3	94.2
	G6-G8, G13-G18	-	91.9	100	93.6	-	-	100	100	100	100	95.3	95.1
	G8, G12	-	-	-	94.6	-	91.8	-	-	-	-	-	-
	G4, G8	96.8	-	-	93.7	-	-	-	-	-	-	-	-
	G4-G8, G11-G18	96.1	90.7	97.8	93.4	94.2	91.3	100	100	100	100	94.7	95.4
	G6-G8, G11, G13-G18	-	93.4	100	93.3	94.6	-	100	100	100	100	95.9	94.6
	G4, G8, G12	97.5	-	-	94.2	-	92.7	-	-	-	-	-	-

generation process. However, for those neutral lines, there is a possibility of mistakenly detecting instability and triggering RCA if the prediction module is designed for the whole network. In addition, for the set of lines with only one critical generator pattern, the accuracy of the critical generator prediction module is 100%. The stability and critical generator prediction accuracies and the number of critical generator patterns for all lines are illustrated in Table 5.

According to Table 5, there are 31 distinct critical generator patterns in the Nordic test system. To show the effectiveness of the individual line evaluation strategy, a comparison is made between the proposed and the conventional methods for critical generator prediction. First, using all patterns and all scenarios in one module, critical generators are predicted for the whole network using an optimized random forest. The obtained prediction accuracy of critical generator prediction is 93.22% in this case. However, the average accuracy of the proposed framework for the Nordic system is 97.42% using the proposed strategy (i.e., predicting the critical generator patterns for each line individually). This comparison shows the satisfactory performance of the proposed framework when implemented for a large-scale system.

Four sets of lines of the Nordic test system are selected to show further details about the performance of the proposed framework regarding the generator rejection prediction. To this end, two non-critical sets of lines (i.e., {59-54} and {46-45, 46-45*}) and two critical sets of lines (i.e., {69-70, 69-70*} and {55-57, 55-57*}) are chosen. The critical generator patterns along with the obtained accuracies in generator rejection prediction for these lines are given in Table 6.

VI. CONCLUSION

This paper presented a novel generator rejection prediction to prevent rotor angle instability in a power network. The following conclusions can be drawn based on the obtained results.

1) Instead of RCA calculation, the RCA prediction is proposed to make real-time RCA practical. The proposed framework can predict the stability status of the power system following a large disturbance and in case instability is predicted, it predicts the critical generators and the proper generator rejection quickly enough to stabilize the network.
2) A heuristic optimization method is utilized to calculate the optimal amount of generator rejection for critical generators in an offline fashion for training the machine learning engines. This method considers accurate dynamic model of the system and hence has high accuracy.
3) Transmission lines are classified into three groups and a specific framework is designed for each transmission line to enhance the accuracy of the prediction modules and reduce the prediction complexity.
4) For each transmission line, three modules (i.e., stability prediction, critical generator prediction, and generator rejection prediction) are trained using the bulk dataset and run subsequently following a fault occurrence in the system.
5) The obtained results based on two small and large test systems show the effectiveness of the proposed framework.

Further research may be conducted to improve the accuracy of the generator rejection module using new machine learning methods including deep learning and reinforcement learning methods.

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