Reinforcement Learning for Intentional Islanding in Resilient Power Transmission Systems

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***Abstract*—Intentional islanding is the process of identifying and deliberately decomposing the transmission network to form self-sustained islands from an endangered network during disruptions to improve resilience and security. Most existing intentional islanding models are offline resilience decision tools and hence do not provide outage responses in a timely manner. In this paper, a reinforcement learning (RL) based model for intentional islanding is developed, which offers real-time switching control, online deployability, and adaptability to varying system conditions. The intentional islanding process is formulated as a Markov decision process, where the optimal transmission switching policy is learned using the RL approach. The control policy is learned over an environment that encompasses a Power System Simulator for Engineering (PSS/E) model of the transmission network, facilitated by an interface to the standard openAI Gym framework. The proposed RL-based methodology aims to form stable and self-sustainable islands by ensuring voltage stability while reducing the power mismatch in the formed islands. A proximal policy optimization algorithm is designed, which is suitable for controlling the on/off status of the switches with multi-layer perceptron as value and actor networks. The effectiveness of the proposed framework in the self-recovery of the grid by island formation is applied on the modified IEEE 39-bus test network and validated by dynamic simulations.**

***Index Terms*—Intentional Islanding, Grid Resilience, Reinforcement Learning, OpenAI Gym, PSS/E.**

I. Introduction

With the latest advances in smart grid technologies and the grid modernization efforts, autonomous monitoring, and control of the power system to ensure security and stability during both normal operations and emergency response are gaining traction. One of the drivers for this trend can be attributed to the deployment of artificial intelligence in control and energy management tools in power systems [1]. On the other hand, the smart grid initiative has led to the increase of remote-controlled switches in the power network, thus facilitating smart control of the transmission line switches [2]. Intentional islanding is a widely used control strategy to prevent blackouts during disruptions caused by damages in the transmission grid under extreme weather conditions or cyber-physical attacks [3]. The goal of intentional islanding is to isolate the damaged part of the grid and ensure the continued operation of the rest of the network through a series of switching operations, thereby improving the grid resilience [4].

Intentional islanding is the process of altering the topology of the power network by switching a minimal set of transmission lines out of service and consequently dividing the grid into several partitions. The islands formed are optimally determined with the objective of minimizing power imbalance and maintaining the voltage, and frequency stability in each island [5]. Given the non-linearity in power flow equations, the class of controlled islanding problems is computationally intensive, which is categorized as NP-hard. On the other hand, these intentional islanding techniques are expected to exhibit real-time control capability to prevent further cascading events.

Several intentional islanding algorithms have been developed over the years to split a large interconnected power grid into islands, to mitigate outages and prevent large-scale blackouts and cascading failures. These are optimal cutset determination problems where the minimum number of lines required to partition the network is determined. Approaches such as mixed-integer programming [6], heuristic methods [7], and graph theoretic techniques [8] have been studied in the intentional islanding literature. For instance, Wu et al. [8], [9] adopted a graph theoretic approach where the transmission network is represented as a graph with a hierarchical spectral clustering scheme and a dendrogram interpretation is used to form clusters. Demetriou et al. [10] presented a real-time islanding algorithm based on the output of a real-time state estimator that monitors the performance of the system while checking sufficient generation capacity. A comparison between transmission switching and intentional islanding based on the DC and AC optimal power flow to maximize load recovery in power systems was performed by Hussain et al. in [11]. Meanwhile, Mishra et al. [12] proposed a ranking-based method for islanding zones based on the information on power generation availability, load demands, and the priority of loads, while checking their bus voltage and frequency stability of microgrids by the small-signal analysis. However, these existing methods are computationally intensive considering the NP-hard nature of optimal switching in transmission systems which are complex interconnected systems spanning a wide area. Therefore, these methods may not be suitable for real-time decision support. Additionally, these methods are model specific and not adaptable to varying system conditions, and hence, cannot be deployed for online control.

Machine learning frameworks have predominantly been explored for distribution network reliability and resilience in tasks such as reconfiguration or intentional islanding as in [13]–[18]. In [14], the authors have developed a reinforcement learning model over graphs to perform reconfiguration in distribution networks to minimize network loss during normal operations. Alternatively, Kumar et al. [16] presented a supervised learning model to form intentional islands in low-voltage DC distribution systems in post-disasters conditions. As opposed to traditional distribution networks, transmission networks have a meshed structure with bidirectional power flow from multiple generators. Additionally, transmission networks are critical systems where the security and stability of the system are of utmost importance. Transmission networks are also significantly impacted by cascading effect of failures and therefore require quick isolation and mitigation of outages to prevent blackouts. It has been observed that little attention has been paid to resilience support in transmission networks using intelligent topology control. To bridge this research gap, in this paper, we propose a reinforcement learning (RL) framework for the intentional islanding of transmission networks.

The intentional islanding of transmission networks during outages is modeled as a Markov decision process and is solved using an RL approach. A proximal policy optimization (PPO) algorithm with multilayer perceptrons for both policy and value networks is used to learn the switching control policy to prevent disruption during outages. The agent is trained with the objective of minimizing power mismatch and maintaining stability. The proposed RL method provides switching decisions in real-time for varying system conditions and hence is suitable for online topology control in transmission networks.

The rest of the paper is organized as follows. In section II, the intentional islanding problem and the modeling of the environment are discussed. Section III presents the RL framework with the formulation of the Markov decision process. The simulation results from the learning process are presented and discussed in Section IV. The conclusion and future research directions are discussed in Section V.

II. Intentional Islanding of Transmission Networks

The power network is a set of $\mathcal{N}$ nodes (or buses) connected by a set of $\mathcal{L}$ branches or edges as transmission lines, with dispatchable demand and generation at buses. Intentional islanding splits the power grid into $j \in J$ sets of islands (i.e., smaller self-sufficient independent subsystems), by removing a set of edges or selecting the cut set of transmission lines $E_s \subset \mathcal{L}$. To prevent the collapsing of the islands formed in this process, it is necessary to ensure that the power system parameters are within safe operating limits and the mismatch between generation and demand is minimized. Therefore, for the voltage stability in each island formation, it is critical to take into account factors such as sufficient availability of generating resources functioning as slack (reference) units, adequate generation capacity to achieve balance with load demand, and necessary voltage control capabilities. Accordingly, intentional islanding is a security-constrained optimization problem with the objective of finding optimal cut sets to divide the network into multiple self-sufficient islands. E_s is, therefore, a set of arcs representing the transmission lines to be disconnected to create the islands and the value of the cut corresponds to the power imbalance in the resulting island. In this study, we also impose constraints on the voltage deviations (to be within an acceptable range) while minimizing the mismatch between generation and demand.

$$\min \quad f(V_i, \theta_i, P_j, Q_j); \quad \forall i \in N, j \in J \tag{1}$$

The function f represents the AC power balance constraints for all possible j within the island set J, which is a function of the nodal voltage magnitudes V and angles θ, as well as the nodal injections of active P and reactive power Q.

The total active and reactive power demands are constrained by the power supplied by generators on each island, which are given as follows.

$$S_i^G - S_i^D = diag(\overline{v})(Y_{bus}\overline{v})^* \tag{2}$$

$$Re(V_i \sum_{k \in N} (Y_{i,k} V_k)^*) = P_i^G - P_i^D \tag{3}$$

$$Im(V_i \sum_{k \in N} (Y_{i,k} V_k)^*) = Q_i^G - Q_i^D \tag{4}$$

$$\sum_{i \in N} P_{i,j,min}^G \leq \sum_{i \in N} P_{i,j}^D \leq \sum_{i \in N} P_{i,j,max}^G \quad \forall j \in J \tag{5}$$

$$\sum_{i \in N} Q_{i,j,min}^G \leq \sum_{i \in N} Q_{i,j}^D \leq \sum_{i \in N} Q_{i,j,max}^G \quad \forall j \in J \tag{6}$$

where $P_{i,j}^G$ and $P_{i,j}^D$ are the generation and demand consumption in the bus i of island j, respectively. The parameters of S_i^G, P_i^G, Q_i^G and S_i^D, P_i^D, Q_i^D are apparent, active, and reactive power for generation and demand, respectively. The operator $()^*$ represents a complex conjugate. Eqs. (5) and (6) ensure that there is sufficient generation capacity to meet the power demand in the formed islands. The parameter Y_{bus} represents the AC bus admittance matrix.

The voltage security check of the islands is modeled in Eqs. (7) and (8), where the magnitude and angle of the bus voltage for all nodes are constrained as follows.

$$V_{i,min} \leq |V_i| \leq V_{i,max} \quad \forall i \in N \tag{7}$$

$$\theta_{i,min} \leq \theta_i \leq \theta_{i,max} \quad \forall i \in N \tag{8}$$

The voltage constraints reduce the possibility of voltage collapse of buses and further improve the stability of the formed islands.

III. REINFORCEMENT LEARNING FRAMEWORK

Reinforcement learning (RL) is a class of machine learning techniques that are well suited for optimal control problems where the control policies are inferred from sample trajectories learned by interacting with the real or simulated systems. In comparison with traditional models, RL methods exhibit real-time control capability and are particularly useful for resilience enhancement where time is critical. Additionally, RL methods are also scalable and suitable for online control as it learns to adapt to variations in system behavior. Fig. 1 illustrates the key components of the RL framework, namely, the environment, observation, action, and reward.

In this work, we use the Power System Simulator for Engineering (PSS/E) software to model the power transmission networks and perform power flow simulations for varying line outages and switching actions. A python interface is developed to integrate the PSS/E software with the standard openAI Gym framework. The environment, therefore, encompasses the PSS/E power system simulator along with subroutines to implement the switching control and to evaluate the network state which includes voltage measurements and power mismatch.

A. Intentional Islanding as Markov Decision Process

The intentional islanding problem can be defined as a Markov Decision Process (MDP) and is expressed as $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{P}_{tr}, \mathcal{R})$. The state $\mathcal{S}$, action $\mathcal{A}$, transition probability $\mathcal{P}_{tr}$, and reward $\mathcal{R}$ are described as follows.

- **State:** The state describes the current operating condition of the transmission network which is represented by the system variables. This is expressed as $\mathcal{S} = \{s|s_t = \{S_{mis}, V_n, \theta_n\}\}$. S_{mis} is the mismatch in apparent power in the network resulting from different switching actions. Other state-defining parameters are obtained from the power flow simulator, such as V_n and θ_n which are the magnitude and angle of the voltage at all buses in the network, respectively.
- **Action:** The action is defined as a binary vector corresponding to the number of elements in $l \subset \mathcal{L}$, where l is the set of switchable lines. Each switching action is encoded as 0 or 1 to represent a switch opening or closing action. The action vector for l lines is thus expressed as $\mathcal{A} = [a_1, a_2, ..., a_l]$. The line-opening actions are responsible for forming islands in the grid.
- **Transition:** The transition refers to the change of state $\mathcal{S}_{t-1}$ at time $t-1$ to a new state $\mathcal{S}_t$ at time t. The transition probability $\mathcal{P}_{tr}$ can be expressed as $\mathcal{P}_{tr} = Prob(\mathcal{S}_t = s'|\mathcal{S}_{t-1} = s)$.
- **Reward Function:** The role of the reward function in RL is to guide the agent by evaluating the quality of the selected action with respect to the updated state, i.e., awarding or penalizing the agent for the action taken at a given state. Here the reward assigned to the agent will guide the intentional islanding or switching process toward minimizing the total power mismatch in all the islands created. Additionally, it is also necessary to ensure that the islanding action will avoid network infeasibilities due to the absence of adequate generating resources in islands. The reward function is subsequently formulated as:

$$r(s,a) = -C_s \tag{9}$$

$$C_s = \begin{cases} 0.01 \times S_{mis} & \text{if power flow converged} \\ S_{mis} & \text{otherwise} \end{cases} \tag{10}$$

$$S_{min} = \sqrt{P_{total}^2 + Q_{total}^2} \tag{11}$$

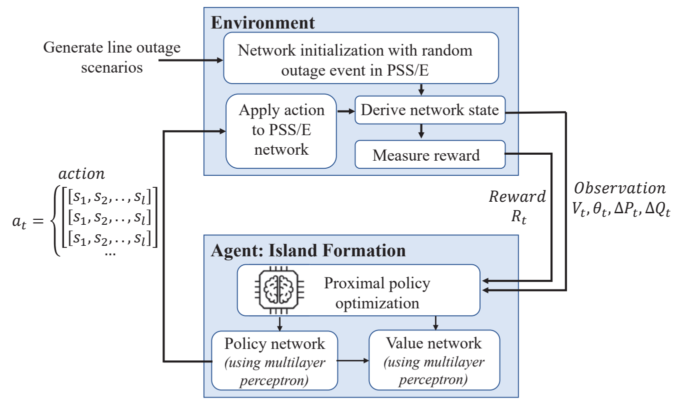

Fig. 1: Block diagram representation of the reinforcement learning algorithm used for intentional islanding during outages in transmission networks

The reward function in Eq. (11) is acquired from the power flow simulator. As seen in (10), the term C_s encompasses the MVA mismatch in the network S_{mis}, which is close to zero if the power flow converges or a large number otherwise.

B. Implementation Details

The proposed RL-based intentional islanding strategy is validated on the IEEE 39-bus test network. Details about the test network can be found in [19]. The transmission network is built in PSS/E, which is used for power flow simulations. The openAI Gym framework is utilized to develop the RL-based topology control model. Additionally, the RL algorithm from the stablebaselines3 library in Python 3.7 is used for learning the intentional islanding problem. The proximal policy optimization (PPO) has been used for training the model. The different parameters set after an empirical tuning process are presented in Table I.

C. Training of The Intentional Islanding Agent

The intentional islanding agent is trained using outage scenarios which include the generation of random line failures in the network. Therefore, for each episode with a specific outage event in the transmission network, the agent learns the optimal switching policy using the RL algorithm, by observing the state and estimating the reward. The goal of the islanding scheme is to continue network operation while ensuring security and generation adequacy. This is reflected in the observation (bus voltages and angles) acquired from power flow simulations and the reward assigned in Eq. (11). The action is designed as a multi-binary vector to represent the switching action.

The PPO algorithm [20] which is suitable for discrete action spaces is adopted for training the intentional islanding agent. PPO belongs to the class of policy gradient methods with an on-policy approach. The policy network is responsible for the observation-action mapping, while the value network determines the expected reward for the agent given a particular state of the network. The policy and value networks are updated continually using stochastic gradient ascent and gradient descent optimizers until the last epoch where the agent is assumed to be trained. The training procedure is described in Algorithm 1. The settings for the parameters in the training process are summarized in Table I.

TABLE I
PARAMETER SETTINGS

PARAMETERS	VALUES
ALGORITHM	PPO
TOTAL STEPS	60,000
OPTIMIZER	ADAM
LEARNING STEP SIZE	0.00001
ROLLOUT BUFFER SIZE	200
BATCH SIZE	100
EPOCHS	100
VALUE FUNCTION COEFFICIENT	0.5
ENTROPY COEFFICIENT	0.1

Algorithm 1 RL-based Intentional Islanding Algorithm

Require:
Import OpenAI Gym, Stable Baselines3 and psspy
Load the original test network modeled in PSS/E

```
for n = 1 to Number of buses do
    Initialize the voltage magnitude, angle and add to observation space
Initialize action space with a binary vector of size l
    for i = 1 to Max Episodes do
        Generate random line outage
        Simulate line outage in PSS/E network and perform powerflow
        Obtain observation (V_n, θ_n, ΔP, ΔQ) ∀n ∈ buses
        return observation to learning agent
        Acquire the action predicted by the policy network
        Implement the action in the PSS/E network by changing status of lines as per a_i ∀i ∈ l
        Determine the islands in the network with status of swing buses defined as generator mode
        if Number of islands >= 2 then
            Change the type of selected buses to swing
            Perform powerflow and obtain observation
            return observation after islanding to agent
            reward = 0.01×S_mis
        else
            reward = C_s
        end if
        return reward to learning agent
```

IV. NUMERICAL RESULTS

The developed intentional islanding strategy is validated on a modified IEEE 39-bus system. The training of the intentional islanding agent aims to maximize the mean rewards obtained per episode and is suitable for deployment after convergence. The learning curve in Fig. 2 exhibits the desirable increasing trend with convergence to near-zero for power mismatch, indicating that the agent is able to learn the optimal policy. The mean loss of the value network update is high during the initial learning and decreases to zero once the agent achieves a stable reward, showing the capability of the learning model to predict the value of each state-action pair.

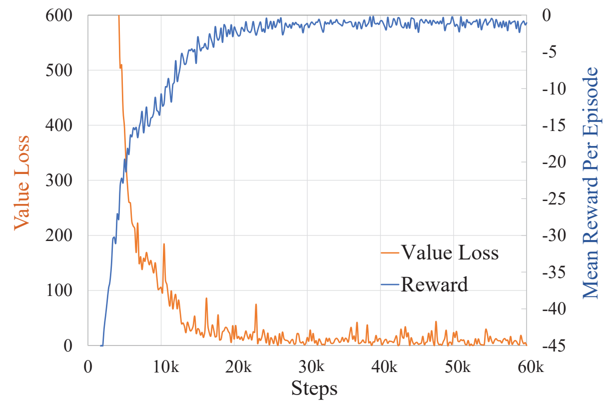

Fig. 2: Mean reward and value loss per step during RL training of intentional islanding on the modified 39-bus test system

To test the developed intentional islanding agent, an outage at the transmission line $(13, 14)$ is simulated as shown in Fig. 3. The policy network returns a suitable action for the outage scenario, resulting in opening lines $(14, 15)$ and $(16, 17)$ after the disruption, thereby forming two operating islands, as depicted in Fig. 3.

Bus39, bus32, and bus33 on each island are considered as swing buses. In PSS/E, the maximum number of possible islands in the grid would be fewer than the number of swing buses. Because the island detection is performed based on the swing bus in each zone, if there is an isolated part with no swing bus, PSS/E considers the zone as one island. Therefore in the proposed algorithm, all swing buses are first changed to non-swing mode, and then after counting the number of islands in the whole grid for each action, the status of all swing buses will return back to their original modes before calculating the power flow disruption.

The bus voltage magnitudes and angles obtained consequently by the islanding are shown in Fig. 4, and both of them fall within safe operating limits. The total power mismatch, in this case, is found to be 0.012 MVA.

Intentional islanding could enhance the flexibility in outage mitigation of large-scale grids and provide fast response control with high damping factors for severe disruptions, thereby avoiding potential instabilities that could ultimately push parameters outside of system tolerances. During network disruption events, intentional islanding could help improve network resilience by stabilizing the grid. Various line outages

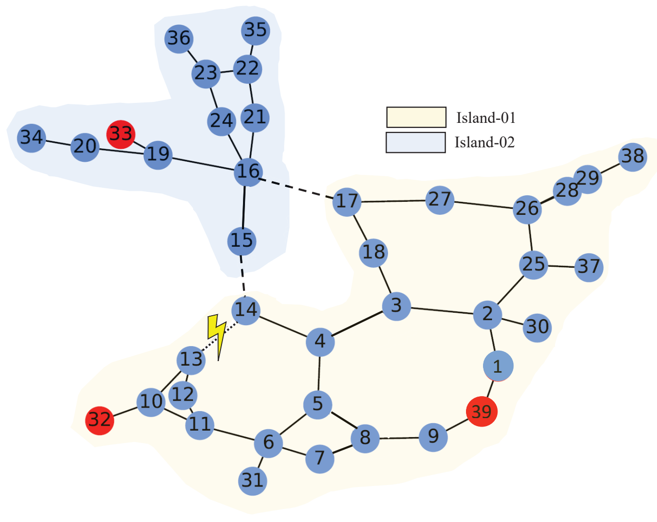

Fig. 3: IEEE 39-bus test system with an optimal islanding solution.

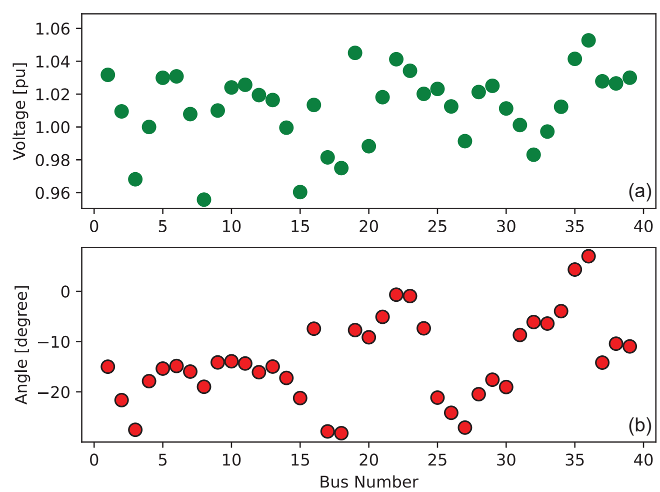

Fig. 4: (a) Voltage magnitude, and (b) bus angle of the grid with islanding.

are considered random events for the training of the agent by RL, to find an overall response for any event in the whole grid. It is important to note that many types of faults, such as a three-phase-to-ground short circuit, could potentially cause a blackout, even with fault removal. Hence it is important to consider splitting the system into self-sustained islands to prevent cascading failures.

To validate the effectiveness of the intentional islanding results on stabilizing of an unstable network after a fault, the dynamic simulation of the system has been performed with one of the worst faults in the grid, i.e., a three-phase-to-ground short circuit that remains in the grid for a while. If the island formation could mitigate the impacts of the selected three-phase-o-ground short circuit scenario, it is expected that the island formation could also work effectively under other transient faults in the grid. To this end, a three-phase-to-ground short circuit is induced at second 2 at bus 38, which is removed after 0.4 second. The intentional islanding strategy is applied at second 3. After the implementation of the intentional islanding strategy, the system dynamic response is analyzed, and Fig. 5 illustrates the transient voltage magnitude measurements for the test network. It is observed that by comparing the scenario without intentional islanding, the voltage with islanding could be quickly stabilized after the disruptive event. The voltage measurements of all buses oscillate with significantly smaller frequencies compared to those without islanding and are stabilized at new steady states around second 8.

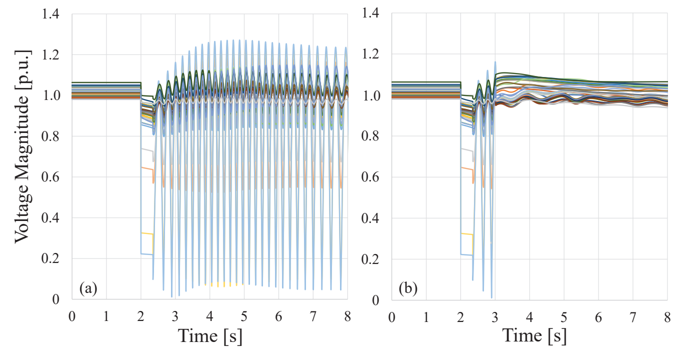

Fig. 5: The voltage profile of the modified IEEE 39-bus network: (a) without intentional islanding, and (b) with intentional islanding.

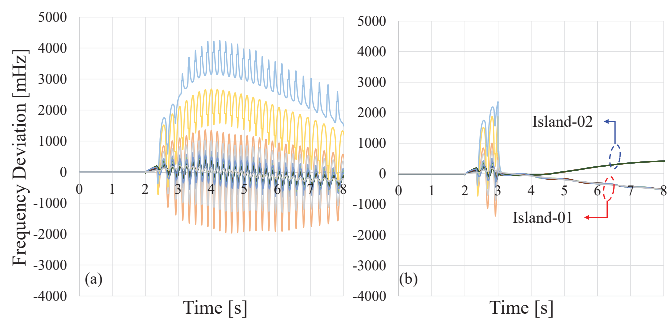

Fig. 6: The bus frequency deviation of the modified IEEE 39-bus network: (a) without intentional islanding, and (b) with intentional islanding.

The smooth transient response of the voltage profile will prevent it from deteriorating from the nominal state to irregular cyclical patterns, because the highly frequent oscillations may lead to inevitable cascading failures across the entire grid. Fig. 6 compares the frequency response of the grid with and without the intentional islanding scheme. The frequency deviation in both cases is within the desired range $\pm 0.5\%$. In the case without intentional islanding, when all of the buses are connected together, any change in frequency could lead to the failure of the entire grid. However, in the case of intentional islanding, the frequency could be controlled on each island separately.

V. Conclusion

This study developed a reinforcement learning (RL) framework for intentional islanding as a real-time network recovery and outage mitigation method during disruptions in power transmission networks. The real-time, automated and online control capability lacking in traditional methods necessitates an RL-based approach for resilience improvement in transmission networks. To this end, a switching control agent was designed to provide optimal cutset (lines out of service) to form islands based on the observations and reward acquired by interacting with a PSS/E based environment. The agent is trained to form optimal islands while minimizing the power mismatch in the network. The PSS/E simulation tool is also used to validate the operational security of the network following the switching actions obtained from the RL model. We have adopted the proximal policy optimization with multilayer perceptrons as the policy network. Case study results showed that the RL-based islanding method could form stable islands with minimum power disruption and stable transient responses during disruptive events.

Potential future work will further: (i) evaluate the scalability of the proposed RL method to large-scale power grid networks, (ii) evaluate the dynamic performance of the power system in the RL environment for calculating the strength of the formed islands by the dynamic stability analysis of the formed sub-systems, and (iii) leverage integrated energy systems (e.g., nuclear, renewable, and hydrogen) in conjunction with the islanding strategy to improve the grid resilience.

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