Deep-Learning-Aided Voltage-Stability-Enhancing Stochastic Distribution Network Reconfiguration

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Abstract—Power distribution networks are approaching their voltage stability boundaries due to the severe voltage violations and the inadequate reactive power reserves caused by the increasing renewable generations and dynamic loads. In the broad endeavor to resolve this concern, we focus on enhancing voltage stability through stochastic distribution network reconfiguration (SDNR), which optimizes the (radial) topology of a distribution network under uncertain generations and loads. We propose a deep learning method to solve this computationally challenging problem. Specifically, we build a convolutional neural network model to predict the relevant voltage stability index from the SDNR decisions. Then we integrate this prediction model into successive branch reduction algorithms to reconfigure a radial network with optimized performance in terms of power loss reduction and voltage stability enhancement. Numerical results on two IEEE network models verify the significance of enhancing voltage stability through SDNR and the computational efficiency of the proposed method.

Index Terms—Stochastic distribution network reconfiguration, voltage stability, deep learning.

NOMENCLATURE

Frequent acronyms:

SDNR Stochastic distribution network reconfiguration.
RVSI Root-mean-squared voltage-dip severity index (for short-term voltage stability).
SBR Successive branch reduction.
CNN Convolutional neural network.

Sets:

$\mathcal{N}$ The set of buses in a distribution network, including substation buses $\mathcal{N}_{s}$ and non-substation buses $\mathcal{N}_{d}$.
$\mathcal{E}$ The set of branches $e = ij \in \mathcal{E}$.
$\mathcal{W}$ The set of scenarios $w \in \mathcal{W}$ for uncertain renewable generations and loads.
$\mathcal{A}$ The set of feasible switch status vectors $\alpha \in \mathcal{A}$ that lead to radial networks.

Given quantities:

$\mathbf{\pi}$ The probability distribution $\mathbf{\pi} = (\pi_{w}, \forall w \in \mathcal{W})$ of the uncertainty scenarios.
$\tilde{p}_{w}^{i}, \tilde{q}_{w}^{i}$ The active and reactive power injections at bus $i$ in scenario $w$.
$\check{p}_{w}^{ij}, \check{q}_{w}^{ij}$ The active and reactive power flows on branch $ij$ in scenario $w$.
$g_{ij}, b_{ij}$ Series conductance and susceptance of branch $ij$.
$L$ The number of redundant branches in a network, which form the same number of chordless loops.

Variable quantities:

$C_{w}^{ij}$ The total active power loss in scenario $w$.
$I_{w}^{i}$ The voltage stability index in scenario $w$.
$\bar{\beta}_{\text{min}}$ The smallest singular value of the power-flow Jacobian matrix (indexing steady-state voltage stability).
$\alpha_{ij}$ The binary variable indicating the switch status on branch $ij$, collected in $\alpha = (\alpha_{ij}, \forall i, j \in \mathcal{E})$.
$p_{w}^{i}, q_{w}^{i}$ The active and reactive power injections at bus $i$ in scenario $w$.
$V_{w}^{i}, \theta_{w}^{i}$ The voltage magnitude and phase angle at bus $i$ in scenario $w$.
$p_{w}^{ij}, q_{w}^{ij}$ The active and reactive power flows on branch $ij$ in scenario $w$.
$\mathbf{x}$ The continuous decision variables: $\mathbf{x} = (\mathbf{x}_{w}, \forall w \in \mathcal{W}) = (\mathbf{p}_{w}^{i}, \mathbf{q}_{w}^{i}, \forall i \in \mathcal{N}_{s}; V_{w}^{i}, \theta_{w}^{i}, \forall i \in \mathcal{N}_{d}; \forall w \in \mathcal{W})$.
$\bar{p}_{w}^{ij}$ The expected active power flow on branch $ij$.
$\bar{p}_{w}^{i}$ The expected active power injection from bus $i$ into loop $\mathcal{P}$.
$n_{r}$ The number of active power-injecting buses that divide loop $\mathcal{P}$ into sub-paths.

P The set of branches that form a loop.
K The set of candidate branches to open.

I. INTRODUCTION

Voltage stability is becoming a major issue in power distribution networks with increasing shares of renewable generations and dynamic loads. A major cause of voltage instability is the lack of reactive power supplies, as the inverters that interface the renewable energy sources are demanding more reactive power compensation [1]. Meanwhile, the larger variations in distributed renewable generations and loads, as well as the increasingly severe contingencies from the upper/external grid [2], are pushing distribution networks closer to their operating limits, particularly voltage stability boundaries. Therefore,
it is critical to enhance voltage stability in the operations of renewables-heavy distribution networks.

It has been recognized that the network topology plays a significant role in voltage stability [3], [4]. The network topology can be optimized through distribution network reconfiguration (DNR), which configures the opening/closure of switches on the branches (power lines) to improve network performance. Typical DNR formulations mainly focused on power loss minimization and load balancing [5]. Other than that, voltage stability is an objective for DNR that should receive more attention than it currently does.

The DNR problem, even without considering voltage stability, is known to be a difficult mixed-integer nonlinear program due to the binary switching actions subject to the nonconvex power flow constraints and the requirement for a radial (tree) topology. Popular solution methods for DNR encompass mathematical programming, heuristics or meta-heuristics, and machine learning, each facing certain challenges in practice. For instance, mathematical programs that exploit various convex approximations [6], [7] need to address non-trivial trade-offs between accuracy, optimality, and computational efficiency; heuristics such as the iterative branch exchange [8] and switch opening and exchange [9] may have sensitive performance to initialization and poor convergence rates; meta-heuristics such as the genetic algorithm [10] and particle swarm optimization [11] may suffer heavy computations and inconsistent outcomes from different randomized runs. Compared to the methods above, a class of successive branch reduction (SBR) heuristics [12], [13] can reach a satisfactory balance between optimality and computational efficiency.

Taking voltage stability into account will make the DNR problem even harder. Most prior efforts for voltage-concerned DNR aimed to flatten voltage profiles [14], [15], [16] or restrict voltage volatility [17]. Fewer studies tried to improve steady-state voltage stability [18], [19], [20] and small-disturbance voltage stability [21] through DNR. The more complicated indices for (large-disturbance) short-term voltage stability are generally calculated from real-world or simulated time-series voltage records rather than expressed explicitly in terms of the DNR and volt/var control decisions [22]. This makes it difficult to integrate the voltage stability indices into the DNR formulations and to optimize them through the traditional mathematical programming, heuristic, or meta-heuristic approaches. This difficulty is partly addressed by the deep learning method we recently developed to predict short-term voltage stability from DNR decisions [23], [24].

It is worth noting that the robust or stochastic version of DNR, rather than the simple deterministic version, need to be implemented to deal with the uncertain scenarios of renewable generations and loads. In this paper, we focus on the stochastic DNR (SDNR), which optimizes the expectation across such scenarios and is thus generally less conservative and more economic than the robust version that concerns about the worst scenario. Grounded in our recent SBR heuristics for SDNR [13] and our deep learning method to predict voltage stability in deterministic DNR [23], we introduce the following new method and result to this research field:

- A deep learning method is proposed to solve SDNR with voltage stability enhancement. First, a convolutional neural network (CNN) model is built to predict the voltage stability index concerned from SDNR decisions. Then, the CNN model is integrated into the one-stage and two-stage SBR algorithms from [13] to reconfigure a radial network with optimized performance in terms of power loss reduction and voltage stability enhancement.

- The proposed method is validated by numerical experiments on two IEEE distribution network models. Compared to a classic mixed-integer nonlinear program solver for SDNR without considering voltage stability, the proposed method improves the steady-state or short-term voltage stability at a minor cost of increased power loss. Moreover, it speeds up the solution process of SDNR by at least an order of magnitude.

This study is not a simple combination of the works in [13] and [23]. First, it studies a new problem, which considers both voltage stability enhancement and uncertain renewables and loads in DNR problems. Second, it improves the algorithms in both works to address this new problem with high efficiency (see Section III for details).

Considering the possibility of neural networks failing to make voltage stability prediction, there have been studies to make neural networks more robust [25], [26] and to prevent the potential failure through the design of the neural network [27]. This is also considered in our proposed algorithm (see Section III-B for details). Moreover, concerning the cybersecurity threat introduced by the CNN model, the state-of-the-art method can be applied to detect cybersecurity vulnerabilities and mitigate their impact [28], which is beyond the scope of this study.

In the following, Section II introduces our model and formulation of voltage-stability-enhancing SDNR. Section III elaborates on our deep-learning-aided method to solve the formulated SDNR problem. The numerical case studies are presented in Section IV. Then Section V concludes the paper.

II. MODEL AND PROBLEM FORMULATION

A. SDNR With Voltage Stability Enhancement

Similar to our settings in [13], we consider a distribution network with a set of buses $\mathcal{N}$ and a set of branches $\mathcal{E}$. The bus set $\mathcal{N}$ is divided into substation buses $\mathcal{N}_s$ and non-substation buses $\mathcal{N}_d$. The substation buses are connected to an upper-level transmission network, while the non-substation buses are connected to loads and/or renewable energy sources.

Each branch in the set $\mathcal{E}$ is arbitrarily assigned a reference direction, say from bus $i$ to bus $j$, and is denoted as $ij \in \mathcal{E}$; the existence of $ij \in \mathcal{E}$ shall exclude the other direction $ji \in \mathcal{E}$, so that the branches are not double counted. In case the quantities associated with both directions of a branch need to be used, we define the unordered relationship $i \sim j$ and $j \sim i$, which simultaneously hold as long as there is a branch between buses $i$ and $j$ in either direction. Without loss of generality, we assume all the branches $ij \in \mathcal{E}$ are switchable. A binary variable $\alpha_{ij}$ indicates the open ($\alpha_{ij} = 0$) and closed ($\alpha_{ij} = 1$) status of the switch on branch $ij$. 

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The uncertain renewable generations and loads are modeled as random variables subject to a joint probability distribution \( \pi = (\pi_w, \forall w \in \mathcal{W}) \) over a finite set of scenarios \( \mathcal{W} \).

With the settings above, we formulate an SDNR problem with voltage stability enhancement as follows.

1) **Objective:** We aim to optimize the expected operational cost across all the scenarios \( w \in \mathcal{W} \) in terms of power loss and voltage stability:

\[
\Gamma(\alpha, x) = \sum_{w \in \mathcal{W}} \pi_w \left( k_l \frac{C_l^w}{C_{l,\max}^w} + k_v \frac{I_v^w}{I_{v,\max}^w} \right) \quad (1)
\]

where the decision variables \((\alpha, x)\) will become clear as we proceed. The total active power loss \( C_l^w \) and voltage stability index \( I_v^w \) are normalized by their upper bounds (set as constants by experience), \( C_{l,\max}^w \) and \( I_{v,\max}^w \) respectively. A desired balance can be reached between the two objectives, by tuning the factors \( k_l \) and \( k_v \). Note that \( k_l, C_l^w, C_{l,\max}^w, I_v^w, I_{v,\max}^w \) are always positive numbers, while \( k_v \) can be positive or negative depending on whether a smaller or larger \( I_v^w \) is more stable for the specific type of voltage stability concerned, as will be explained in Section II-B. The formulation of \( C_l^w \) will be introduced shortly with the bus power injections.

2) **Branch Power Flows:** The active and reactive branch power flows are \( \forall \, i \in \mathcal{E}, \forall \, w \in \mathcal{W} \):

\[
p_{ij}^w = \alpha_{ij} \left[ (V_{ij}^w)^2 g_{ij} - V_{ij}^w V_{ji}^w (b_{ij} \sin \theta_{ij}^w + g_{ij} \cos \theta_{ij}^w) \right] \quad (2a)
\]

\[
p_{ji}^w = \alpha_{ij} \left[ (V_{ji}^w)^2 g_{ji} - V_{ij}^w V_{ji}^w (b_{ij} \sin \theta_{ji}^w + g_{ij} \cos \theta_{ji}^w) \right] \quad (2b)
\]

\[
q_{ij}^w = \alpha_{ij} \left[ -(V_{ij}^w)^2 b_{ij} - V_{ij}^w V_{ji}^w (g_{ij} \sin \theta_{ij}^w - b_{ij} \cos \theta_{ij}^w) \right] \quad (2c)
\]

\[
q_{ji}^w = \alpha_{ij} \left[ -(V_{ji}^w)^2 b_{ji} - V_{ij}^w V_{ji}^w (g_{ij} \sin \theta_{ji}^w - b_{ij} \cos \theta_{ji}^w) \right] \quad (2d)
\]

where \( V_{ij}^w, V_{ji}^w \) are the voltage magnitudes at buses \( i, j \) and \( \theta_{ij}^w := \theta_{ij}^w - \theta_{ji}^w \) is the angle difference between them. Due to power loss, we cannot say \( p_{ij}^w = -p_{ji}^w, q_{ij}^w = -q_{ji}^w \), i.e., the power sent onto a branch from one end generally does not equal the power received by the other end. The power at both ends are calculated onto a branch from one end generally does not equal the power lost in the branch, i.e., the power sent onto a branch from one end generally does not equal the power lost in the branch, respectively. A desired balance can be reached between the two objectives, by tuning the factors \( k_l \) and \( k_v \). Note that \( k_l, C_l^w, C_{l,\max}^w, I_v^w, I_{v,\max}^w \) are always positive numbers, while \( k_v \) can be positive or negative depending on whether a smaller or larger \( I_v^w \) is more stable for the specific type of voltage stability concerned, as will be explained in Section II-B. The formulation of \( C_l^w \) will be introduced shortly with the bus power injections.

3) **Bus Power Injections:** The power injection at each bus balances the total power flow sent to its adjacent buses:

\[
p_{i}^w = \sum_{j: i \leftarrow j} p_{ij}^w, \quad q_{i}^w = \sum_{j: j \leftarrow i} q_{ij}^w, \quad \forall \, i \in \mathcal{N}, \forall \, w \in \mathcal{W} \quad (3)
\]

The power imported at the substation buses are restricted as:

\[
p_{i}^{\min} \leq p_{i}^w \leq p_{i}^{\max}, \quad q_{i}^{\min} \leq q_{i}^w \leq q_{i}^{\max}, \quad \forall \, i \in \mathcal{N}_d, \forall \, w \in \mathcal{W} \quad (4)
\]

where \((\cdot)^{\min}\) and \((\cdot)^{\max}\) are the given minimum and maximum limits. The power injections at non-substation buses are:

\[
p_{i}^w = \tilde{p}_{i}^w - \tilde{p}_{i}^\prime, \quad q_{i}^w = \tilde{q}_{i}^w - \tilde{q}_{i}^\prime, \quad \forall \, i \in \mathcal{N}_d, \forall \, w \in \mathcal{W} \quad (5)
\]

where \((\tilde{p}_{i}^w, \tilde{q}_{i}^w)\) are the active and reactive power generation of the aggregate renewable energy source, and \((\tilde{p}_{i}^\prime, \tilde{q}_{i}^\prime)\) are the active and reactive power consumption of the aggregate load, at bus \( i \). As mentioned, they are uncertain quantities subject to probability distribution \( \pi \) over scenarios \( w \in \mathcal{W} \).

Summing up the active power injections at all the buses leads to the total active power loss in objective (1):

\[
C_l^w := \sum_{i \in \mathcal{N}} p_{i}^w. \quad (4)
\]

4) **Safety Limits:** The bus voltages are limited as:

\[
V_i^{\min} \leq V_i^w \leq V_i^{\max}, \quad \forall i \in \mathcal{N}, \forall w \in \mathcal{W} \quad (6)
\]

and the apparent power flows are limited as:

\[
(p_{ij}^w)^2 + (q_{ij}^w)^2 \leq (s_{ij}^{\max})^2, \quad \forall i, j, \forall w \in \mathcal{W} \quad (7)
\]

5) **Network Topology:** Denote the network graph under switch status \( \alpha = (\alpha_{ij}, \forall i, j \in \mathcal{E}) \) as \( G(\alpha) \). The feasible set of \( \alpha \) is defined as [12]:

\[
A := \{ \alpha \mid G(\alpha) \text{ has no loop}; \text{and each bus in } \mathcal{N}_d \text{ is connected to a single bus in } \mathcal{N}_s \}. \]

A network \( G(\alpha) \) is radial if it satisfies the condition in \( A \).

To reduce the variable space, we treat \((p_{ij}^w, q_{ij}^w, \theta_{ij}^w)\) in (2) as expressions rather than variables. Now we are ready to introduce the SDNR with voltage stability enhancement:

\[
\text{SDNR-VD : minimize } \Gamma(\alpha, x) \quad \text{over } \alpha := (\alpha_{ij}, \forall i, j \in \mathcal{E}) \in A, \quad x := (x^w, \forall w \in \mathcal{W}) \quad \text{subject to } (2)–(7).
\]

Other discrete components (e.g., tap-changing transformers) can also be considered by adding the corresponding constraints to the SDNR-VD problem.

For each given and fixed switch status \( \alpha \), the SDNR-VD problem is specified as a stochastic optimal power flow (OPF) problem taking voltage stability into account. As part of the proposed procedure to solve SDNR-VD in Section III, we will deal with a reduced version of this stochastic OPF problem, which minimizes the expected total active power loss only, without considering voltage stability:

\[
\text{SOPF}(\alpha) : \text{minimize } \sum_{w \in \mathcal{W}} \pi_w C_l^w \quad \text{subject to } (2)–(7).
\]

Classic SDNR problems are mixed-integer nonlinear programs solvable by off-the-shelf software such as Gurobi [29]. Compared to them, a major hurdle in our formulation SDNR-VD is that the voltage stability index \( I_v^w \) in objective (1) may not have an explicit expression in terms of the decision variables. For instance, the large-disturbance short-term voltage stability index is generally calculated from real-world or simulated time-series voltage records. Therefore, it will be difficult for the existing mathematical program solvers to handle SDNR-VD. This motivates the deep-learning-aided method in this paper.
B. Voltage Stability Evaluation

The deep learning method to be proposed shortly can predict the voltage stability index \( I_{\alpha} \) from the SDNR decisions, for various types of voltage stability defined in [30]. In this paper, we just focus on the steady-state and short-term voltage stability as representative examples.

1) Steady-State Voltage Stability: At a steady-state operating point (i.e., a power flow solution), the smallest singular value of the Jacobian matrix, denoted by \( \delta_{\min} \), indicates the margin of this operating point from a voltage collapse [31]. As \( \delta_{\min} \) approaches zero, even a small variation in active or reactive power injection will cause a large voltage excursion. Therefore, one can apply the singular value decomposition method to calculate \( \delta_{\min} \) as a stability index.

2) Short-Term Voltage Stability: It focuses on the dynamic behavior of a network after a large disturbance such as a short-circuit fault. It is typically assessed via the time-series simulation of voltage dynamics [22], [24], which often involves induction motor and ZIP load models [32]. The short-term voltage stability problems generally encompass two issues: the voltage instability and the fault-induced delayed voltage recovery [23]. The former can be directly identified from the time-series voltage records. The latter can be evaluated by the root-mean-squared voltage-dip severity index (RVSI), which should be smaller for a more stable network [22].

III. DEEP-LEARNING-AIDED SOLUTION METHOD

A. CNN-Based Prediction of Voltage Stability

As the basis of the proposed algorithms to solve the challenging SDNR-VS problem, we briefly introduce the convolutional neural network (CNN) model from our recent work [23] to predict voltage stability. CNN has achieved significant success in image classification and regression [33]. In this study, each network state is represented as a matrix \( G \). Through proper training, a CNN can learn the nonlinear mapping

\[
F_{vs}: G(\alpha, x) \rightarrow I_v
\]

that maps a network state to its corresponding voltage stability index. Here \( G(\alpha, x) \) collects the network state as

\[
G(\alpha, x) := (\ell_{ij}, \forall ij \in \mathcal{E}_{\alpha})
\]

where \( \mathcal{E}_{\alpha} := \{ ij \in \mathcal{E} | \alpha_{ij} = 1 \} \) is the set of closed branches determined by the switch status vector \( \alpha \), and vectors

\[
\ell_{ij} := [i, j, g_{ij}, b_{ij}, p_{ij}, q_{ij}, q_{ij}]^T, \forall ij \in \mathcal{E}_{\alpha}
\]

contain the parameters and variables associated with the closed branches. The output \( I_v \) can be any voltage stability index of the operator's interest, e.g., the smallest singular value of the power-flow Jacobian matrix for steady-state voltage stability or the RVSI for short-term voltage stability, as already reviewed in Section II-B. The structure of the CNN model is introduced in more detail in Appendix A.

Other neural network structures, such as graph neural networks [34], may also be applied to learn the nonlinear mapping

| Algorithm 1: Deep-Learning-Aided One-Stage SBR |
|------------------------------------------------|
| 1 Initialize switch status as \( \alpha_\xi := (\alpha_{ij} = 1, \forall ij \in \mathcal{E}) \); |
| 2 Solve SOPF(\( \alpha_\xi \)) to get optimal \( x_\xi = (x_{\xi}^w, \forall w \in \mathcal{W}) \); |
| 3 At \( x_\xi \), calculate \( p_{\xi}^p \) by (8) for each bus \( i \in \mathcal{N}_p \). Buses with \( p_{\xi}^p > 0 \) divide loop \( P \) as sub-paths \( \{P_1, ..., P_{n_P}\} \); |
| 4 for \( m = 1 \) to \( n_s \) do |
| 5 \( \hat{\ell}_m \leftarrow \arg\min_{\ell \in \mathcal{P}_m} E_\pi[|p_e(x_\xi)|]; \) |
| 6 end |
| 7 for \( e \in \cup_{m=1}^{n_s} K(\hat{\ell}_m) \) do |
| 8 Solve SOPF \( (x_\xi(\ell)) \) to obtain optimal solution \( x_{\xi}(\ell) \) and minimum objective value \( C_1(\ell); \) |
| 9 \( \hat{I}_v(\ell) \leftarrow E_\pi \left[ F_{vs}(G(\alpha_{\xi}(\ell), x_{\xi}(\ell))); \right]; \) |
| 10 end |
| 11 \( e^* \leftarrow \arg\min_{e \in \cup_{m=1}^{n_s} K(\hat{\ell}_m)} \left( k_1 \frac{C_1(\ell)}{C_{\max}} + k_2 \frac{\hat{I}_v(\ell)}{\hat{I}_{\max}} \right); \) |
| 12 return \( \alpha^* = \alpha_{\xi}(e^*). \) |

\( F_{vs} \), which is out of the scope of this study and will be an interesting research direction for our future work.

B. Deep-Learning-Aided One-Stage SBR Algorithm

The proposed algorithms to solve SDNR-VS extend the successive branch reduction (SBR) heuristics in our recent work [13] to incorporate the deep-learning-aided prediction of voltage stability. When introducing the proposed algorithms below, we shall just highlight their key differences and skip their common details and rationales with those in [13].

We assume the distribution network has a single station bus in \( N_s \), since merging multiple substations into one would not change the applicability of the proposed algorithms. First, we present a one-stage SBR algorithm, Algorithm 1, for a simple special network with a single redundant branch than radial. We then present a two-stage SBR algorithm, Algorithm 2, that can be applied to a general network with multiple redundant branches. In its second stage, Algorithm 2 will iteratively call Algorithm 1.

We make the following remarks to facilitate understanding of the descriptions in the Algorithm 1 box.

- (Line 1) The algorithm is initialized from all the branches being closed, including a redundant branch to open.
- (Line 3) \( \mathcal{P} \) denotes the set of branches forming the single loop in the network, and \( \mathcal{N}_p \) is the set of buses in that loop. From any bus \( i \in \mathcal{N}_p \), the expected active power injection into loop \( \mathcal{P} \) is

\[
\tilde{p}_i^p := E_\pi \left[ \sum_{j:i-j} p_{ij} \right] = \sum_{w \in \mathcal{W}} \sum_{j:i-j} p_{ij}^w. \tag{8}
\]

There are \( n_r \geq 1 \) buses \( i \in \mathcal{N}_p \) satisfying \( \tilde{p}_i^p > 0 \) since the total active power loss in \( \mathcal{P} \) must be supplied by at least one source. These \( n_r \) buses divide loop \( \mathcal{P} \) into \( n_r \) sub-paths \( \{P_m, m = 1, ..., n_r\} \).
- (Lines 4–6) \( p_e(x_\xi) \) denotes the active power flow on branch \( e \) at the optimal solution \( x_\xi \) of SOPF(\( \alpha_\xi \)). In
each sub-path $\mathcal{P}_m$, $m = 1, \ldots, n_r$, Line 5 finds the branch $e_m$ that carries the minimum expected absolute value of active power flow.

- (Line 7) For an arbitrary branch $e = ij \in \mathcal{P}$, denote its upstream branch (in loop $\mathcal{P}$) incident to node $i$ as $e^{up}$, and downstream branch incident to node $j$ as $e^{down}$. Based on the expected active branch flow $\hat{p}_{ij} := \mathbb{E}[p_{ij}]$ at the optimal solution $x_{\mathcal{E}}$, we identify a set of candidate branches

$$\mathcal{K}(e) := \begin{cases} \{e, e^{down}\}, & \text{if } \hat{p}_{ij} > 0 \text{ and } e^{down} \text{ exists}; \\ \{e, e^{up}\}, & \text{if } \hat{p}_{ij} < 0 \text{ and } e^{up} \text{ exists}; \\ \{e\}, & \text{otherwise}. \end{cases}$$

Starting from Line 7, the algorithm searches in the union of $\mathcal{K}(\hat{e}_m)$ over all the minimum-flow branches ($\hat{e}_m$, $m = 1, \ldots, n_r$) found in Lines 4–6.

- (Line 8) Under switch status $\alpha x_{\mathcal{E}}(e)$ that opens a candidate branch $e$ only and closes all other branches, the algorithm first solves a stochastic OPF problem to minimize the expected total active power loss $C_l(e)$ only, without considering voltage stability yet (because it lacks the explicit expression of the voltage stability index).

- (Lines 9 and 11) We highlight them as the key difference from [13, Algorithm 1]. First, Line 9 predicts the expected voltage stability index $I_{\mathcal{E}}(e)$ at the solution obtained in Line 8, using the CNN model from Section III-A. Then Line 11 picks a candidate branch $e^*$ that (if opened) can minimize the weighted sum of the expected power loss $C_l(e)$ and voltage stability index $I_{\mathcal{E}}(e)$.

For a network with uncontrollable branches, Algorithm 1 only searches the controllable branches in Line 5 while excluding the uncontrollable branches from the union of $\mathcal{K}(\hat{e}_m)$ in Line 7. In this way, the CNN model only predicts the voltage stability index for the candidate branches in the union of $\mathcal{K}(\hat{e}_m)$. As shown in [13], these candidate branches have good performance in minimizing the expected total active power loss. Thus, even if the CNN model fails to identify voltage-stable network topologies, Algorithm 1 can still find a good solution with small expected power loss.

C. Deep-Learning-Aided Two-Stage SBR Algorithm

We now extend the one-stage SBR, Algorithm 1, to the two-stage Algorithm 2 for a general network with $L > 1$ redundant branches. The network has $L$ chordless loops $\mathcal{P}^l$, $l = 1, \ldots, L$.

The first stage (Lines 1–11) of Algorithm 2 is the same as [13, Algorithm 2]. It starts from all the branches being closed, solves a stochastic OPF problem, and sequentially opens a branch carrying the minimum expected active power flow in each of the $L$ loops. Similar to Algorithm 1, it only searches the controllable branches in Line 5 for a network with uncontrollable branches. If such an open branch simultaneously lies in two loops, then opening it will also require updating the other loop. The $L$ open branches, collected in a set $\mathcal{E}^o$, serve as the initial candidate branches to open for the next stage.

The second stage of Algorithm 2 inherits the iterative close-and-open idea from [13, Algorithm 2]: in each of the $L$ (inner) iterations, it opens all but one branches in the set $\mathcal{E}^o$ (Line 15).

Algorithm 2: Deep-Learning-Aided Two-Stage SBR.

1 First stage:
2 Initialize switch status as $\alpha x_{\mathcal{E}} := (\alpha_{ij} = 1, \forall ij \in \mathcal{E})$;
3 Solve SOPF($\alpha x_{\mathcal{E}}$) to get optimal $x_{\mathcal{E}} = (x^w_{ij}, \forall w \in \mathcal{W})$;
4 for $l = 1$ to $L$ do
5 $e^*_l \leftarrow \text{argmin}_{e \in \mathcal{E}^o} \mathbb{E}[|p_{le}(x_{\mathcal{E}})|]$;
6 Open branch $e^*_l$;
7 if $e^*_l$ is a common branch of $\mathcal{P}^l$ and $\mathcal{P}^k$ then
8 update loop $\mathcal{P}^k$ with $e^*_l$ open;
9 end
10 end
11 $\mathcal{E}^o \leftarrow \{e^*_l, l = 1, \ldots, L\}$;
12 Second stage: Set $N = N_{\text{max}}$;
13 for $n = 1$ to $N_{\text{max}}$ do
14 for $l = 1$ to $L$ do
15 Define a set of open branches $\mathcal{E}^o_{n,l} := \mathcal{E}^o \setminus \{e^*_l\}$;
16 Call Algorithm 1 with initial switch status $\alpha x_{\mathcal{E}}(e^*_{n,l})$ to obtain an optimal open branch $e^*_{n,l}$ and the corresponding minimum objective value $\Gamma^*_{n,l}$ (in Line 11, Algorithm 1);
17 $e^*_l \leftarrow e^*_{n,l}$, which also updates $\mathcal{E}^o$;
18 end
19 if $\Gamma^*_{n,1} = \Gamma^*_{n,2} = \ldots = \Gamma^*_{n,L}$ then
20 $N \leftarrow n$; break;
21 end
22 end
23 $(n^*, l^*) \leftarrow \text{argmin}_{n=1, \ldots, N, l=1, \ldots, L} \Gamma^*_{n,l}$;
24 return $\alpha^* = \alpha x_{\mathcal{E}}(e^*_{n^*, l^*})$.

It then calls Algorithm 1 to find the single redundant branch that remains to open (Line 16), and uses that branch to update the set $\mathcal{E}^o$ (Line 17). Besides the CNN-based prediction of voltage stability already in Algorithm 1, another difference from [13] lies in the outer iteration with index $n$ (Line 13). After traversing (and perhaps updating) all the $L$ branches in $\mathcal{E}^o$, the next outer iteration will repeat the close-and-open procedure on $\mathcal{E}^o$, until the minimum objective value of SDNR-VS gets steady as the close-and-open procedure continues (Line 19) or the limit $N_{\text{max}}$ of outer iterations is reached. Algorithm 2 ultimately returns the best radial topology found throughout all the outer and inner iterations.

The case studies in Section IV will show that Algorithm 2 has satisfactory computational efficiency. Indeed, the CNN-based prediction of voltage stability takes moderate extra time than [13, Algorithm 2], and a high-quality SDNR-VS solution is usually obtained within $N = 2$ outer iterations.

One advantage of the proposed algorithms is that they can guarantee the topological feasibility of the returned solutions, since the SOPF($\alpha$) problem is solved for each of the feasible candidate topologies $\alpha$, in Line 8 of Algorithm 1 and Line 16 of Algorithm 2. However, the optimality of the solutions may not be guaranteed. Such optimality gap would be formally analyzed in our future work.
IV. CASE STUDIES

A. Experimental Setup

To validate the proposed method, we conduct numerical experiments on the IEEE 33-bus and 123-bus distribution network models that were also used in [13]. Each network has one substation bus. The 33-bus network has four renewable generation buses (each connected to a small wind turbine and a solar panel) and five redundant branches; the 123-bus network has six renewable generation buses and four redundant branches (after removing the branch between bus 17 and bus 52). Other non-substation buses connect to a load each. We use the load, wind and solar generation data in Germany from January 2018 to June 2020 in hourly resolution [35] and scale them to fit the test network capacities. After getting the active power of loads and renewable generations, we obtain their reactive power using fixed power factors [9]. The scaled data from January 2018 to March 2020 are sampled for training and testing the CNN-based voltage stability prediction model, and the remaining data from April to June 2020 are clustered into a certain number of scenarios (depending on the test case) using k-medoids [23] to validate the proposed method.

We split the data into 70% for training and 30% for testing the CNN model. Each data sample consists of an input \( G(\alpha, x) \) (network state) and an output \( I_v \) (the smallest singular value \( \delta_{\text{min}} \) of the power-flow Jacobian for steady-state voltage stability; or the RVSI for short-term voltage stability):

- For steady-state voltage stability, we solve the OPF problems given all the possible radial configurations (there are 33,913 and 42,658 of them, respectively, for the 33-bus and 123-bus networks) and the sampled loads and renewable generations (discarding those without feasible power flow solutions). The stability index \( \delta_{\text{min}} \) is calculated for each of the OPF solutions using singular value decomposition.

- For short-term voltage stability, we connect the distribution substation to the IEEE 39-bus transmission network, at transmission bus 37 as the default point of common coupling (PCC). Among all the possible radial configurations of the distribution network, 20,000 cases are sampled. For each sample, time-series simulation is conducted in a 5-second window for a three-phase short-circuit fault at the PCC. An RVSI is calculated from the time-series voltage trajectories in each simulation. The induction motor models for the simulation are generated from the field measurements in [36], and the ZIP loads are uniformly randomly sampled within \([1, 2]\) per unit. In case a voltage collapse occurs in a simulation, the corresponding RVSI is set to a very large value.

Our CNN model is composed of four convolutional layers with 8, 16, 32, and 64 filters, respectively; each filter is \(3 \times 3\); the learning rate is \(1 \times 10^{-3}\); the maximum epoch is 30; the mini-batch size is 20; and the dropout rate is 0.2. The experiments are run on a 64-bit MacBook with 8-core CPU and 32 GB RAM. We use the Matpower Interior Point Solver for OPF, the PSAT for time-series simulation, and the MATLAB Deep Learning Toolbox to build the CNN.

The following methods are compared in the case studies:

- **The proposed method:** The deep-learning-aided two-stage SBR for SDNR-VS, i.e., Algorithm 2. The weighting factors in objective (1) are set as \( k_1 = 0.5 \) and \( k_2 = \pm 0.5 \) (negative when \( I_w = \delta_{\text{min}} \) for steady-state stability and positive when \( I_w = \text{RVSI} \) for short-term stability).

- **Method 1:** Using the mixed-integer nonlinear program solver Gurobi to solve SDNR without considering voltage stability. We use Method 1 as a benchmark by defining the relative errors of other methods compared to it: \( r_{\text{MC}} \), for the expected total active power loss, \( \eta_{\text{MC}} \) for the expected \( \delta_{\text{min}} \), and \( \eta_{\text{RVSI}} \) for the expected RVSI. Note that a higher \( \eta_{\text{MC}} \) indicates better stead-state voltage stability and a lower \( \eta_{\text{RVSI}} \) indicates better short-term voltage stability.

- **Method 2:** The two-stage SBR for SDNR without considering voltage stability, i.e., [13, Algorithm 2].

- **Method 3:** Replacing the CNN model in the proposed method with singular value decomposition for steady-state voltage stability and simulation-based evaluation for short-term voltage stability. It thus provides accurate voltage stability evaluation at high computational expenses.

B. Accuracy of CNN Prediction for Voltage Stability

For the \( i \)-th data sample, let \( I_i, I_w, \) and \( I_{\hat{v}, i} \) denote the real and CNN-predicted voltage stability indices, respectively. It is actually the order, in which the voltage stability indices of different configurations are ranked, that matters most. Therefore, we measure the accuracy of the CNN prediction by the consistency between the real and predicted orders [23]:

\[
\text{Consistency} := \frac{2 \sum_{i,j=1}^{H} c(i,j)}{H(H-1)} \times 100\%
\]

where for each pair \( i,j \), \( H \) of data samples, \( c(i,j) = 1 \) if the order between \( (I_i, I_w) \) is the same as that between \( (I_{\hat{v},i}, I_{\hat{v},j}) \), and \( c(i,j) = 0 \) otherwise.

We run ten CNN training processes with different random samples, which all result in good consistency as Table I shows. Fig. 1 compares the real and predicted voltage stability indices for samples from the 33-bus network. It shows good accuracy of the proposed CNN prediction model.

| Network | Voltage stability index | mean (%) | max (%) | min (%) |
|---------|-------------------------|----------|---------|---------|
| 33-bus  | \( \delta_{\text{min}} \) (steady-state) | 94.9     | 95.1    | 94.6    |
|         | RVSI (short-term)       | 94.6     | 94.7    | 94.4    |
| 123-bus | \( \delta_{\text{min}} \) (steady-state) | 97.7     | 97.9    | 97.6    |
|         | RVSI (short-term)       | 98.8     | 98.8    | 98.7    |

C. Voltage Stability Enhancement

Table II shows the results of different methods applied to the 33-bus and 123-bus networks (except that Method 3 is not applied to the 123-bus network due to its huge computation time). Different renewable penetration levels are realized by scaling the renewable generation capacities with a factor \( k_r \). The numbers are the relative errors of different methods in power
Table II

| Network | $k_r$ | Method | $\delta_{\text{min}}$ | RVSI | $\eta_{C_T}$ | $\eta_{C_T}$ |
|---------|-------|--------|-----------------------|-------|--------------|--------------|
|         |       |        | mean | max | mean | max | mean | max | mean | max |
| 33-bus  | 1.0   | Method 2 | -1.07 | 0.21 | 36.06 | -14.30 | -1.07 | 0.21 | 0.23 | 28.29 |
|         |       | Method 3 | -1.03 | 0.21 | 42.66 | -14.30 | -0.50 | 0.64 | -6.69 | 0 |
|         |       | Proposed | -1.03 | 0.21 | 42.66 | -14.30 | -0.31 | 2.24 | -6.09 | 0.82 |
|         | 1.5   | Method 2 | -0.86 | 0.22 | 51.15 | -0.28 | -0.86 | 0.22 | -5.78 | 23.12 |
|         |       | Method 3 | -0.71 | 1.81 | 51.97 | -0.28 | -0.31 | 1.39 | -7.92 | 11.91 |
|         |       | Proposed | -0.86 | 0.22 | 51.15 | -0.28 | 3.77 | 12.79 | -9.42 | 3.11 |
|         | 2.0   | Method 2 | -1.29 | 0.57 | 41.01 | -44.37 | -1.29 | 0.57 | - | - |
|         |       | Method 3 | -1.09 | 0.65 | 55.19 | -15.32 | -0.16 | 4.55 | -10.90 | 2.08 |
|         |       | Proposed | -1.32 | 0.65 | 51.93 | -15.32 | 1.33 | 4.95 | -8.59 | 62.72 |
| 123-bus | 1.0   | Method 2 | -0.06 | 0 | 1.44 | -0.77 | -0.06 | 0 | -6.61 | 0.85 |
|         |       | Proposed | -0.05 | 0.02 | 2.22 | 0 | -0.05 | 0.02 | -6.83 | 0.02 |
|         | 1.5   | Method 2 | -0.05 | 0 | 0.58 | -0.72 | -0.05 | 0 | -2.44 | 1.05 |
|         |       | Proposed | -0.03 | 0.02 | 1.37 | 0.03 | 0.13 | 3.82 | -2.63 | 0.29 |
|         | 2.0   | Method 2 | -0.12 | 0 | 1.20 | -0.70 | -0.12 | 0 | -5.37 | 1.14 |
|         |       | Proposed | -0.10 | 0.02 | 2.06 | 0 | -0.11 | 0.02 | -5.57 | 0.24 |

Fig. 1. Comparison of real and CNN-predicted (a) $\delta_{\text{min}}$ for steady-state voltage stability and (b) RVSI for short-term voltage stability. Samples are taken from the 33-bus network and ranked in an ascending order of the voltage stability indices.

Fig. 2. Voltages after a fault at different buses (in different colors) in the 33-bus network, under (a) Method 2 without enhancing voltage stability and (b) the proposed method. Renewable penetration level $k_r = 2$.

The main observations from Table II are:

- In most cases, the proposed method and Method 3 improve the voltage stability index $\delta_{\text{min}}$ or RVSI, compared to Methods 1 and 2 (especially Method 1) that do not include voltage stability in their objectives. Indeed, the SDNR decisions from Method 2 may lead to voltage collapses, which can be prevented by the proposed method. Such an example is shown in Fig. 2: the 5-second record of bus voltages after a fault, in the 33-bus network.

- The improvement in voltage stability is mostly achieved with minor difference in power loss. The worst (highest) mean increase of power loss is $\eta_{C_T} = 3.77\%$ when renewable penetration $k_r = 1.5$ and the proposed method enhances RVSI. This is still an acceptable trade-off.

- The proposed method and Method 3 show similar results in most cases in the 33-bus network. This further verifies the accuracy of the CNN-based prediction of voltage stability. There is a rare case where the proposed method gets much worse RVSI (maximum $\eta_{\text{RVSI}} = 62.72\%$) than Method 3, which is likely due to the large prediction error of the CNN under a high renewable penetration level $k_r = 2$. Note that our CNN model is trained with data sampled under $k_r = 1$ only. Hence it is reasonably conjectured that training different CNNs under different renewable penetration levels may further improve the accuracy of prediction and the performance of the proposed method.

The observations above are supplemented by Fig. 3, which displays the 24-hour power loss and voltage stability indices when different methods are applied. It verifies that the proposed method can significantly improve voltage stability with minor (if any) increase in power loss, and its CNN-based performance is very close to Method 3 that makes “ground-truth” voltage stability evaluation.
We perform extended experiments on the 33-bus network with increasing numbers of uncertainty scenarios $|\mathcal{W}|$. The results are shown in Table III. As $|\mathcal{W}|$ increases, the proposed method obtains better solutions with smaller power loss and better voltage stability. Compared to Method 2, the proposed method makes significant improvement in voltage stability index $\delta_{\text{min}}$ or RVSI, with small changes in power loss.

Fig. 4 compares the RVSI of the 33-bus networks reconfigured by different methods and connected to different PCC buses in the transmission. An RVSI is calculated for a three-phase short-circuit fault in each of the 24 hours. Both Methods 1 and 2 (without enhancing voltage stability) encounter voltage collapses (indicated by RVSI $\geq 10$) at some time, which are fixed by the proposed method. Still, the proposed method achieves similar performance to Method 3 that makes accurate RVSI evaluation from the time-series voltage record.

### Table III

| $|\mathcal{W}|$ | Method | The proposed method: enhance $\delta_{\text{min}}$ | The proposed method: enhance RVSI |
|---------------|--------|-------------------------------------------------|----------------------------------|
|               |        | $\eta_C$ (%) | $\eta_{\text{RVS}}$ (%) | $\eta_C$ (%) | $\eta_{\text{RVS}}$ (%) |
| 20            | Method 2 | -2.44 | -6.64 | 60.71 | 174.93 | 1.63 | -2.44 | 0.33 | -6.64 | 5.60 | 238.90 | -36.07 |
|               | Proposed | -2.40 | -6.64 | 65.67 | 174.93 | 15.30 | -1.78 | 1.02 | -6.47 | 15.69 | 15.69 | -37.35 |
| 40            | Method 2 | -14.51 | -55.31 | 185.05 | 1056.10 | 44.83 | -14.54 | -2.76 | -55.31 | -31.78 | 23.13 | -75.45 |
|               | Proposed | -14.51 | -55.31 | 192.89 | 1056.10 | 76.02 | -13.90 | -0.68 | -55.31 | -37.21 | 3.17 | -77.27 |

### D. Computational Efficiency

Table IV compares the average computation time of Method 1 (using Gurobi) and the proposed method over 24 hours, under different uncertainty scenario numbers $|\mathcal{W}|$. Compared to Method 1, the proposed method speeds up the computation by at least an order of magnitude.
Table IV

| Network | $|V|$ | Method 1 | Enhance $\delta_{\text{max}}$ | Enhance RVSI |
|---------|-----|---------|-------------------|-------------|
| 33-bus  | 5   | 166.2   | 4.1               | 5.1         |
|         | 20  | 316.9   | 15.9              | 19.7        |
|         | 40  | 901.3   | 31.8              | 40.4        |
| 123-bus | 5   | 494.1   | 5.1               | 4.9         |
|         | 20  | 832.4   | 24.2              | 20.0        |
|         | 40  | 3333.9  | 56.2              | 46.6        |

V. CONCLUSION

We proposed a deep learning method to solve stochastic distribution network reconfiguration (SDNR) with voltage stability enhancement. A convolutional neural network (CNN) model for voltage stability prediction is integrated into successive branch reduction (SBR) algorithms to search for a radial topology with optimized performance in terms of power loss reduction and voltage stability enhancement. Numerical experiments on the IEEE 33-bus and 123-bus network models verified that the proposed method can significantly improve steady-state or short-term voltage stability with a minor compromise in power loss optimization. Moreover, it speeds up the solution process of SDNR by at least an order of magnitude, compared to a classic mixed-integer nonlinear program solver.

In the future, we plan to formally analyze the optimality of the proposed SBR algorithms (which are currently heuristics), incorporating the CNN-induced prediction errors in voltage stability indices. Another objective of our ongoing work is to co-optimize the placement of volt/var control resources (capacitor banks, smart inverters, D-STATCOMs, etc.) in synergy with the topology reconfiguration.

APPENDIX

A. Structure of the CNN Model

As shown in Fig. 5, the CNN model is composed of an input layer, several convolution blocks, several average pooling layers, a dropout layer, a fully-connected layer, and a regression layer. The input layer normalizes the matrix $G(\alpha, \mathbf{x})$ and inputs it to the convolution block. Each convolution block consists of a convolution layer, a batch normalization (BN) layer, and a rectified linear unit (ReLU) layer. The convolution layer learns critical features from $G(\alpha, \mathbf{x})$ and is the key part of the CNN model. The BN layer normalizes the activations of the convolution layer, which improves the learning speed, performance, and stability while reducing the sensitivity of results to neural network initialization. The ReLU layer is used to address the vanishing gradient problem and to improve the learning performance. The average pooling layer generally follows the convolution block, except for the final one. It can lower the computational burden and prevent overfitting. The dropout layer is also used to prevent overfitting. It randomly sets the output from the previous layer to zero with a given probability. The fully-connected layer is used for high-level reasoning, which improves the generalization capability of the CNN model. The final regression layer computes the half-mean-squared-error loss for the regression task. More details can be found in [23].

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