Deep Learning based Security-Constrained Unit Commitment Considering Locational Frequency Stability in Low-Inertia Power Systems

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Abstract—With the goal of electricity system decarbonization, conventional synchronous generators are gradually replaced by converter-interfaced renewable generations. Such transition is causing concerns over system frequency and rate-of-change-of-frequency (RoCoF) security due to significant reduction in system inertia. Existing efforts are mostly derived from uniform system frequency response model which may fail to capture all characteristics of the systems. To ensure the locational frequency security, this paper presents a deep neural network (DNN) based RoCoF-constrained unit commitment (DNN-RCUC) model. RoCoF predictor is trained to predict the highest locational RoCoF based on a high-fidelity simulation dataset. Training samples are generated from models over various scenarios, which can avoid simulation divergence and system instability. The trained network is then reformulated into a set of mixed-integer linear constraints representing the locational RoCoF-limiting constraints in unit commitment. The proposed DNN-RCUC model is studied on the IEEE 24-bus system. Time domain simulation results on PSS/E demonstrate the effectiveness of the proposed algorithm.

Index Terms—Deep learning, Frequency stability, Learning-embedded optimization, Low-inertia power systems, Renewable integration, Rate of change of frequency, Unit commitment.

I. INTRODUCTION

Zero-carbon wind and solar energy sources dominate the new electricity generation installed over the past decades. Besides the increasing penetration of converter-based renewable energy sources (RES), the development of energy storage systems and high-voltage dc (HVDC) transmission systems have resulted in large-scale application of power-electronic devices [1]. As a result of this transition, current power systems may ultimately shift towards power systems with 100% renewable-based generation.

Traditionally, the characteristics of power systems is primarily dominated by synchronous generators (SGs). Due to the strong coupling between the synchronous generator’s rotor and the power system, the inertia stored in synchronous generator rotors plays an important role in regulating the power system frequency dynamics. With more generation coming from converter-based resources, insufficient inertia would be a main challenge for power systems stability [2]. Moreover, due to the retirement and replacement of conventional generation, the system kinetic energy is decreasing significantly, leaving the system more likely to subject to high rate of change of frequency (RoCoF) and large frequency excursion. When RoCoF violates the necessary industrial control and operation standards, protection devices would disconnect generators from the grid [3]. In particular, insufficient inertia exacerbates the need for fast frequency response services to secure frequency stability [4]. Altering RoCoF protection and enabling emulated inertia measures were found to be the most effective in reducing the frequency stability risk of future converter-based power system in Ireland [5].

As a mitigation strategy in the category of preventive actions, several transmission system operators (TSO) impose extra RoCoF related constraints in the conventional unit commitment model to keep the minimum amount of synchronous inertia online [6]. Requirements for adequate frequency control of the electric power system were suggested by Federal Energy Regulatory Commission [7]. EirGrid has also introduced a synchronous inertial response (SIR) constraint to ensure that the available inertia does not fall below a static limit of 23,000 MWs in Ireland [8]. The Swedish TSO ordered the Oskarshamn Kraftgrupp to reduce its nuclear power output by 100 MW to mitigate the risk of loss of the power plant in Sweden [9].

Traditionally, by looking at the collective performance of all generators using a system equivalent model, frequency related constraints can be derived and incorporated into the optimization formulation. The system equivalent model-based frequency constrained stochastic economic dispatch is considered in [10]. Reference [11] incorporated frequency-related constraints into traditional unit commitment enforcing limitations on RoCoF that is derived from a uniform frequency response model. A mixed analytical-numerical approach based on multi-regions has been studied in [12], which investigated the model combining evolution of the center of inertia and certain inter-area oscillations. Despite the previous efforts of modelling system frequency response (SFR) in mathematical programming-based scheduling, they ignored the nodal inertial response and the impact of disturbance propagation [13].

Reference [14] evaluates a fast transient frequency stability assessment using a data-driven tool, based on deep neural network (DNN). The actual input-output feature data is utilized to train the network parameters, which effectively extracts
system characteristics. A DNN-based trajectory constraint encoding framework is proposed in [15], which incorporates frequency nadir and stability characteristics related constraints against the worst-case contingency. However, none of these methods considers locational RoCoF security and the impact of generator aggregations on system stability is not handled well.

This paper is to address the aforementioned issues. The contributions of this paper are as follows. First, we proposed a novel DNN-based RoCoF-constrained unit commitment (DNN-RCUC) model to secure the system locational frequency stability against worst contingencies. The proposed DNN-RCUC model shows better performance in handling the conservativity issues. Secondly, a model-based data generation approach is introduced to generate practical and ideal cases for RoCoF predictor training. The proposed method covers vast ranges of operating conditions, being able to avoid divergent time domain simulations. In addition, infeasible cases that may degrade the RoCoF predictor’s accuracy are filtered out. Thirdly, the impact of generator aggregations is considered in our case study, showing the proposed DNN-RCUC model can secure locational frequency stability in various conditions.

The remainder of this paper is organized as follows. Section II discusses the power system mathematical based model and DNN-based model thoroughly. Section III presents the methodology of model-based data generation and DNN-RCUC formulation. Section IV shows the simulation results. Section V presents the concluding remarks and future work.

II. SYSTEM FREQUENCY DYNAMICS

A. System Equivalent Model

The frequency of the power system is one of the most important metrics that indicate the system stability. Traditionally, the frequency is treated as unique of the whole system, which is derived from the system equivalent model extended from one-machine swing equation. The rotating inertia of a synchronous generator is equal to the stored energy in the rotors of the machine at nominal speed, which is defined as:

\[ E_i = \frac{1}{2} J_i \omega_i^2 \]  

(1)

The rotational inertia of a single shaft is commonly defined using its inertia constant and the rated apparent power [16]. For a single machine, the inertia constant is expressed as follows:

\[ H_i = \frac{J_i \omega_i^2}{2 S_{Bi}} \]  

(2)

where \( H_i \) is the inertia constant of the generator in seconds; \( J_i \) is the moment of inertia of the shaft in kg∙m²∙s⁻¹; \( S_{Bi} \) is the base power in MVA; and \( \omega_i \) is the nominal rotational speed instead of the actual speed of the machine.

Power system inertia is defined as the total amount of rotational energy stored in all rotating synchronous units; dynamics of these generators’ rotors are directly coupled with the grid electrical dynamics. It can be expressed as follows.

\[ E_{sys} = \sum_{i=1}^{N} \frac{1}{2} J_i \omega_i^2 = \sum_{i=1}^{N} H_i S_{Bi} \]  

(3)

For a single generator \( i \), the swing equation is expressed as:

\[ \frac{d \omega_i}{dt} = \frac{P_m - P_{load}}{2H_i S_{Bi}} \omega_n \]  

(4)

where \( P_m \) is the mechanical power and \( P_{load} \) is the load from the power system, while \( \omega_n \) is the rated steady state frequency of the system. \( \omega_i \) is more commonly known as RoCoF. The swing equation of the system equivalent model can be then applied to the whole grid [17]. After a disturbance of power mismatch occurrence, the system RoCoF related to the total system inertia can be defined as,

\[ RE^t = \frac{-\Delta P}{2H_{sys} S_B} \omega_n \]  

(5)

where \( \Delta P \) is the sudden change in active power in MW at \( t=t_0 \).

B. Dynamic Model

Following a sudden change in load or a generation contingency, the dynamic behavior of the system frequency can be described using the swing equation of system equivalent single-machine representation,

\[ P_m - P_e = M \frac{\partial \Delta \omega}{\partial t} + D \Delta \omega \]  

(6)

where \( M \) and \( D \) are the aggregated system inertia constant and damping coefficient corresponding to the committed synchronous generators respectively. \( P_m \) is the mechanical input power. \( P_e \) is the electrical output power. However, only considering the dynamics of the equivalent model in systems would underestimate the actual need for frequency ancillary services, leading to higher locational RoCoF and larger regional frequency deviation than expected.

Using the topological information and the system parameters, the transmission network can be modeled as a graph consisting of nodes (buses) and edges (branches). The oscillatory behavior of each individual bus can be expressed as follows,

\[ m_i \dot{\theta}_i + d_i \dot{\theta}_i = P_{in,i} - \sum_{j=1}^{n} b_{ij} \sin (\theta_i - \theta_j), \]  

(7)

where \( m_i \) and \( d_i \) denote the inertia coefficients and damping ratio for node \( i \) respectively, while \( P_{in,i} \) denotes the power input. With inertia on certain nodes \( m_i > 0 \), it is an approximation model for the swing dynamics of high-voltage transmission network within a short period following the event [18]. A network-reduced model with \( N \) generator buses can be obtained by eliminating passive load buses via Kron reduction [19]. The phase angle \( \theta \) of generator buses can be expressed by the following dynamic equation,

\[ M \ddot{\theta} + D \dot{\theta} = P - L \theta \]  

(8)

where \( M = \text{diag}(m_i) \), \( D = \text{diag}(d_i) \). And for the Laplacian matrix \( L \), its off-diagonal elements are \( l_{ij} = -b_{ij} V_i^{(0)} V_j^{(0)} \), and diagonals are \( l_{ii} = \sum_{j=1,j \neq i}^{n} b_{ij} V_i^{(0)} V_j^{(0)} \). Under the assumption of homogeneous inertia, the frequency deviations at bus \( i \) can then be derived [18].
The disturbance feature vector is defined against the loss of largest generation, the magnitude is expressed as,

\[ p^S_r = \max_{g \in G}(P_{r,1}, \ldots, P_{r,2}, \ldots, P_{N_G,s}) \]  

The location of the disturbance is then represented by the index of the generator,

\[ g^s = \arg \max_{g \in G}(P_{1,s}, \ldots, P_{2,s}, \ldots, P_{N_G,s}) \]  

We encode the information of magnitude and location into the disturbance feature vector as,

\[ x^s = [u^s, g^s, P_r] \]  

Now consider a fully connected neural network with \( N_h \) hidden layer. Each layer uses a rectified linear unit (ReLU) activation function as \( \sigma(\cdot) = \max(\cdot, 0) \) and the output layer is a linear activation function. The predicted RoCoF can be expressed as follows,

\[ z_1 = x_3 W_1 + b_1 \]
\[ z_m = z_{m-1} W_m + b_m \]
\[ z_m = \max(z_m, 0) \]

where \( W_m \) and \( b_m \) represent the weight and bias for the \( m \)-th hidden layer, and \( W_{N_h+1} \) and \( b_{N_h+1} \) represent the set of weight and bias of the output layer.

### III. METHODOLOGY

#### A. Model-based Data Generation

Wide-range space of all power injections is utilized in [15] to ensure reliability under vast ranges of operating conditions. However, such random injections may lead to divergence during the simulation initialization process. If time-domain simulation is initialized successfully, the transient stability may still be subject to system oscillation mode as well as large rotor angle differences. It has also shown that many randomly sampled power injections are not stable under the worst-case disturbance even with stability predictor applied. In addition, stability predictor in random generation approach may also increase the computational burden and compromise the efficiency of the algorithm.

Unlike randomly data generation considering wide-range space of dispatching, a model-based systematic data generation approach is proposed to generate reasonable and representative data that will be used to train RoCoF Predictors. Training samples are generated from models over various load and RES scenarios, traditional SCUC (T-SCUC) models and frequency constrained SCUC models are implemented in this process [20].

Given the load forecast and RES forecast, the T-SCUC is the base model generating dispatching samples. Objective function (19a) is to minimize the total system cost consisting of variable fuel costs, no-load costs, start-up costs, and reserve costs.

\[ \min_{\Phi} \sum_{g \in G} \sum_{t \in T} (c^g_{NL,s} + c^L_{NL,s} u^g_{s,t} + c^U_{NL,s} u^g_{s,t} + c^RE_{NL,s} r^g_{s,t}) \]  

Laplacian matrix \( L \) of the grid and Fiedler mode value depend on the power-angle characteristics, which are determined by the active power injection [13]. Thus, the active power injection of all SGs will be encoded into the feature vector.

\[ P_r = [P_{1,s}, \ldots, P_{2,s}, \ldots, P_{N_G,s}] \]
The constraints on RoCoF for locational frequency dynamics are nonlinear. In order to incorporate these frequency-related constraints into the proposed LRC-SCUC model, a linear approximation method is introduced. The SCUC models used for data generation are summarized in TABLE I, the detail of all models is presented in [20].

**TABLE I**

| Different SCUC Models | Model | Objective Function | Shared Constraints | Unique Constraints |
|-----------------------|-------|--------------------|--------------------|-------------------|
| T-SCUC                | (19a) | (19b)-(19o)        | None               | (19p)             |
| ERC-SCUC              |       | (19a)              | (19b)-(19o)        | (19q)-(19r)       |
| LRC-SCUC              |       | (19a)              | (19b)-(19o)        | (19q)-(19r)       |

**B. DNN Linearization**

To encode the DNN into the MILP SCUC problem, decision variables are introduced to build the disturbance feature vector. Binary variable \( \lambda_g^{G,t} \) is used to indicate the status of largest output power of generator \( g \) in scheduling period \( t \), a big-M method is introduced to express the disturbance vector,

\[
P_{g,t} - P_{g,t-1} \leq R_{g,t}^{pr}, \quad \forall g, t
\]

where \( M \) is a big positive number. Equation (20) enforces \( \lambda_g^{G,t} \) to be zero is the dispatched output power of other generators \( p \) is larger than generator \( g \) at period \( t \), while (21) limit the number of potential largest generator to be one at one period. When generator \( g \) has the largest output power, (20) and (21) would set the status of largest output power \( \lambda_g^{G,t} \) to be 1. To express the magnitude of disturbance, variable \( \varepsilon_{g,t} \) is defined as the indicators of disturbance,

\[
\varepsilon_{g,t} = \lambda_{g,t}^{G} - P_{g,t} \geq - M(1 - \lambda_{g,t}^{G}), \forall g, t, \quad (22)
\]

\[
\varepsilon_{g,t} = \lambda_{g,t}^{G} - P_{g,t} \leq M(1 - \lambda_{g,t}^{G}), \forall g, t, \quad (23)
\]

\[
0 \leq \varepsilon_{g,t} \leq M \lambda_{g,t}^{G}, \forall g, t, \quad (24)
\]

Thus, the input feature vector can be expressed as follows,

\[
x_t = [u_{t,1}, \ldots, u_{N_G,t}, \varepsilon_{g,t}, \ldots, \varepsilon_{N_G,t}, p_{1,t}, \ldots, p_{N_G,t}]
\]

(25)

RoCoF-lmiting constraints can be derived from the pre-trained RoCoF predictor \( \hat{R}(x, W, b) \), the nonlinear constraints can be incorporated into MILP problems by introducing auxiliary binary variables \( a \). The reformulation of DNN-based RoCoF predictor is as follows,

\[
\hat{R}_{L,t} = x_{L,t} W_{L+1}^a + b_{L+1}, \forall t,
\]

(26a)

\[
\hat{z}_{m,t}^{a} = z_{m-1,t}^{a} W_{m}^{a} + b_{m}^{a}, \forall m, \forall t,
\]

(26b)

\[
z_{m[l],t} \leq \hat{z}_{m[l],t} - M(1 - a_{m[l],t}), \forall m, l, t
\]

(26c)

\[
z_{m[l],t} \leq \hat{z}_{m[l],t} + a_{m[l],t}, \forall m, l, t
\]

(26d)

\[
z_{m[l],t} \leq M a_{m[l],t}, \forall m, l, t
\]

(26e)

\[
a_{m[l],t} \geq 0, \forall m, l, \forall t
\]

(26f)

\[
\hat{R}_{L,t} = z_{L,t} W_{L+1} + b_{L+1}, \forall t,
\]

(26h)
Then the RoCoF related constrained can be formulated as,
\[ \dot{R}_{ht} \leq -\alpha_{rocof} R_{\text{lim}} \quad \forall t, \]

IV. CASE STUDIES

A case study on IEEE 24-bus system [21] is provided to demonstrate the effectiveness of the proposed methods. This test system contains 24 buses, 33 generators and 38 lines, which also considers decarbonized generation characterized by wind power. The base case has a total demand from 1,195 MW to a peak of 2,116 MW. To ensure the practicality of the dataset and the generality of the trained model, load profile and RES profile are sampled based on Gaussian distribution while the deviation of means value ranges from [-20%, 20%] of the based value. The mathematical model-based data generation is operated in Python using Pyomo [22]. Regarding post-contingency frequency limits, RoCoF must be higher than -0.5Hz/s to avoid the tripping of RoCoF-sensitive protection relays, and the optimality gap is set to 0.1%. The PSS/E software is used for time domain simulation and labeling process, and full-scale models with detailed generator dynamics are implemented for more realistic data. GENROU for the synchronous generators; IEEEX1 for the excitation system; IEESGO for the turbine governor; PSS2A for the power system stabilizer. The computer with Intel® Xeon(R) W-2195 CPU @ 2.30GHz and 128 GB of RAM was utilized to conduct the numerical simulations.

A. Predictor Training

The base vector has a dimension of 99. For the DNN layers, the number of neurons is set 10 for each layer. Rectified linear unit (ReLU) is used as the activation function. The training was operated in batches of 32 data points. An MSE based dynamic learning rate strategy is used for the training. Learning rate schedule is applied in the training process by reducing the learning rate accordingly, the factor by which the learning rate will be reduced is set to 0.5 and the patience value is set to 10 epochs. A total of 9,600 samples were collected based on strategies proposed in previous section. The entire dataset is divided into two subsets: 7,680 samples (80%) for training and 1,920 samples (20%) for validation.

TABLE II shows the validation accuracy of the RoCoF predictor under different tolerances. The validation accuracy is 99.27% with 10% tolerance, implying high performance of the trained model. It should be noted that the accuracy is still above 93.55% even with a small tolerance of 5%, indicating the robustness of the trained predictor.

| Tolerance | 10% | 9% | 8% | 7% | 6% | 5% |
|-----------|-----|----|----|----|----|----|
| Accuracy  | 99.3% | 99.0% | 98.5% | 96.6% | 95.5% | 93.6% |

B. DNN-RCUC Results

The forecast load and wind power for test case are plotted in Fig. 1 and Fig. 2. Due to the computational efficiency, one interval in the simulation process represents 4 hours in periods. The test case has a demand ranging from 1,633 MW to a peak of 1,853 MW. The peak wind generation is 266 MW. All three RoCoF-constrained models are tested on the same test case.

TABLE III compares the unit commitment results of the proposed DNN-based RCUC model and the two mathematical-based SCUC models. It can be observed that the proposed DNN-RCUC has the highest operational cost among all three models; the extra cost results from the efforts in handling the generator aggregation situations, which would be discussed later. On the other hand, the reserve cost is less in LRC-SCUC and DNN-RCUC models. For DNN-RCUC case, the total reserve cost is $46,608, which is slightly lower than the cost of LRC-SCUC model. Additional synchronous machines are committed to cover the loss of largest generation for DNN-RCUC model, which accordingly increases the operation cost as well as the start-up cost.

Additionally, we run the dynamic simulation of G-1 contingency for all three models when the system netload is the lowest. The loss of largest generation at this period is more likely to result in highest RoCoF and largest system deviations due to least synchronous generators online [11]. The highest RoCoF of three cases are listed in TABLE IV. Although with system equivalent model-based RoCoF constraints, ERC-SCUC model still cannot ensure system RoCoF security under such situation. The highest RoCoF of LRC-SCUC model is 0.3920 Hz/s, which gives a relatively high RoCoF violation gap at -21.60% below limit. The proposed DNN-RCUC has a highest RoCoF of 0.4952 Hz/s following the loss of largest generation. From TABLE III and Fig.3, it can be concluded that the proposed DNN-RCUC model can secure the system with...
minimal RoCoF violation gap while LRC-SCUC leads to conservative results.

### TABLE IV

| Model       | ERC-SCUC | LRC-SCUC | DNN-RCUC |
|-------------|----------|----------|----------|
| Highest RoCoF [Hz/s] | 0.6127   | 0.3920   | 0.4952   |

![RoCoF Violation Gap](image)

Fig. 3. RoCoF violation gaps for different cases.

Furthermore, the stability issue of generator aggregation is investigated [15]. In this work, we run time domain simulation of two locational RoCoF constrained models in the scenario considering the aggregation of generators on bus 23. Following the loss of the largest generation at hour 11, the highest RoCoF of two models are compared in TABLE IV. It can be observed that in the case of LRC-SCUC model, trip of the largest generation on bus 23 may cause generator on the same event bus violates the pre-specified RoCoF limit 0.5 Hz/s easily. When the constraints based on DNN are implemented, the system RoCoF can be secured just below the threshold.

### TABLE IV

| Model       | LRC-SCUC | DNN-RCUC |
|-------------|----------|----------|
| Highest RoCoF [Hz/s] | 0.8125   | 0.4993   |

V. CONCLUSIONS

In this paper, we comprehensively discussed the mathematical model and machine learning model for limiting RoCoF. Mathematical model based RCUC approaches may not capture all characteristics in various conditions. DNN-based RoCoF predictor is first constructed, and the constraints derived from the well-trained predictor are then incorporated into the RCUC model to ensure system stability. In addition, the proposed model-based data generation approach can avoid divergence in time domain simulation, which often occurs with random data generation method.

The simulation results on the IEEE 24-bus system indicate that the incorporation of DNN-based RoCoF constraints can improve power system inertial responses. Our proposed DNN-RCUC method has been proved to handle the condition of generator aggregations well. Future work on this topic should explore how to efficiently incorporate such complex DNN network into SCUC formulation.

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