

Article

Optimization of Tripping Times in Adaptive Overcurrent Protection Coordination for Distribution Networks with Distributed Generation Using Deep Reinforcement Learning

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Abstract

Modern electrical distribution systems face increasingly complex protection coordination challenges due to variations in power flows under different operating conditions. In this context, this work proposes an adaptive coordination scheme based on deep reinforcement learning (DRL) to reduce the operating times of overcurrent relays while maintaining sensitivity, selectivity, and speed requirements. The methodology was implemented in Python 3.13 using the IEEE 33-bus distribution network with distributed generation (DG), and the coordination problem was addressed using the Deep Deterministic Policy Gradient (DDPG) algorithm, which adjusts the protection settings from previously calculated fault currents. The results show that the DDPG-based approach reduces fault-clearing times compared with the conventional methodology, achieving reductions between 17.01% and 77.5% for three-phase faults and between 18.5% and 74.1% for single-phase-to-ground faults across the analyzed scenarios, without compromising coordination between primary and backup relays. In addition, a comparison with a PSO-based offline optimization approach was included as an additional benchmark, showing that the proposed method provides competitive operating times while preserving its adaptive learning-based nature. These findings show that the proposed methodology is a viable option for adaptive protection coordination in modern distribution networks.

Keywords: protection coordination; overcurrent relays; distributed generation; deep reinforcement learning; Deep Deterministic Policy Gradient



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1. Introduction

In recent years, electrical energy has become one of the most essential services for social, industrial, and technological development. The sustained growth in electricity demand has driven the integration of new generation sources and, consequently, the progressive expansion of conventional distribution networks [1,2]. This process not only increases the installed capacity of the system but also requires adequate operating conditions, safety, and continuity of electric service.

In this context, protection systems play a fundamental role in power system operation because they detect and clear faults only in the affected area and in the shortest possible time. This helps prevent service interruptions, severe equipment damage, and negative impacts on end users [3]. In distribution networks, overcurrent relays are among the most widely used protection devices because of their simplicity, low maintenance cost,

and ease of implementation [3]. Their performance mainly depends on two parameters: the pickup current (I_s) and the time multiplier setting (TMS), both of which must be properly adjusted to ensure sensitivity, selectivity, and speed [3,4].

Historically, distribution networks were designed with a radial structure, in which power flows mainly from the substation to end users. Under this scheme, protection settings are determined from load current and short-circuit current levels, which are used to establish coordination margins between the primary and backup relays through a coordination time interval (CTI) [3]. However, the integration of distributed generation changes the electrical behavior of the system by modifying the magnitude and direction of current flows and transforming passive networks into active ones [1,2,5]. As a result, load and fault currents are no longer fixed and depend on factors such as the location, installed capacity, and operating condition of the distributed generation units. This may lead to loss of selectivity, incorrect relay operation, and unwanted operation of backup protection devices [1,5,6].

To address this issue, several studies have proposed new methodologies for protection setting and coordination based on artificial intelligence and optimization techniques [1,2,7], as well as studies focused on the performance analysis of protection systems in networks with high penetration of distributed generation [5], hybrid algorithms designed to improve the response of protection systems [8], and coordination strategies based on heuristic optimization [9–11]. These approaches have shown improvements over conventional methods by reducing operating times while maintaining coordination margins. However, a common limitation is that many of these methods depend on predefined scenarios, offline recalculation processes, or operating conditions associated with a particular network, which makes their application difficult in real distribution systems where network topology, load level, and distributed generation penetration may vary continuously.

In recent years, machine learning has emerged as a promising alternative for electric protection applications in distribution networks due to its ability to identify complex operating patterns and support decision-making in dynamic environments [12]. Some researchers have introduced approaches that incorporate deep reinforcement learning techniques for the adaptive adjustment of protection systems, including long-term reward-based strategies to adapt the network to possible changes [13], new architectures such as nested reinforcement learning [14], robust protection schemes based on deep reinforcement learning for networks with high penetration of distributed generation [15], and adaptive coordination strategies based on local measurements and data for active networks [16,17]. These studies show that the use of DRL in electric protection has already become a relevant line of research, although it still requires further development in specific applications related to the adaptive coordination of overcurrent relays.

Despite these advances, there is still a need for methodologies that treat relay coordination as a dynamic optimization problem and can readjust protection parameters under changing operating conditions without compromising sensitivity, selectivity, and speed. Deep reinforcement learning offers an important advantage because it enables an agent to learn decision-making strategies through interaction with a changing environment, without requiring a previously known optimal solution [12,18]. The DDPG agent is suitable for this problem because it works with continuous action spaces, allowing parameters such as I_s and TMS to be directly adjusted within technically feasible ranges [14,15,19].

The DDPG algorithm employs an actor-critic architecture based on deep neural networks, in which the actor network proposes control actions and the critic network evaluates their performance through a reward function associated with fault-clearing time and compliance with coordination intervals [14,15,19]. This model makes it possible to represent relay coordination as a sequential decision-making process in which protection settings

can be updated according to the operating state of the system. Under this perspective, the problem is no longer treated as a static setting procedure, but rather as an adaptive process aimed at enabling the system to respond to topological and operational changes in the network.

Based on the above, this work proposes an adaptive coordination methodology for overcurrent protection based on DDPG, applied to the IEEE 33-bus distribution system with distributed generation [20]. The simulation environment is developed in Python using specialized libraries for load-flow and short-circuit current calculations under IEC 60909 [21] in order to represent realistic operating conditions. Starting from conventionally calculated settings, the agent uses these values as a reference and explores new combinations of I_s and TMS while considering previously defined technical constraints, with the aim of reducing operating times without compromising coordination between primary and backup protections.

Therefore, the objective of this article is to propose and validate an adaptive coordination methodology capable of dynamically adjusting the operating parameters of overcurrent relays in distribution networks with distributed generation. The main contribution is to show that deep reinforcement learning can be used as a technically viable tool to improve protection coordination under different operating conditions.

Compared with the methodology reported in [22], the present work extends the adaptive coordination analysis by applying the DDPG-based approach to the IEEE 33-bus distribution system under different distributed generation placements and considering both three-phase and single-phase-to-ground faults. In addition, the proposed framework is supported by a simulation environment implemented in Python and complemented with validation in DIGSILENT PowerFactory, which allows the obtained relay settings and operating times to be evaluated under different operating conditions. In this way, the contribution of this work is not limited to the use of DDPG itself but also to its application and validation in a broader protection coordination context with varying DG scenarios and fault conditions.

2. Methodology

The methodology developed in this work is based on a deep reinforcement learning approach for the adaptive coordination of overcurrent relays in distribution networks with distributed generation. The procedure begins with the electrical system model and the definition of operating and fault scenarios. Based on this framework, the coordination problem is formulated as a dynamic optimization process in which the relay parameters can be readjusted as the system conditions change.

Unlike conventional approaches, in which relay settings are usually calculated for a single operating condition, this work considers changes in load levels, system topology, DG output, and short-circuit current levels. For this reason, protection coordination is addressed as an adaptive problem in which I_s and TMS are adjusted within previously established technical limits to improve the protection response under different system conditions [14–16].

Based on these considerations, a simulation environment is developed to represent the electrical behavior of the network and to evaluate, for each analyzed scenario, the performance of the settings proposed by the deep reinforcement learning algorithm. Using the information provided by the system, the DDPG algorithm explores new combinations of settings and progressively learns configurations that reduce fault-clearing times without compromising coordination between the primary and backup relays. In this way, the proposed methodology integrates network modeling, fault evaluation, and adaptive optimization of protection parameters within a single framework for further analysis.

2.1. System Modeling and Scenarios

The system considered in this study is the IEEE 33-bus distribution network, which is used as the base case to analyze the behavior of protection coordination under different operating conditions. The main line, load, and impedance data of the test system are provided in Appendix A. Based on this network, several scenarios are defined by considering changes in demand and different levels of distributed generation penetration, with the aim of representing the behavior of an active distribution network in a more realistic way [17,23,24].

For each scenario, the electrical parameters required for the simulation are defined, including the technical characteristics of the lines and loads, the location of the overcurrent relays, and the location and capacity of the distributed generation units. Likewise, the relay operating curves and the coordination margins between primary and backup devices are established, since these elements determine the time response of the protection system under fault conditions [3,10,24].

Once the system is fully defined, a time-delayed overcurrent protection scheme is implemented, making it possible to calculate the fault current seen by each protection device under every analyzed scenario. These currents are a fundamental part of the analysis because they are used to assess the performance of the conventional protection scheme and to provide the learning environment with the information required by the optimization algorithm.

The inclusion of scenarios with distributed generation is essential, since the presence of these units modifies power flows and may alter the magnitude of the fault currents observed by each relay. As a consequence, settings that may be valid under one operating condition can become unsuitable when the network operating conditions change, making recalculation necessary. This allows the adaptive capability of the proposed methodology to be properly evaluated [5,6,25].

The DG units considered in this study correspond to photovoltaic systems connected to the distribution network through step-up transformers from 0.46 kV to 12.66 kV. For their representation in the load-flow and short-circuit studies, the main electrical parameters of each unit were considered, including active power (P), rated apparent power (S), nominal voltage (V), and power factor (pf). In particular, a voltage level of 12.66 kV, corresponding to the operating level of the studied network, a power factor of 0.95, and a YN connection were adopted for all units, while the rated power and short-circuit parameters were defined individually for each generator.

For the short-circuit analysis, the photovoltaic distributed generation units were modeled using an equivalent current-limited representation, consistent with the typical behavior of inverter-based sources. The fault current contribution of each DG unit was defined through a short-circuit current factor k_{sc} , expressed with respect to the rated current of each generator. This approach avoids assuming excessive fault current contributions and provides a more realistic representation of photovoltaic generation within the IEC 60909-based short-circuit calculations.

This study considers both three-phase faults and single-phase-to-ground faults in order to evaluate the behavior of the protection system under different contingency conditions. Three-phase faults are included because they represent the most severe scenario in terms of short-circuit current levels, allowing the protection scheme to be assessed under critical operating conditions.

In addition, the inclusion of single-phase-to-ground faults makes it possible to analyze more realistic operating conditions for distribution systems, as this type of fault is the most common in practice. In this way, the capability of the DDPG-based model to adapt to both

balanced and unbalanced conditions is evaluated, taking into account variations in fault current magnitude and their impact on relay coordination and operating times.

The modeled system corresponds to the IEEE 33-bus radial distribution network operating at 12.66 kV, which is used in this work as the reference system for the coordination study. In the proposed protection scheme, Relay A is located at the main feeder and acts as backup protection, whereas Relays B, C, and D are assigned to downstream sections of the network as primary protection devices. The study considers a base case without distributed generation and additional scenarios in which photovoltaic DG units are connected at selected buses. In addition, fuse devices are incorporated in selected lateral feeders as complementary protection elements, allowing local permanent faults to be isolated while maintaining coordination with the upstream overcurrent relays. This configuration makes it possible to analyze how changes in DG location and operating conditions affect short-circuit current levels and, consequently, relay coordination performance.

2.2. Fundamentals of Reinforcement Learning (RL)

Reinforcement learning is a decision-making framework in which an agent interacts with an environment, selects actions, and receives rewards according to the resulting performance. In this work, this concept is used to represent relay coordination as an adaptive process, where relay settings are adjusted according to the electrical conditions of the system.

Deep reinforcement learning extends this framework by using neural networks to represent the decision policy and the value function. This is useful in protection coordination problems because the relationship between fault currents, relay settings, and coordination constraints is nonlinear and depends on the operating condition of the network.

DDPG Algorithm

Among deep reinforcement learning methods, the Deep Deterministic Policy Gradient (DDPG) algorithm is suitable for this work because it operates with continuous action variables. This is especially relevant for overcurrent relay coordination, since the pickup current I_s and the time multiplier setting TMS must be adjusted within continuous operating ranges to obtain feasible and realistic solutions [15,16,19].

Figure 1 illustrates the general actor–critic structure of the DDPG algorithm adopted in this work. The actor network proposes the relay settings, while the critic network evaluates the quality of the selected action through the expected reward. In addition, the replay buffer helps improve the stability of the learning process by reusing past experiences during training. Based on this structure, DDPG is adopted in this work as the optimization tool for adaptive relay coordination under changing operating conditions.

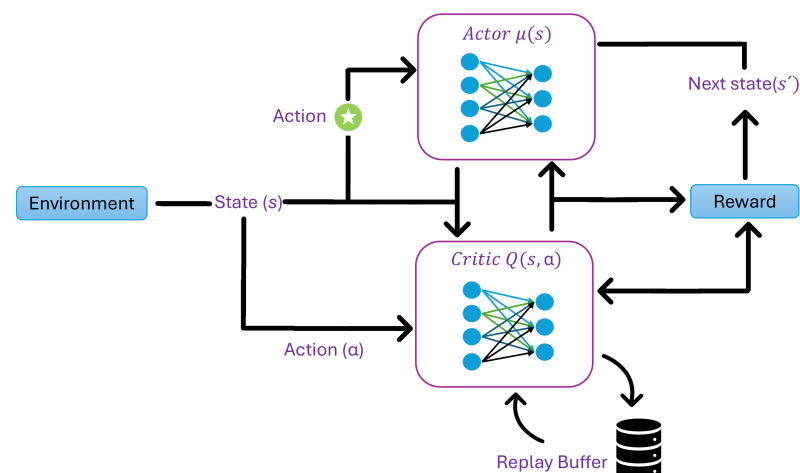


Figure 1. DDPG architecture.

2.3. Mathematical Formulation

Adaptive coordination of overcurrent relays is formulated as an optimization problem aimed at reducing fault-clearing times without affecting selectivity between the primary and backup relays. To achieve this, the classical relay behavior is first defined through its operating equations. Based on this formulation, the objective function and the constraints used by the DDPG algorithm during the learning process are established.

2.3.1. Relay Modeling and Operating Curves

The operating time of a time-delayed overcurrent relay depends on the fault current seen by the relay and on its setting parameters. In this work, inverse-time curves defined according to IEC 60255 [26] are used, specifically the Normal Inverse (NI), Very Inverse (VI), and Extremely Inverse (EI) types. These curves reduce the operating time as the fault current increases, with different levels of sensitivity depending on the curve formulation. The NI curve provides a more moderate variation, the VI curve gives a faster response at higher current levels, and the EI curve produces a more pronounced time reduction under severe fault currents. For these reasons, these curves are widely used in protection coordination studies [3,10,24].

As a starting point, the pickup current of each relay is calculated from the load current by means of an overload factor OLF, as presented in Equation (1):

$$I'_s = \text{OLF} \cdot I \quad (1)$$

where I'_s represents the initial pickup current of the relay, OLF is the overload factor, and I corresponds to the load current seen by the device. The use of the overload factor makes it possible to establish an initial setting value that keeps the relay stable under normal operating conditions while preserving sensitivity to faults within its protection zone. In this study, OLF is considered within a typical range from 1.2 to 1.5 depending on the location of the relay and the electrical conditions of the protected section.

Once the pickup current has been determined, the relay operating time is calculated using Equation (2):

$$t = \frac{\beta \cdot \text{TMS}}{\left(\frac{I}{I_s}\right)^\alpha - 1} + L \quad (2)$$

where t is the operating time of the relay, I corresponds to the fault current seen by the device, I_s is the pickup current, and TMS is the time multiplier setting. In addition, the parameters α , β , and L depend on the selected curve type, namely Normal Inverse, Very Inverse, or Extremely Inverse. Based on the above, the pickup current defines the minimum level at which the relay begins to operate, while the TMS adjusts the speed with which the device responds under fault conditions.

2.3.2. Objective Function and Coordination Constraints

Based on the relay operating model, the problem is formulated as the search for optimal combinations of I_s and TMS that reduce fault-clearing times while maintaining coordination margins between the primary and backup relays. Under this criterion, the objective function is defined by Equation (3):

$$\text{OF} = \alpha_1 \sum_{i=1}^n t_i(I_{s,i}, \text{TMS}_i) + \alpha_2 \sum_{i=1}^n \left[\max\left(0, \text{CTI} - (t_{\text{backup},i} - t_{\text{primary},i})\right) \right]^2 \quad (3)$$

where α_1 and α_2 are weighting factors associated with fault-clearing time minimization and the penalty imposed for violation of the coordination interval. The term t_{primary}

represents the operating time of the primary relay, whereas t_{backup} corresponds to the operating time of the backup relay, and CTI is the minimum coordination margin required between both devices. The section expressed as $\max(0, \dots)$ is used to introduce penalties according to the established CTI. If the expression is negative or equal to zero, no penalty is applied; otherwise, if the expression is greater than zero, a penalty is assigned. In this way, the objective function combines selectivity and speed in a single formulation so that α_1 helps achieve shorter fault-clearing times, while α_2 enforces proper coordination without violating the imposed constraints [22].

In addition to the objective function, operational constraints are incorporated to delimit the search space and prevent physically infeasible settings:

$$I_{s,\min,i} \leq I_{s,i} \leq I_{s,\max,i} \quad (4)$$

$$\text{TMS}_{\min,i} \leq \text{TMS}_i \leq \text{TMS}_{\max,i} \quad (5)$$

Equation (4) establishes I_s within minimum and maximum values defined by the device characteristics, thereby defining the range in which the agent can search for a solution. In this way, the algorithm does not select I_s randomly, which could otherwise lead to unwanted or unintended relay tripping during normal operation. Equation (5) sets the upper and lower limits for TMS, ensuring that the resulting operating times remain within ranges that can be properly set in the relay.

$$t_{\text{backup}} - t_{\text{primary}} \geq \text{CTI} \quad (6)$$

On the other hand, Equation (6) imposes the selectivity condition between the primary and backup relays, requiring the operating time of the backup relay to be greater than that of the primary relay according to the established CTI [10,11,24].

2.3.3. Mathematical Model of the DDPG Algorithm

Once the classical relay setting methodology has been established, the deep reinforcement learning environment is incorporated in this section so that the algorithm can optimize the protection parameters under electrical and operational criteria previously defined through the objective function and the coordination constraints. In this context, the system state is represented by the electrical variables that are most relevant to coordination, mainly those associated with the fault currents seen by each relay and the operating limits that must be satisfied.

The action generated by the actor network is represented by Equation (7):

$$\alpha = \mu(s \mid \theta^\mu) \quad (7)$$

where α is the action proposed by the agent, s represents the state of the environment, and θ^μ corresponds to the parameters of the actor network.

In turn, Equation (8) represents how the critic network evaluates the quality of the executed action through the action-value function:

$$Q_{\theta^Q}(s, \alpha) \quad (8)$$

where Q is the action-value function and θ^Q represents the parameters of the critic network.

Based on the reward received and the new state reached, the target value used to update the critic network is expressed in Equation (9):

$$y = r + \gamma Q_{\theta^Q}(s', \mu_{\theta^\mu}(s')) \quad (9)$$

where r is the reward obtained, s' is the new state of the system, and γ is the discount factor that weights the importance of future rewards.

The loss function used to train the critic network is given by Equation (10):

$$L(\theta^Q) = \mathbb{E}_{(s, \alpha, r, s')} \left[(y - Q_{\theta^Q}(s, \alpha))^2 \right] \quad (10)$$

Meanwhile, the update of the actor policy is carried out using the gradient shown in Equation (11):

$$\nabla_{\theta^\mu} J = \mathbb{E}_s \left[\nabla_\alpha Q_{\theta^Q}(s, \alpha) \Big|_{\alpha=\mu(s)} \nabla_{\theta^\mu} \mu(s | \theta^\mu) \right] \quad (11)$$

Finally, the target networks are updated smoothly according to Equation (12):

$$\theta^{Q'} \leftarrow \tau \theta^Q + (1 - \tau) \theta^{Q'}, \quad \theta^{\mu'} \leftarrow \tau \theta^\mu + (1 - \tau) \theta^{\mu'} \quad (12)$$

where τ is the parameter that controls the update rate of the target networks.

These expressions describe, in general terms, how the agent learns to improve its decision policy. In other words, the algorithm does not replace the classical relay formulation, but rather uses it as the basis for building an adaptive decision policy capable of responding to different operating conditions of the system [14–16,19].

For reproducibility, the state space is defined by the electrical variables that directly influence relay coordination, namely, the fault current seen by the relay under analysis, the current relay setting limits, and the coordination condition associated with the corresponding primary–backup pair. The action space is continuous and is given by the pair $[I_s, \text{TMS}]$, which represents the relay settings proposed by the actor network. The reward is constructed from the objective function in Equation (3) so that lower relay operating times are favored while violations of the minimum coordination interval are penalized. The actor and critic models are implemented as fully connected feedforward neural networks. As summarized in Table 1, the actor network uses a 128–128–2 structure and the critic network uses a 128–128–1 structure, which were adopted as practical architectures for representing the relationship between the electrical state variables and the relay setting decisions.

2.4. Initialization and Training Environment

At this stage, the training process begins through the interaction between the algorithm and the environment, using the electrical and operational information of the system described in the previous sections in order to evaluate different setting combinations for the overcurrent relays. The training initialization does not start from a previously known optimal solution. Instead, it takes as reference a set of conventional settings obtained through the classical protection coordination procedure. These initial values make it possible to define a technically feasible search space, preventing the agent from exploring completely arbitrary combinations. In this way, the learning process is supported by a coherent basis that is consistent with the criteria of sensitivity, selectivity, and speed, while preserving its adaptive behavior as training progresses.

During each episode, the agent observes the current state of the environment, proposes an action associated with new values of I_s and TMS, and receives a reward calculated according to the performance obtained from the selected decision. Based on this interaction, the algorithm progressively updates its learning policy, preserving those solutions that provide better results within the operating limits and coordination constraints. This procedure is repeated iteratively for each relay in the system, while the experience stored in the replay buffer helps improve the stability and convergence of the learning process.

To improve the reproducibility of the proposed methodology, Table 1 summarizes the main training hyperparameters of the DDPG model used in this work. It includes the optimization parameters, learning factors, replay memory configuration, exploration strategy, and architecture adopted for the actor and critic networks. The inclusion of this information provides a clearer description of the implemented training environment and facilitates future replication of the proposed model by other researchers seeking to reproduce the results presented in this study.

Table 1. Main training hyperparameters of the DDPG model.

Hyperparameter	Value
Learning rate (actor/critic)	0.001/0.001
Discount factor, γ	0.99
Soft update rate, τ	0.005
Batch size	64
Replay buffer size	20,000
Exploration noise, σ	0.10
Episodes per relay	350
Actor architecture	128–128–2
Critic architecture	128–128–1

The hyperparameters reported in Table 1 were selected from preliminary tests carried out to obtain stable training behavior and a consistent convergence trend of the reward function. Their final values were chosen after verifying their effect on learning stability, exploration capability, and computational effort within the studied coordination problem. In particular, the number of episodes per relay was defined from the convergence trend shown in Figure 2, where the reward tends to stabilize around 350 episodes. Therefore, the selected hyperparameters were not assigned arbitrarily, but were adopted as practical values that provided a suitable balance between solution quality and training time.

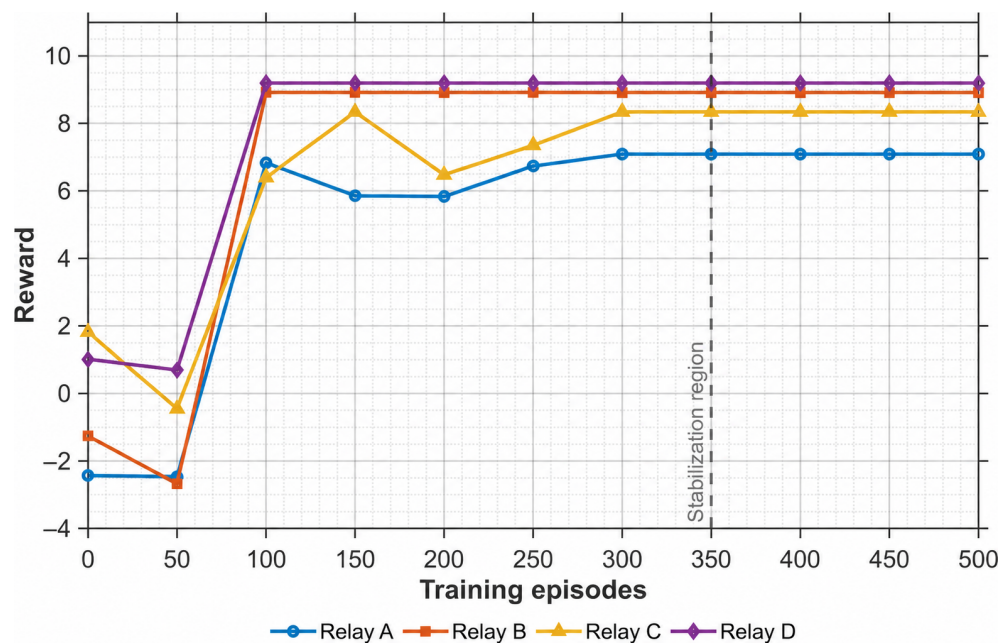


Figure 2. DDPG learning curve.

Accordingly, 350 episodes per relay were adopted as a practical training reference, since the reward shown in Figure 2 tends to stabilize around this value. This choice

provided a suitable balance between learning quality and computational effort, although the number of episodes can be adjusted according to the complexity of the analyzed scenario.

To present the methodological sequence developed in this work in a structured manner, the general procedure followed for the proposed adaptive coordination approach is described below. This procedure begins with the definition of the electrical system data and the protection devices, together with the load-flow and short-circuit current calculations. Subsequently, the conventional settings are determined, the objective function and its technical constraints are established, and the reinforcement learning environment to be used by the DDPG agent is constructed. Finally, the algorithm provides both calculated and optimized values of I_s and TMS for each relay, allowing their validation through simulation in order to obtain the corresponding operating times. In this way, Algorithm 1 summarizes the overall logic of the methodology implemented throughout the development of this work.

Algorithm 1 DRL–DDPG based adaptive coordination procedure for overcurrent relays

```

1: Input: Network data (buses, lines, loads, DG units), relay locations, IEC curve parameters, and coordination constraints.
2: Perform load-flow analysis and short-circuit calculations.
3: Compute conventional relay settings ( $I_{s,i}^{\text{cal}}, \text{TMS}_i^{\text{cal}}$ ) for each relay  $i$ .
4: Define the objective function and constraints according to Equations (3)–(6).
5: for each relay  $i$  do
6:   Build the reinforcement learning environment  $\text{RelayEnv}_i$ .
7:   Initialize actor network  $\mu(s | \theta^\mu)$  and critic network  $Q(s, a | \theta^Q)$ .
8:   Initialize target networks and replay buffer.
9:   for  $k = 1$  to  $N_{\text{episodes}}$  do
10:    Reset environment and obtain initial state  $s$ .
11:    Set  $\text{done} = \text{false}$ .
12:    while  $\text{done}$  is false do
13:      Select action
      
$$a = \mu(s | \theta^\mu) + \text{noise}, \quad a = [I_{s,i}, \text{TMS}_i]$$

14:      Apply action  $a$  to the environment.
15:      Observe next state  $s'$ , reward  $r$ , and termination flag  $\text{done}$ .
16:      Store transition  $(s, a, r, s', \text{done})$  in the replay buffer.
17:      Update actor and critic networks using sampled experience.
18:      Set  $s \leftarrow s'$ .
19:    end while
20:  end for
21:  Store the best optimized settings
      
$$(I_{s,i}^*, \text{TMS}_i^*)$$

      obtained for relay  $i$ .
22: end for
23: Output: Calculated and optimized relay settings for each relay.

```

3. Case Studies and Results

This section presents the results obtained from the considered cases when applying the proposed adaptive coordination methodology based on deep reinforcement learning to the IEEE 33-bus system with DG. The agent performance is evaluated under different scenarios with varying load levels and DG capacities. The aim is to analyze fault-clearing times and the robustness of the obtained settings under operational changes and fault conditions. For this purpose, traditional overcurrent relay settings calculated using conventional criteria are used as a reference to compare them with the settings proposed by the DDPG algorithm.

3.1. Case Study 1

Case Study 1 corresponds to the base operating condition of the IEEE 33-bus distribution system without distributed generation. This first scenario is included as a reference case to assess the behavior of the proposed methodology under conventional radial operating conditions. In this way, the relay settings obtained with the conventional coordination procedure can be directly compared with those obtained using the DDPG-based adaptive approach under representative fault conditions.

Figure 3 shows the base IEEE 33-bus system without distributed generation. Tables 2 and 3 compare the conventional and optimized settings of relay RA for three-phase and single-phase-to-ground faults, respectively.

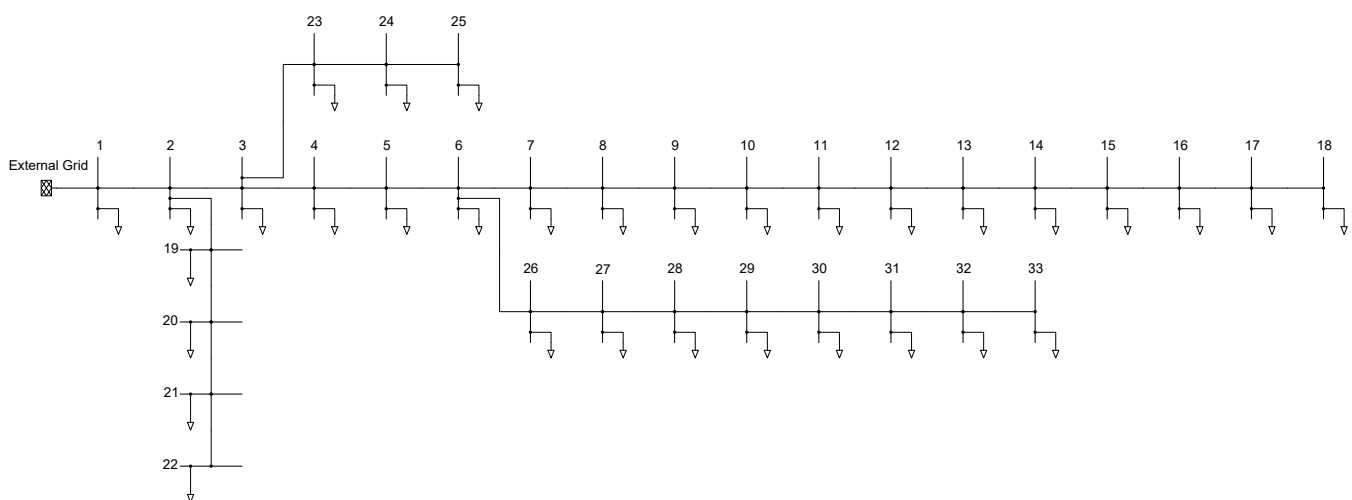


Figure 3. Single-line diagram of the IEEE 33-bus distribution system for Case Study 1.

Table 2. Phase Overcurrent Relay Settings (51) for Case Study 1.

Relay	Setting	Calculated Value	Optimized Value
RA	I_s	1.582	1.297
	TMS	0.363	0.094

Table 3. Ground Fault Overcurrent Relay Settings (51N) for Case Study 1.

Relay	Setting	Calculated Value	Optimized Value
RA	I_s	0.633	0.633
	TMS	0.464	0.261

The difference between the calculated *TMS* and the optimized *TMS* is related to the role of each value in the coordination process. The calculated setting is obtained from the conventional procedure and is used as an initial reference based on static operating criteria. In contrast, the optimized setting is obtained through the DDPG training process, where the objective is to reduce relay operating time while maintaining the required coordination constraints. For this reason, the optimized *TMS* may differ significantly from the conventional value, since it reflects the adaptive adjustment capability of the proposed methodology rather than a simple manual recalculation.

This reference case provides the baseline for comparison with the scenarios that include distributed generation.

Figure 4 compares the conventional and DDPG-optimized settings for the three-phase fault at bus 7. The operating time is reduced from 1.429 s to 0.321 s, showing a clear improvement in relay response.

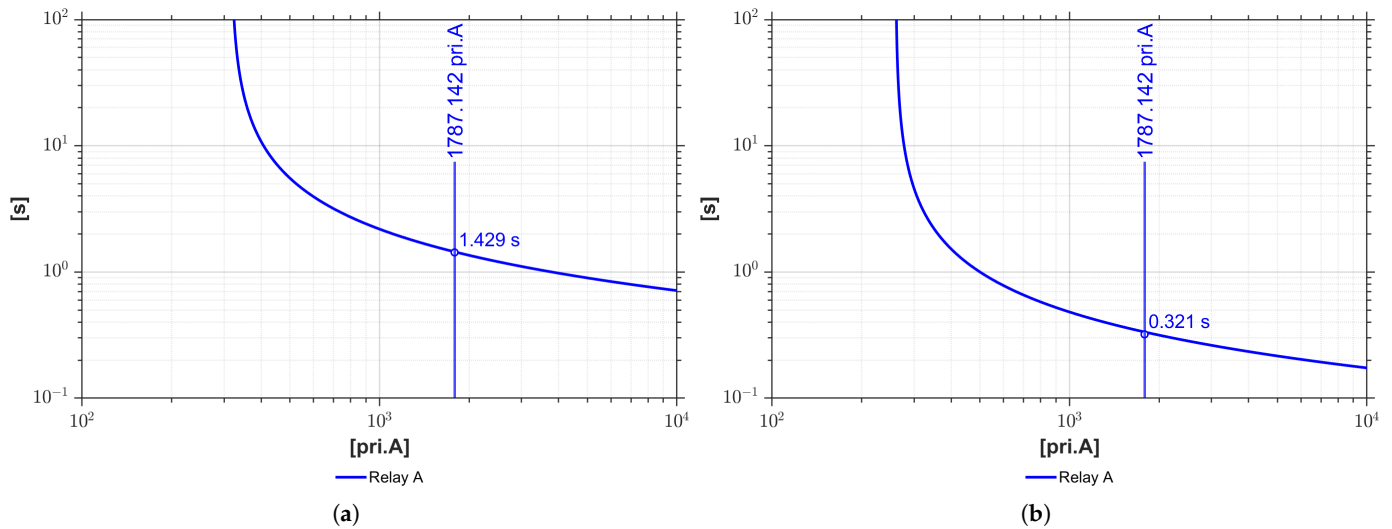


Figure 4. Time–current curves for a three-phase fault without DG: (a) Conventional settings for Relay RA at bus 7; (b) DDPG-optimized settings for Relay RA at bus 7.

Figure 5 presents the corresponding single-phase-to-ground fault case. The relay operating time decreases from 1.431 s to 0.809 s, which confirms that the proposed methodology remains effective under both balanced and unbalanced fault conditions.

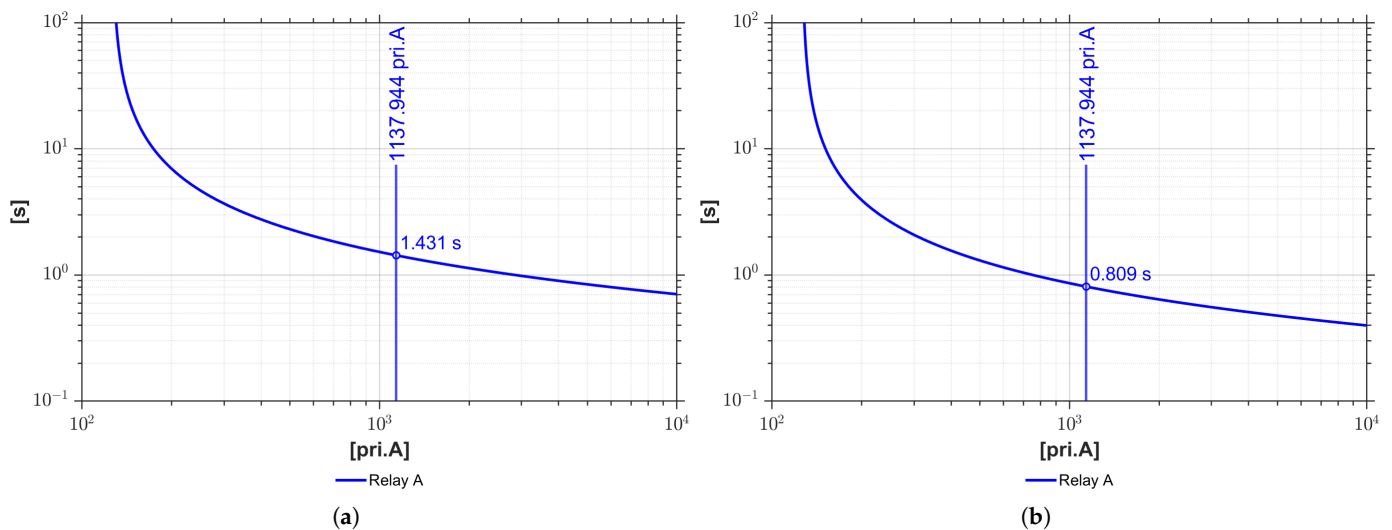


Figure 5. Time–current curves for a single-phase-to-ground fault without DG: (a) Conventional settings for Relay RA at bus 7; (b) DDPG-optimized settings for Relay RA at bus 7.

3.2. Case Study 2

Case Study 2 extends the analysis by incorporating distributed generation units at different locations of the IEEE 33-bus system. This scenario is intended to evaluate how the proposed adaptive coordination methodology responds when the network operating conditions change due to the presence of DG. Under these conditions, the fault current levels and the relay operating behavior may differ from the base case, which makes it possible to assess the ability of the DDPG-based approach to adjust the relay settings while preserving coordination.

Figure 6 presents the IEEE 33-bus system used for Case Study 2, where three DG units are connected at buses 10, 29, and 20, as summarized in Table 4. Tables 5 and 6 compare the conventional and optimized relay settings for three-phase and single-phase-to-ground faults. In this scenario, DG modifies the short-circuit current levels seen by the relays, which makes it possible to evaluate the adaptive response of the DDPG-based methodology under changing operating conditions.

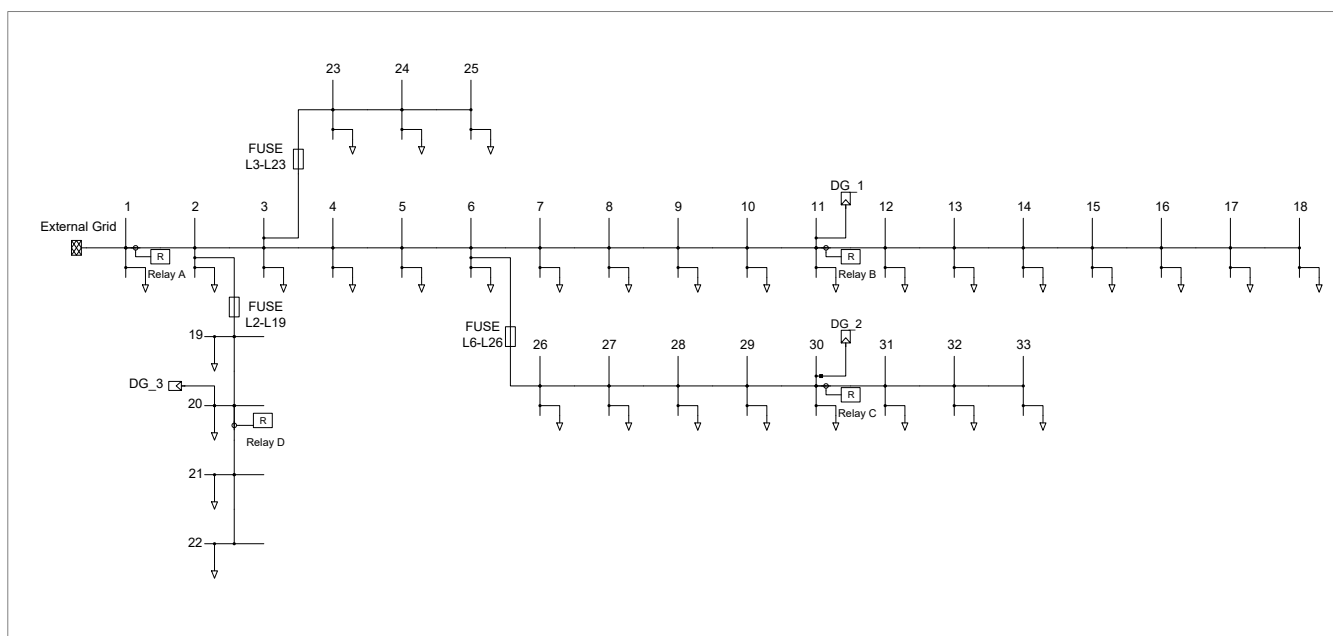


Figure 6. Single-line diagram of the IEEE 33-bus distribution system for Case Study 2.

Table 4. DG parameters for Case Study 2.

Node	Distributed Generation	P [MW]
10	DG1	1.000
29	DG2	1.300
20	DG3	0.800

Table 5. Phase Overcurrent Relay Settings (51) for Case Study 2.

Relay	Adjustment	Calculated Value	Optimized Value
RA	I_s	0.835	0.687
	TMS	0.439	0.397
RB	I_s	0.750	0.693
	TMS	0.336	0.203
RC	I_s	1.152	1.152
	TMS	0.314	0.100
RD	I_s	0.215	0.215
	TMS	0.581	0.156

Figure 7 presents the time–current curves for the analyzed three-phase faults.

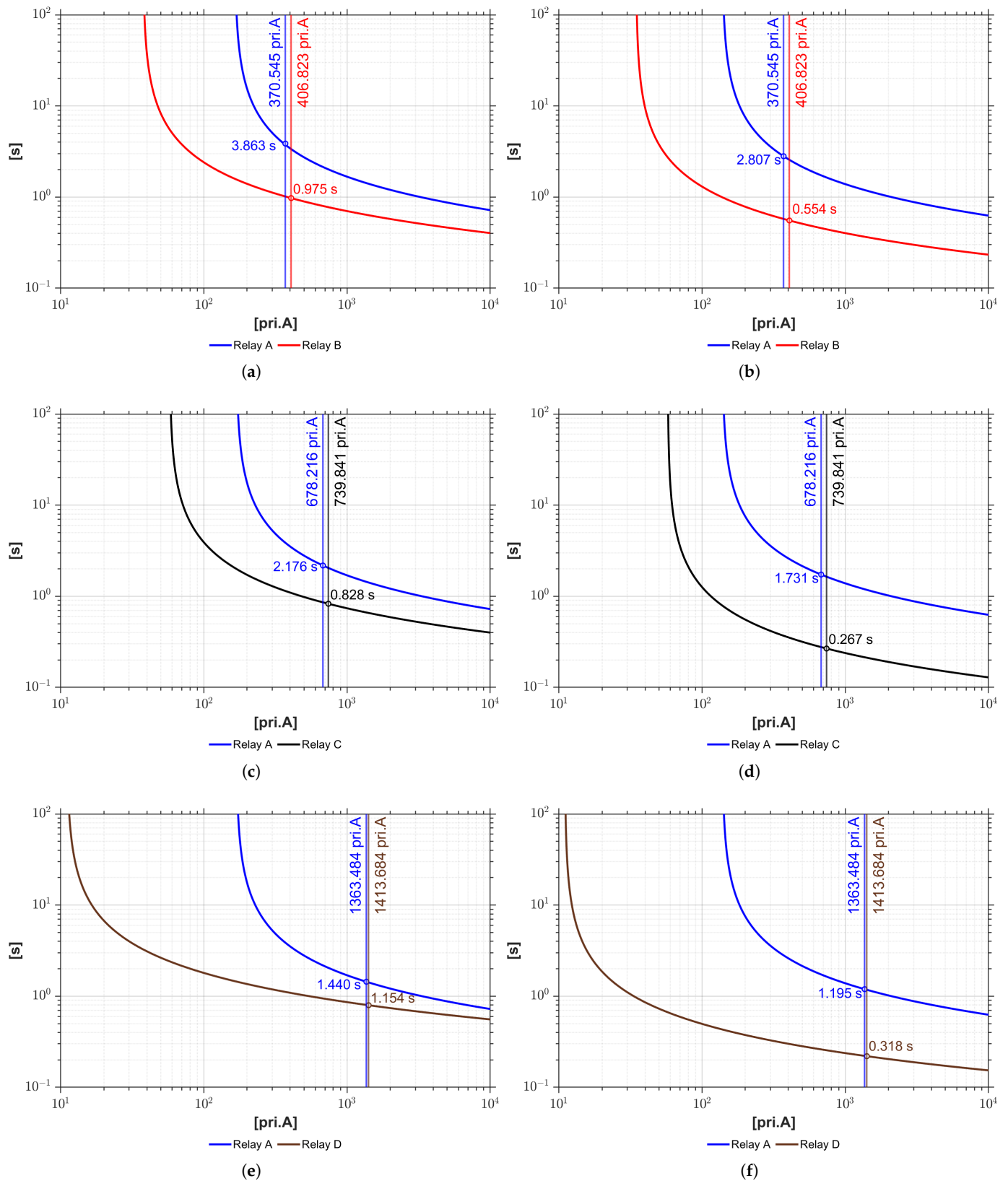


Figure 7. Time–current curves for Case Study 2 with DG: (a) three-phase fault at bus 18 for relays RA and RB without DDPG; (b) three-phase fault at bus 18 for relays RA and RB with DDPG; (c) three-phase fault at bus 33 for relays RA and RC without DDPG; (d) three-phase fault at bus 33 for relays RA and RC with DDPG; (e) three-phase fault at bus 22 for relays RA and RD without DDPG; (f) three-phase fault at bus 22 for relays RA and RD with DDPG.

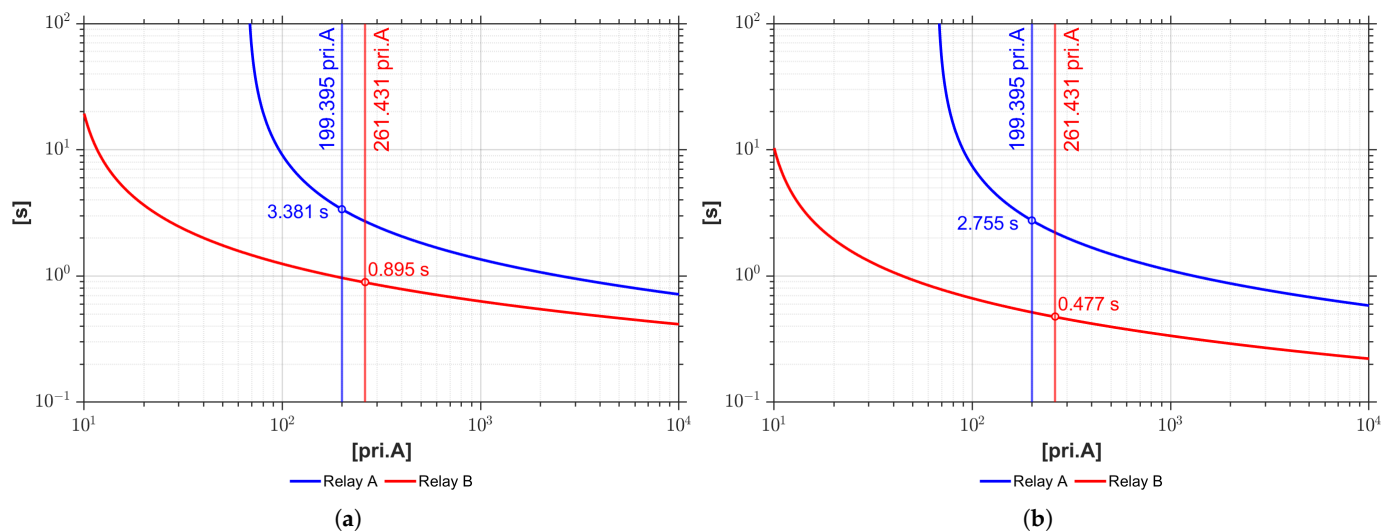
Table 6. Ground Fault Overcurrent Relay Settings (51N) for Case Study 2.

Relay	Adjustment	Calculated Value	Optimized Value
RA	I_s	0.334	0.334
	TMS	0.540	0.437
RB	I_s	0.173	0.173
	TMS	0.449	0.241
RC	I_s	0.288	0.288
	TMS	0.418	0.112
RD	I_s	0.100	0.100
	TMS	0.621	0.167

For the three-phase faults in Figure 7, the optimized settings reduce the operating times of the primary and backup relays in all analyzed locations. For the bus 18 fault, the operating times decrease from 3.863 s to 2.807 s for RA and from 0.975 s to 0.554 s for RB. For the bus 33 fault, the times are reduced from 2.176 s to 1.731 s for RA and from 0.828 s to 0.267 s for RC. For the bus 22 fault, the reduction is from 1.440 s to 1.195 s for RA and from 1.154 s to 0.318 s for RD. These results confirm that the proposed methodology improves fault-clearing performance while preserving relay coordination.

Figure 8 presents the corresponding single-phase-to-ground faults at the same buses. Again, the DDPG-based settings produce lower operating times in all cases, showing that the proposed methodology remains effective under more realistic unbalanced fault conditions.

For the single-phase-to-ground faults in Figure 8, the operating times are reduced from 3.381 s to 2.755 s for RA and from 0.895 s to 0.477 s for RB at bus 18, from 2.115 s to 1.723 s for RA and from 0.835 s to 0.219 s for RC at bus 33, and from 1.447 s to 1.179 s for RA and from 1.233 s to 0.338 s for RD at bus 22. The results again show consistent improvement without loss of selectivity.

**Figure 8.** Cont.

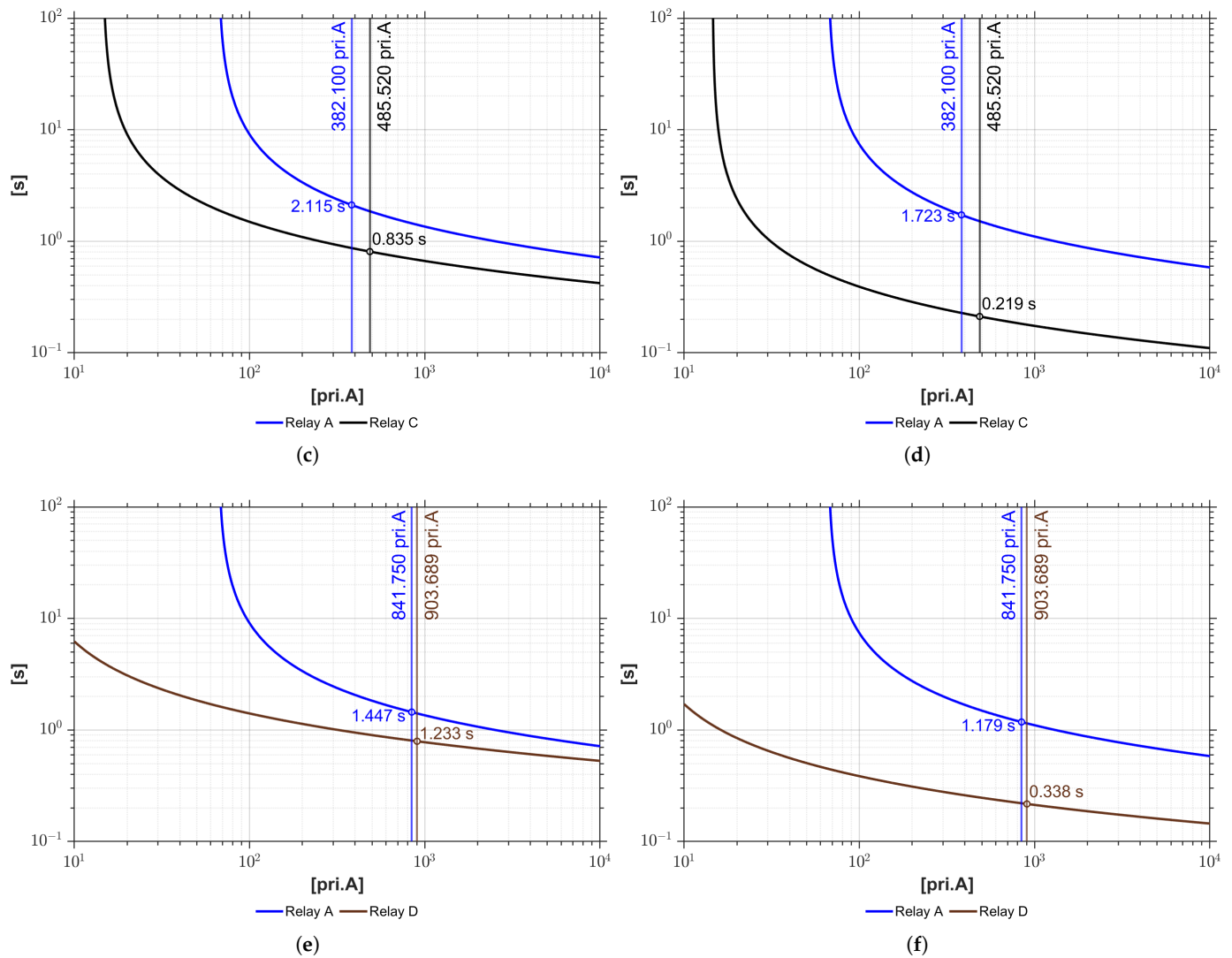


Figure 8. Time–current curves for Case Study 2 with DG: (a) single-phase-to-ground fault at bus 18 for relays RA and RB without DDPG; (b) single-phase-to-ground fault at bus 18 for relays RA and RB with DDPG; (c) single-phase-to-ground fault at bus 33 for relays RA and RC without DDPG; (d) single-phase-to-ground fault at bus 33 for relays RA and RC with DDPG; (e) single-phase-to-ground fault at bus 22 for relays RA and RD without DDPG; (f) single-phase-to-ground fault at bus 22 for relays RA and RD with DDPG.

3.3. Case Study 3

Case Study 3 considers a different distributed generation arrangement in the IEEE 33-bus system in order to further examine the adaptability of the proposed methodology under a new operating condition. By modifying the location of the DG units, the resulting short-circuit current distribution and relay behavior also change, which provides an additional scenario for evaluating the robustness of the DDPG-based coordination approach. In this way, the performance of the proposed method can be analyzed under a system condition that differs from both the base case and the previous DG configuration.

Figure 9 shows the IEEE 33-bus system used in Case Study 3, where the DG units are relocated to buses 11, 30, and 23, as summarized in Table 7. Tables 8 and 9 present the conventional and optimized settings for three-phase and single-phase-to-ground faults. This case provides an additional DG arrangement for assessing the robustness of the proposed methodology under a different distribution of fault current contributions.

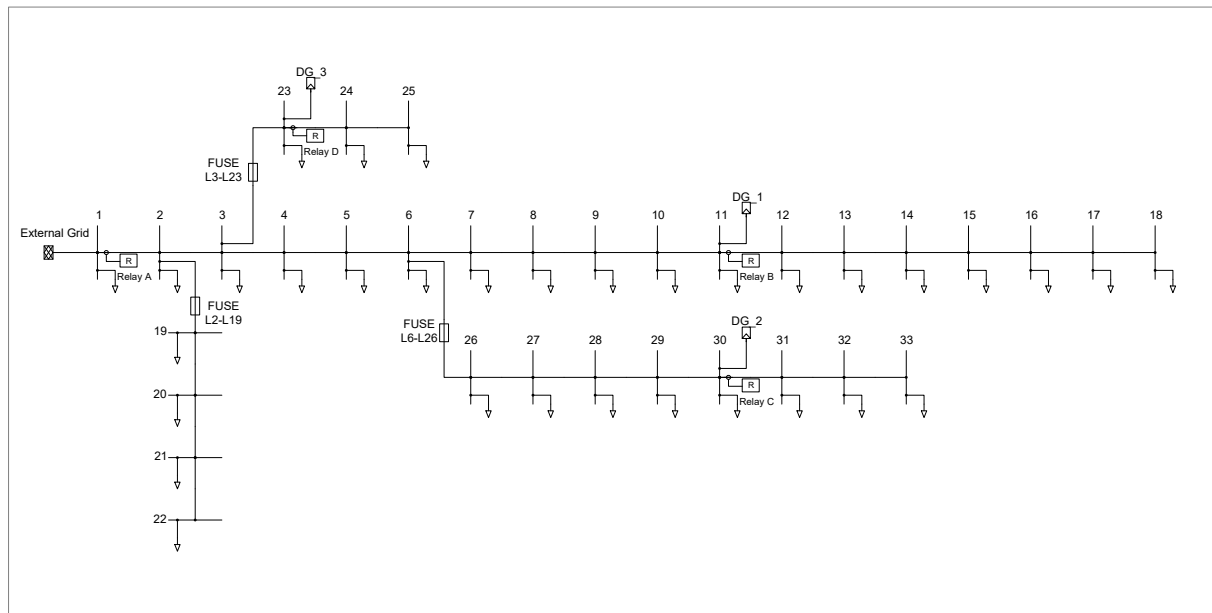


Figure 9. Single-line diagram of the IEEE 33-bus distribution system for Case Study 3.

Table 7. DG parameters for Case Study 3.

Node	Distributed Generation	P [MW]
11	DG1	0.900
30	DG2	1.100
23	DG3	1.300

Table 8. Phase Overcurrent Relay Settings (51) for Case Study 3.

Relay	Adjustment	Calculated Value	Optimized Value
RA	I_s	0.832	0.666
	TMS	0.439	0.376
RB	I_s	0.683	0.631
	TMS	0.340	0.188
RC	I_s	0.528	0.528
	TMS	0.380	0.102
RD	I_s	1.033	1.033
	TMS	0.419	0.113

Table 9. Ground Fault Overcurrent Relay Settings (51N) for Case Study 3.

Relay	Adjustment	Calculated Value	Optimized Value
RA	I_s	0.333	0.333
	TMS	0.542	0.437
RB	I_s	0.158	0.158
	TMS	0.456	0.254
RC	I_s	0.132	0.132
	TMS	0.488	0.131
RD	I_s	0.258	0.258
	TMS	0.535	0.144

Figure 10 shows that the DDPG-based settings again reduce relay operating times for all three-phase faults considered in Case Study 3. At bus 16, the times decrease from 3.013 s to 2.143 s for RA and from 0.862 s to 0.468 s for RB. At bus 33, the reduction is from 2.157 s

to 1.614 s for RA and from 0.773 s to 0.203 s for RC. At bus 25, the times decrease from 1.342 s to 1.056 s for RA and from 0.835 s to 0.219 s for RD. Compared with Case Study 2, the changed DG placement modifies the short-circuit current distribution, but the proposed methodology still preserves coordination and improves relay response.

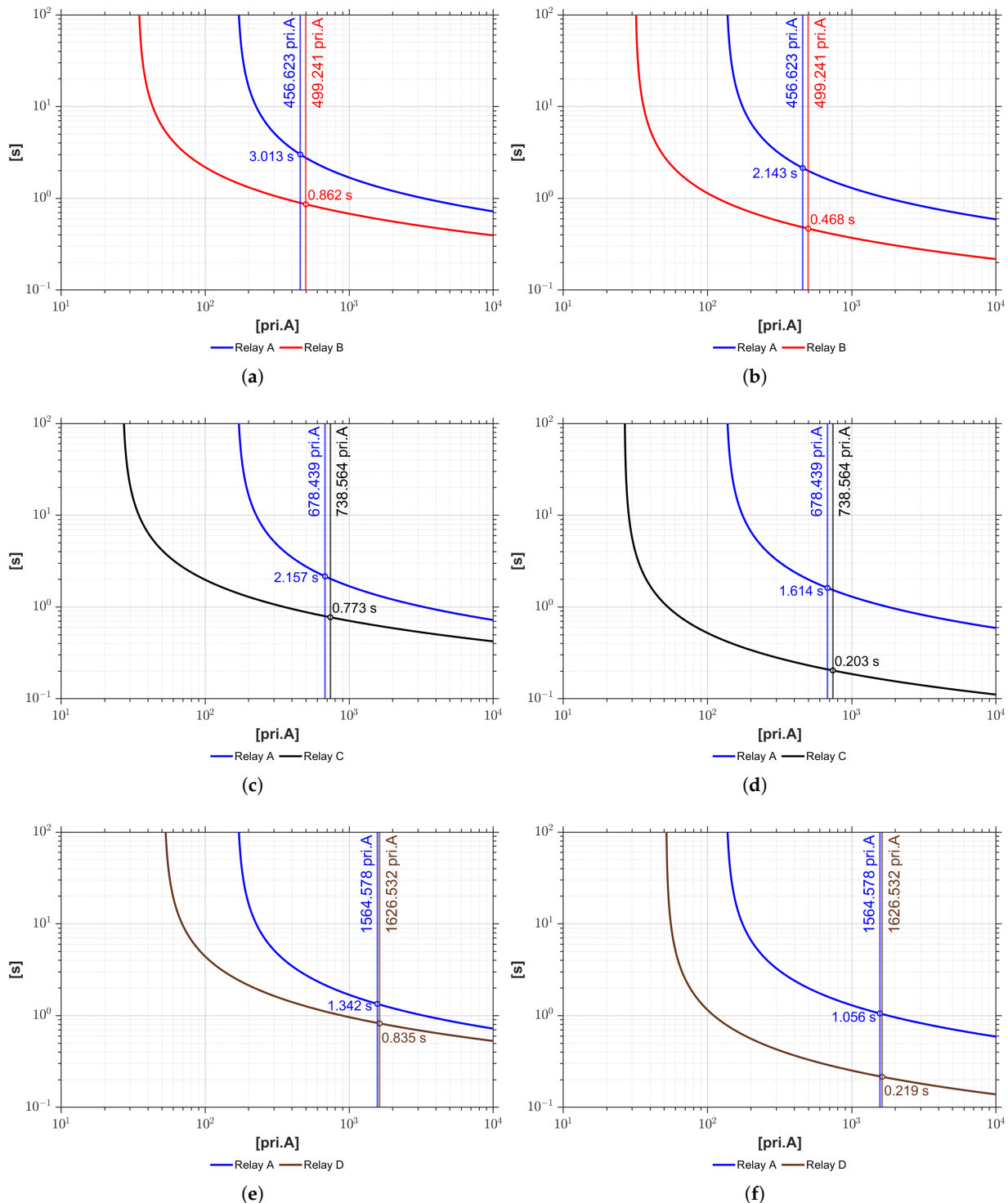


Figure 10. Time–current curves for Case Study 3 with DG: (a) three-phase fault at bus 16 for relays RA and RB without DDPG; (b) three-phase fault at bus 16 for relays RA and RB with DDPG; (c) three-phase fault at bus 33 for relays RA and RC without DDPG; (d) three-phase fault at bus 33 for relays RA and RC with DDPG; (e) three-phase fault at bus 25 for relays RA and RD without DDPG; (f) three-phase fault at bus 25 for relays RA and RD with DDPG.

Figure 11 presents the corresponding single-phase-to-ground faults, allowing the same DG arrangement to be evaluated under unbalanced fault conditions.

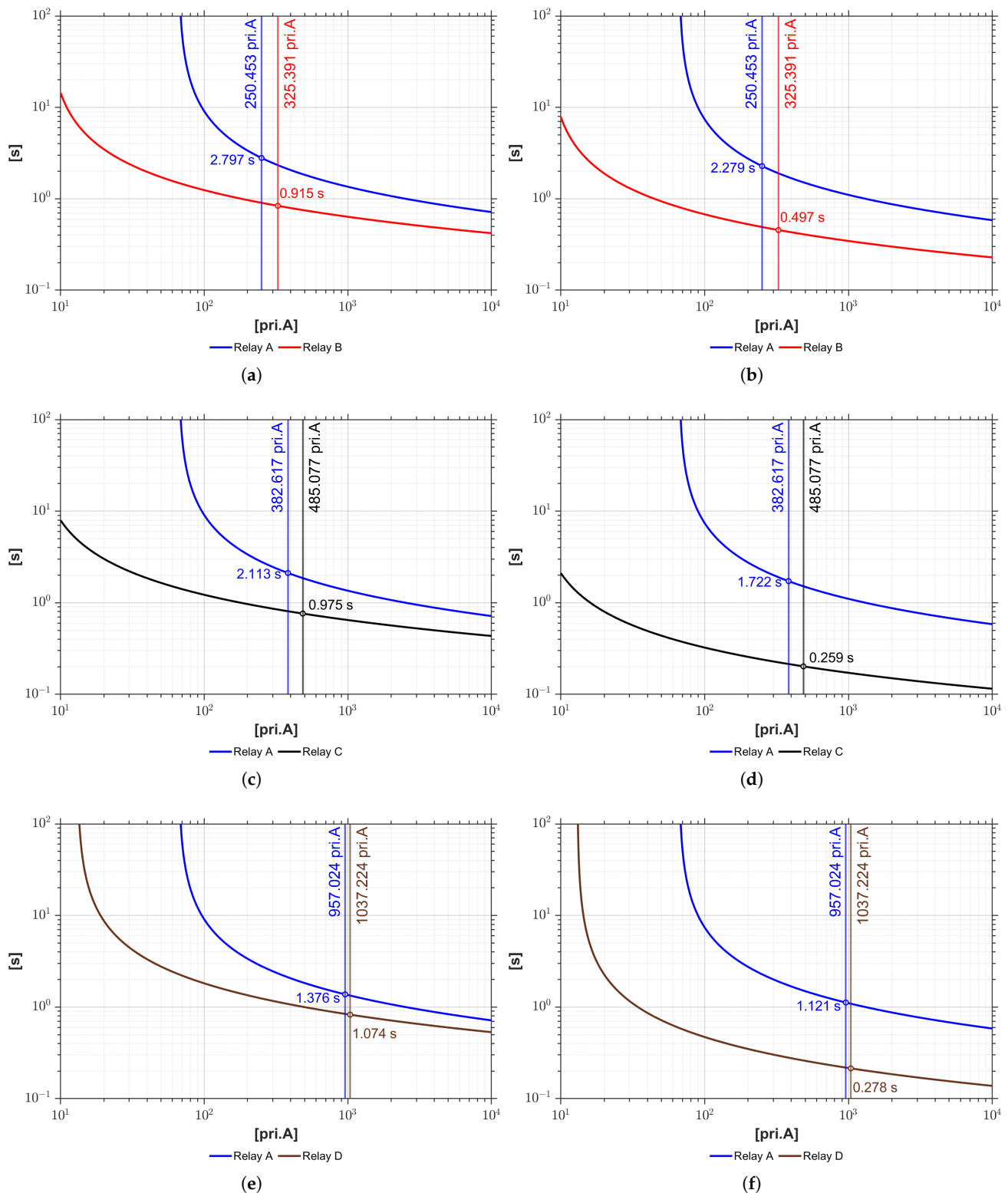


Figure 11. Time–current curves for Case Study 3 with DG: (a) single-phase-to-ground fault at bus 16 for relays RA and RB without DDPG; (b) single-phase-to-ground fault at bus 16 for relays RA and RB with DDPG; (c) single-phase-to-ground fault at bus 33 for relays RA and RC without DDPG; (d) single-phase-to-ground fault at bus 33 for relays RA and RC with DDPG; (e) single-phase-to-ground fault at bus 25 for relays RA and RD without DDPG; (f) single-phase-to-ground fault at bus 25 for relays RA and RD with DDPG.

For the single-phase-to-ground faults in Figure 11, the operating times are reduced from 2.797 s to 2.279 s for RA and from 0.915 s to 0.497 s for RB at bus 16, from 2.113 s to 1.722 s for RA and from 0.975 s to 0.259 s for RC at bus 33, and from 1.376 s to 1.121 s for RA and from 1.074 s to 0.278 s for RD at bus 25. These results confirm that the proposed methodology maintains the same adaptive behavior under both balanced and unbalanced fault conditions.

3.4. Incorporation of Fuses in Lateral Feeders

To complement the relay coordination analysis, fuse devices were incorporated into selected lateral branches of the IEEE 33-bus distribution system. The fuses were installed on lines 2–19, 3–23, and 6–26 and were selected according to the short-circuit current level and the time–current characteristic required for coordination with the upstream relays. In all cases, the relay configuration presented for Case Studies 2 and 3 was preserved, so the fuse analysis is intended only to verify that the addition of lateral protection does not compromise the selectivity of the relay–relay scheme.

Figures 12–14 show representative fuse–relay coordination curves for three-phase faults in the lateral branches.

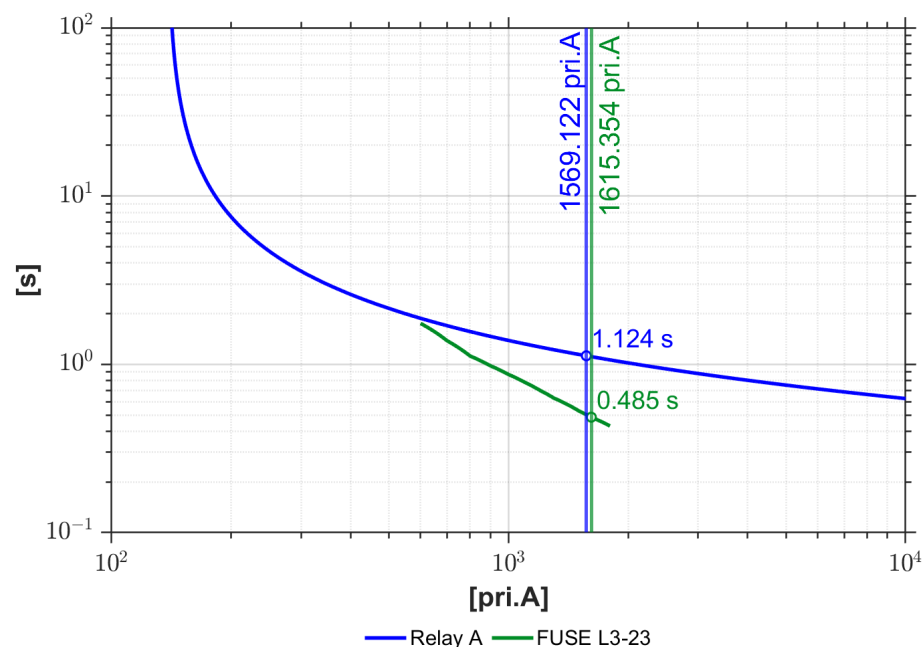


Figure 12. Time–current coordination curve between Relay A and the fuse installed on lines 3–23 for a three-phase short-circuit fault at bus 25.

Figures 13 and 14 show the corresponding coordination results for the fuses installed on lines 6–26 and 2–19. In both cases, the protection sequence remains selective: the downstream device operates first and the upstream relay remains as backup protection.

Table 10 summarizes the relay operating times for the analyzed three-phase faults, while Table 11 presents the corresponding results for single-phase-to-ground faults.

Together, these tables provide a compact view of the operating-time reduction achieved by the proposed methodology in all analyzed cases.

The main methodology was implemented in Python 3.13, where load-flow analysis, short-circuit calculations, conventional relay parameterization, and optimization with the proposed algorithm were carried out.

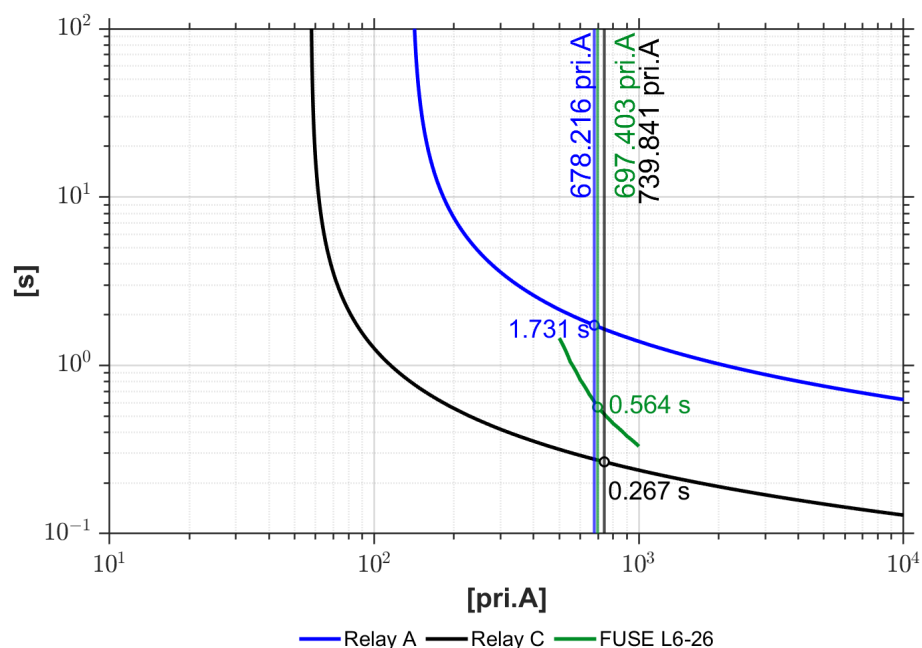


Figure 13. Time–current coordination curve between Relay A, Relay C, and the fuse installed on lines 6–26 for a three-phase short-circuit fault at bus 33.

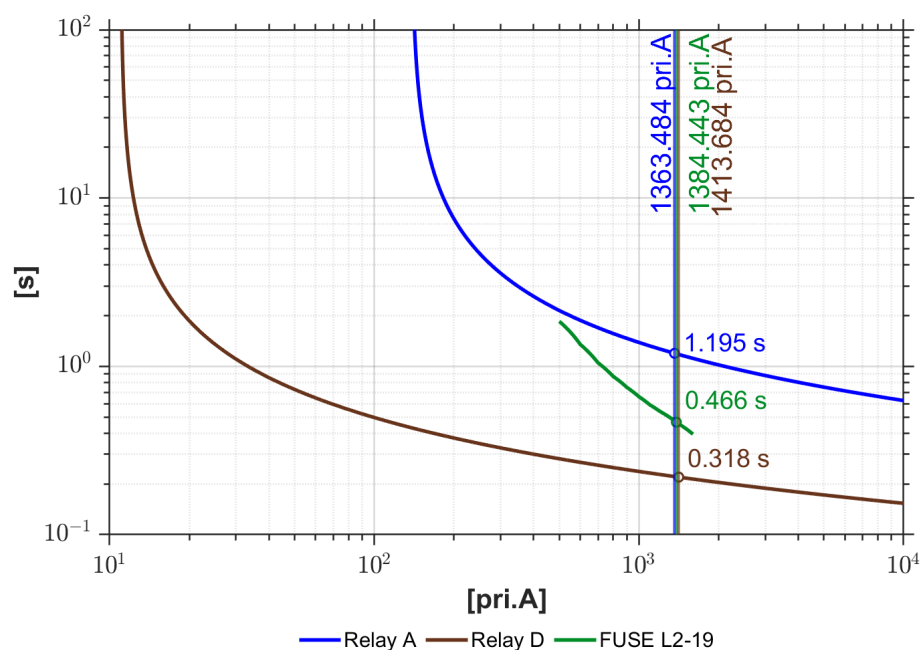


Figure 14. Time–current coordination curve between Relay A, Relay D, and the fuse installed on lines 2–19 for a three-phase short-circuit fault at bus 22.

To validate the obtained results, the same network was also modeled in DIGSI-LENT PowerFactory, preserving the topology, electrical parameters, and IEC 60909-based approach. First, the load-flow and short-circuit results obtained in Python were compared with those from PowerFactory simulations, showing very close agreement between both platforms.

Then, the conventional and optimized relay settings obtained in Python were transferred to PowerFactory to evaluate protection performance and generate the time–current curves, allowing the relay operating times under fault conditions to be visualized.

This validation process confirms that the parameters obtained with the proposed methodology are suitable for relay operation, supporting the reliability of the results reported for each analyzed scenario.

Table 10. Summary of relay operating time reduction for three-phase faults using the proposed DDPG-based methodology.

Case	Fault Bus	Relay	Conventional [s]	DDPG [s]	Reduction [%]
Three-phase faults					
1	7	RA	1.429	0.321	77.5
2	18	RA	3.863	2.807	27.33
2	18	RB	0.975	0.554	43.20
2	33	RA	2.176	1.731	20.50
2	33	RC	0.828	0.267	67.77
2	22	RA	1.440	1.195	17.01
2	22	RD	1.154	0.318	72.40
3	16	RA	3.013	2.143	28.87
3	16	RB	0.862	0.468	45.70
3	33	RA	2.157	1.614	25.17
3	33	RC	0.773	0.203	73.73
3	25	RA	1.342	1.056	21.31
3	25	RD	0.835	0.219	73.77

Table 11. Summary of relay operating time reduction for single-phase-to-ground faults using the proposed DDPG-based methodology.

Case	Fault Bus	Relay	Conventional [s]	DDPG [s]	Reduction [%]
Single-phase-to-ground faults					
1	7	RA	1.431	0.809	43.47
2	18	RA	3.381	2.755	18.50
2	18	RB	0.895	0.477	46.70
2	33	RA	2.115	1.723	18.53
2	33	RC	0.835	0.219	73.80
2	22	RA	1.447	1.179	18.52
2	22	RD	1.233	0.338	72.60
3	16	RA	2.797	2.279	18.51
3	16	RB	0.915	0.497	45.70
3	33	RA	2.113	1.722	18.50
3	33	RC	0.975	0.259	73.40
3	25	RA	1.376	1.121	18.50
3	25	RD	1.074	0.278	74.11

The fault simulations considered in this work were generated within a Python-based implementation of the IEEE 33-bus distribution system, where load-flow analysis, IEC 60909 short-circuit calculations, conventional relay parameterization, and DDPG-based optimization were carried out in an integrated simulation environment. In this framework, the reinforcement learning agent interacts directly with the simulated system by receiving electrical variables derived from the network analysis as state information, proposing updated relay settings as actions, and obtaining a reward based on relay operating performance and coordination compliance. In addition, the same network was modeled in DIgSILENT PowerFactory to validate the electrical results and to verify the relay operating behavior obtained from the Python-based methodology.

3.5. Performance Comparison with an Offline Optimization Method

To further address the performance assessment of the proposed methodology, an additional comparison with a particle swarm optimization (PSO)-based approach was included. PSO was selected as a representative offline optimization method because it has been widely used in overcurrent relay coordination problems and can handle continuous decision variables such as the pickup current I_s and the time multiplier setting TMS . In this comparison, the PSO-based approach uses the same objective function, technical limits, and coordination time interval adopted in the proposed DDPG-based framework. Therefore, the comparison is carried out under equivalent coordination criteria.

Unlike the proposed DDPG-based methodology, which learns a setting policy from the interaction with the simulated protection environment, the PSO-based approach solves the optimization problem for a specific operating condition. For this reason, PSO is used here as an offline benchmark, while DDPG is evaluated as an adaptive learning-based strategy. This distinction is important because a conventional or offline optimization method generally requires a new execution when the DG location, loading condition, or fault scenario changes.

Table 12 provides a direct comparison between the conventional coordination procedure, the PSO-based offline optimization approach, and the proposed DDPG-based methodology. The results show that the PSO-based approach reduces relay operating times with respect to the conventional method in all analyzed cases, confirming the benefit of using an optimization-based coordination strategy. However, the proposed DDPG-based methodology achieves the lowest operating times for all the evaluated faults and relays, with reductions that are consistently higher than those obtained with PSO. These results indicate that the proposed method is not only competitive with an established optimization technique but also provides improved fault-clearing performance within the analyzed operating range.

Table 12. Performance comparison between conventional coordination, PSO-based optimization, and the proposed DDPG-based methodology for Case Study 2 under three-phase faults.

Fault Bus	Relay	Conventional [s]	PSO [s]	DDPG [s]
18	RA	3.863	3.157	2.807
18	RB	0.975	0.743	0.554
33	RA	2.176	1.957	1.731
33	RC	0.828	0.361	0.267
22	RA	1.440	1.298	1.195
22	RD	1.154	0.472	0.318

It should be noted that the adaptive capability of the proposed agent is limited to the operating range represented by the analyzed DG placements, fault locations, and relay configuration. If the network topology, DG penetration level, or protection scheme changes substantially, additional validation or retraining may be required.

4. Discussion

The obtained results show that the adaptive coordination scheme based on DDPG improves the performance of overcurrent protection compared with the conventional methodology. In all analyzed cases, the optimized settings reduced relay operating times while preserving the coordination condition defined by Equation (6). This indicates that the proposed approach not only accelerates relay response but also maintains selectivity between primary and backup protection under changing operating conditions.

A relevant aspect of the analysis is the effect of distributed generation on relay coordination. The incorporation of DG modifies short-circuit current levels and, in many cases, changes the direction of power flow in a system that was originally radial. In the analyzed scenarios, the DG fault current contribution ranged approximately from 1.2130 p.u. to 1.3920 p.u. in Case Study 2 and from 1.2570 p.u. to 1.3557 p.u. in Case Study 3. These variations affect the currents seen by the relays and may make conventional static settings less suitable. In this context, the proposed DDPG-based methodology is able to adapt the relay settings according to the updated electrical condition of the system.

Another important result is the reduction in relay operating times obtained with the proposed methodology. Since relay operation follows the IEC inverse characteristic represented by Equation (2), shorter operating times also reduce the duration of fault current in the system. From a practical perspective, this helps lower thermal and electromechanical stress on electrical equipment. Figures 15–19 illustrate this behavior by comparing the relay operating times obtained with conventional settings and with the DDPG-based methodology.

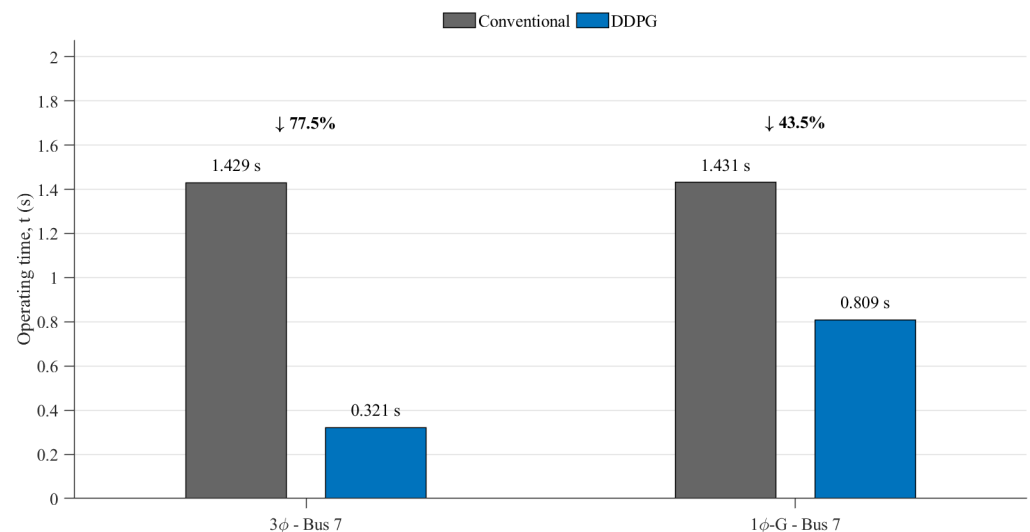


Figure 15. Comparison of relay operating times for Case Study 1 under three-phase and single-phase-to-ground faults.

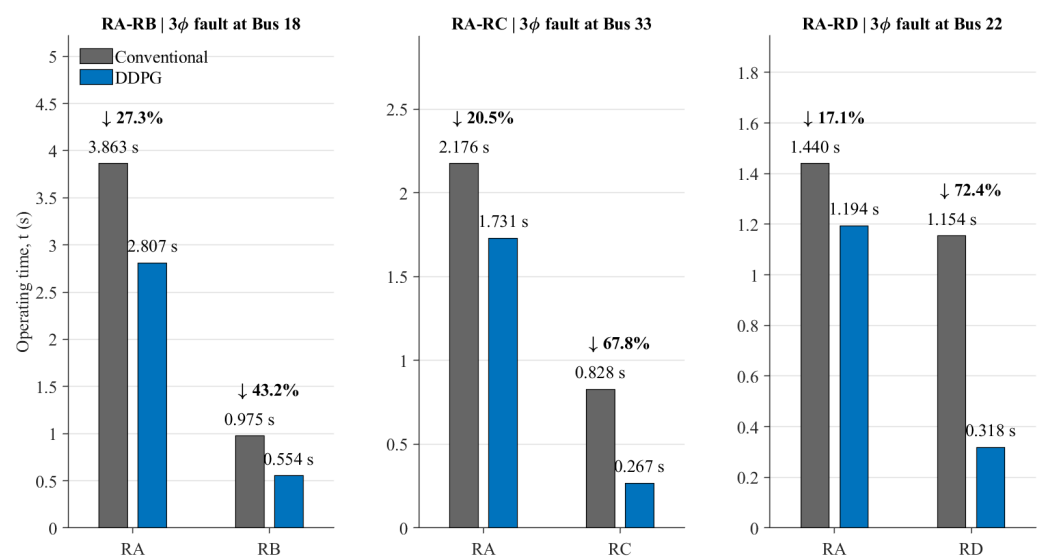


Figure 16. Comparison of relay operating times for Case Study 2 under three-phase faults.

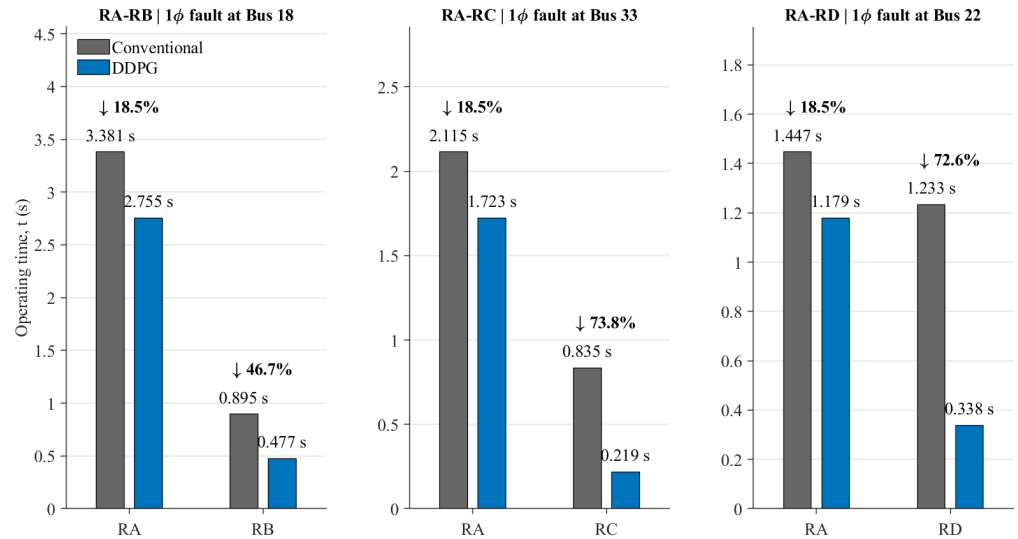


Figure 17. Comparison of relay operating times for Case Study 2 under single-phase-to-ground faults.

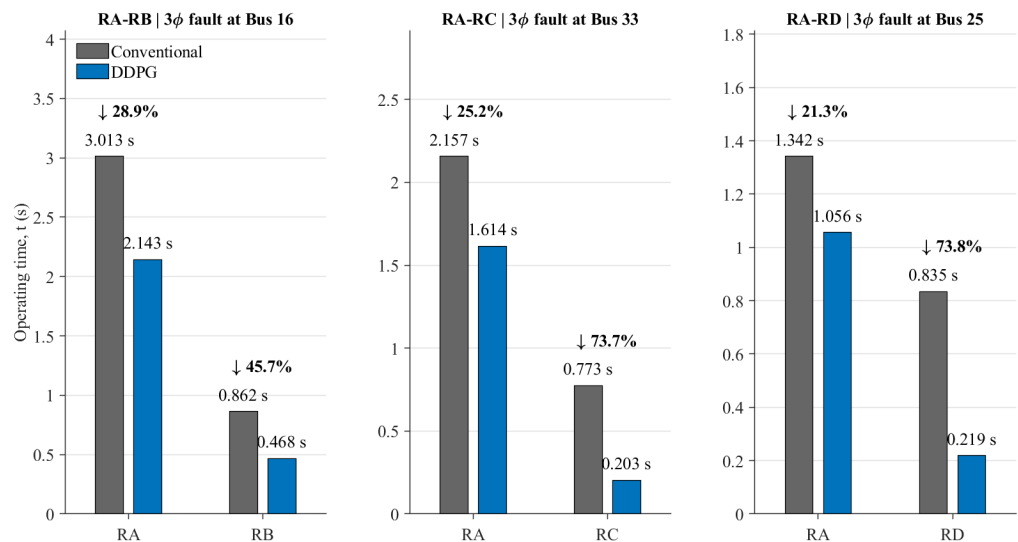


Figure 18. Comparison of relay operating times for Case Study 3 under three-phase faults.

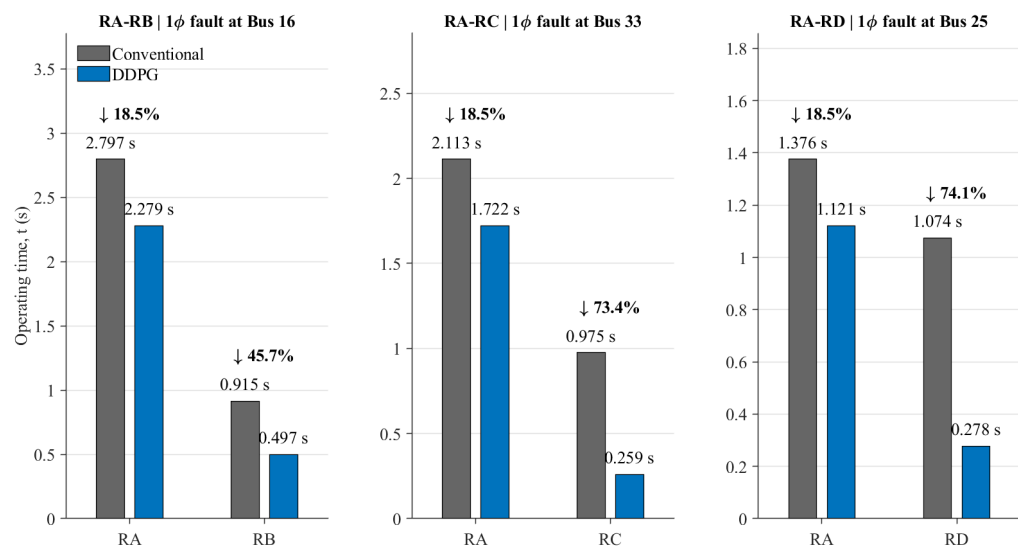


Figure 19. Comparison of relay operating times for Case Study 3 under single-phase-to-ground faults.

As shown in the previous figures, the proposed methodology consistently provides shorter operating times than the conventional approach in the analyzed scenarios. From the learning point of view, the DDPG agent also showed stable convergence toward solutions that satisfy both the objective function and the coordination constraints. The penalty term included in the objective function guides the agent toward solutions that satisfy the minimum coordination interval and can be expressed as:

$$\max\left(0, \text{CTI} - (t_{\text{backup}} - t_{\text{primary}})\right)$$

which means that no penalty is applied when the coordination margin is satisfied, whereas violations of the required CTI are penalized during training. In this way, the optimization promotes a balance between speed and selectivity rather than simply favoring faster relay operation.

The robustness of the proposed methodology is supported by the results obtained under different DG locations and fault scenarios. The model was not restricted to a single operating condition, but maintained acceptable coordination behavior in all considered cases. Although the proposed agent was trained and evaluated using a set of representative DG scenarios and fault locations, the obtained results suggest that the learned policy is able to adapt within the range of operating conditions considered in this study. However, the present work does not assume unrestricted generalization to any arbitrary DG penetration level or location outside the analyzed cases. If the system undergoes operating changes that are substantially different from the studied scenarios, additional training or retraining of the agent may be required. Therefore, the current results should be interpreted as evidence of adaptive capability within the analyzed conditions, while broader generalization remains an important aspect for future research.

In this work, the performance of the proposed DDPG-based methodology was compared with the conventional relay coordination procedure and with a PSO-based offline optimization approach. The comparison with PSO was included to provide an additional benchmark against an established optimization technique for overcurrent relay coordination. While PSO is useful for obtaining optimized relay settings for a specific operating scenario, the proposed DDPG-based framework aims to learn an adaptive policy within the range of operating conditions represented during training. Therefore, the comparison highlights both the reduction in operating time and the adaptive nature of the proposed learning-based methodology.

Although the obtained results are favorable, some limitations should be recognized. The analysis was carried out on the IEEE 33-bus test system, which is still a simplified representation of real distribution networks. In addition, communication delays, measurement uncertainty, and more complex transient phenomena were not explicitly included in the simulation environment. The proposed methodology was formulated for adaptive coordination between overcurrent relays, with relay A acting as backup protection and relays B, C, and D acting as primary protection devices for their respective sections. Even with these limitations, the results provide consistent evidence that deep reinforcement learning can be applied effectively to adaptive protection coordination in active distribution systems.

In addition, recent studies in distribution networks have begun to incorporate domain knowledge into reinforcement learning models to improve decision-making quality and generalization capability [27]. While the present work uses network topology and electrical parameters within the simulation environment, one possible future extension would be to incorporate this information more directly into the structure of the learning model.

5. Conclusions

This work developed and evaluated an adaptive coordination methodology for over-current relays in distribution networks with distributed generation using deep reinforcement learning through DDPG. The proposed approach formulates relay coordination as a dynamic optimization problem in which relay settings can be readjusted according to changes in network operating conditions, fault location, and DG integration.

Across the analyzed cases, the joint optimization of I_s and TMS reduced relay operating times without compromising coordination margins between primary and backup relays. The obtained reductions ranged from 17.1% to 75.5% for three-phase faults and from 18.5% to 74.1% for single-phase-to-ground faults. Furthermore, the additional comparison with the PSO-based offline optimization approach showed that the proposed DDPG-based methodology provides competitive operating times while maintaining its adaptive learning-based nature within the analyzed operating range. This result reinforces the potential of the proposed framework not only as a relay setting optimization tool for specific scenarios but also as an adaptive coordination strategy for active distribution networks.

Overall, the results show that the proposed DDPG-based methodology improves protection speed while preserving selectivity and coordinated operation under changing scenarios. The study also confirms that distributed generation modifies fault current levels and may reduce the effectiveness of conventional static settings, which highlights the value of adaptive coordination strategies in active distribution networks. However, the applicability of the trained agent is limited to the range of operating conditions represented in the analyzed scenarios; therefore, substantially different network topologies, DG penetration levels, or protection schemes may require additional validation or retraining. Finally, this work focuses on overcurrent relay coordination; the inclusion of other protection devices, such as reclosers and a broader fuse coordination framework, remains an important extension for future work.

Author Contributions: Conceptualization, A.T.-Y. and C.B.-S.; methodology, A.T.-Y. and C.B.-S.; software, A.T.-Y. and C.B.-S.; validation, A.T.-Y. and C.B.-S.; formal analysis, A.T.-Y. and C.B.-S.; investigation, A.T.-Y. and C.B.-S.; resources, A.T.-Y. and C.B.-S.; data curation, A.T.-Y. and C.B.-S.; writing—original draft preparation, A.T.-Y. and C.B.-S.; writing—review and editing, A.T.-Y. and C.B.-S.; visualization, A.T.-Y. and C.B.-S.; supervision, A.T.-Y. and C.B.-S.; project administration, A.T.-Y. and C.B.-S.; funding acquisition, A.T.-Y. and C.B.-S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data supporting the findings of this study are available upon request from the corresponding author. The simulation model and results were obtained through simulations on the IEEE 33-bus test system using specialized software for load-flow analysis and short-circuit current calculations.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

IEEE	Institute of Electrical and Electronics Engineers
DG	Distributed generation
RL	Reinforcement learning
DRL	Deep reinforcement learning

DDPG	Deep Deterministic Policy Gradient
I_s	Pickup current
TMS	Time multiplier setting
OLF	Overload factor
NI	Normal inverse
VI	Very inverse
EI	Extremely inverse
k_{sc}	Short-circuit current factor of the DG unit

Appendix A

This section includes additional information that supports the development of this work and facilitates its reproducibility. Therefore, Table A1 presents the parameters of the 33-bus IEEE test system used in this study, including impedance values, lines, load levels, and network operating characteristics. This information is included as supporting material for other researchers who wish to replicate or extend the adaptive protection coordination methodology.

Table A1. IEEE 33-buses' parameters.

Line	R [Ω]	X [Ω]	Bus	P [kW]	Q [kvar]
Line 1–2	0.0022	0.0470	1	0	0
Line 2–3	0.4930	0.2511	2	100	60
Line 3–4	0.3660	0.1864	3	90	40
Line 4–5	0.3811	0.1941	4	120	80
Line 5–6	0.8190	0.7070	5	60	30
Line 6–7	0.1872	0.6188	6	60	20
Line 7–8	1.7114	1.2351	7	200	100
Line 8–9	1.0300	0.7400	8	200	100
Line 9–10	1.0440	0.7400	9	60	20
Line 10–11	0.1966	0.0650	10	60	20
Line 11–12	0.3744	0.1238	11	45	30
Line 12–13	1.4680	1.1550	12	60	35
Line 13–14	0.5416	0.7129	13	60	35
Line 14–15	0.5910	0.5260	14	120	80
Line 15–16	0.7463	0.5450	15	60	10
Line 16–17	1.2890	1.7210	16	60	20
Line 17–18	0.7320	0.5740	17	60	20
Line 2–19	0.1640	0.1565	18	90	40
Line 19–20	1.5042	1.3554	19	90	40
Line 20–21	0.4095	0.4784	20	90	40
Line 21–22	0.7089	0.9373	21	90	40
Line 3–23	0.4512	0.3083	22	90	40
Line 23–24	0.8980	0.7091	23	90	50
Line 24–25	0.8960	0.7011	24	420	200
Line 6–26	0.2030	0.1034	25	420	200
Line 26–27	0.2842	0.1447	26	60	25
Line 27–28	1.0590	0.9337	27	60	25
Line 28–29	0.8042	0.7006	28	60	20
Line 29–30	0.5075	0.2585	29	120	70
Line 30–31	0.9744	0.9630	30	200	600
Line 31–32	0.3105	0.3619	31	150	70
Line 32–33	0.3410	0.5302	32	210	100
—	—	—	33	60	40

Table A2 presents the comparison of short-circuit currents for three-phase faults obtained using PowerFactory and the model developed in Python. The results show a high

level of agreement between both tools across all system buses, with values that are nearly identical in most cases. This close correspondence indicates that the Python-based model accurately reproduces the system behavior under balanced fault conditions. The observed consistency is mainly due to the fact that three-phase fault calculations rely primarily on the positive-sequence network, which reduces the complexity of the analysis and minimizes discrepancies between simulation approaches.

Table A2. Comparison of three-phase short-circuit currents (PowerFactory vs. Python).

Bus	PowerFactory [kA]	Python [kA]	Error [%]
1	9.2838	9.2993	0.17
2	8.5946	8.6184	0.28
3	5.4509	5.5192	1.25
4	4.1232	4.1955	1.75
5	3.2623	3.3306	2.09
6	2.1461	2.1970	2.37
7	1.8441	1.8829	2.10
8	1.1614	1.1897	2.43
9	0.9518	0.9763	2.57
10	0.8066	0.8282	2.69
11	0.7858	0.8071	2.71
12	0.7489	0.7694	2.73
13	0.6111	0.6274	2.66
14	0.5649	0.5794	2.57
15	0.5274	0.5408	2.54
16	0.4888	0.5012	2.54
17	0.4225	0.4326	2.38
18	0.3973	0.4068	2.39
19	6.8851	6.9212	0.52
20	2.2535	2.2922	1.72
21	1.8494	1.8812	1.72
22	1.3905	1.4137	1.66
23	3.7416	3.8032	1.65
24	2.2268	2.2695	1.92
25	1.5831	1.6154	2.04
26	1.9966	2.0453	2.44
27	1.8188	1.8647	2.52
28	1.3189	1.3534	2.62
29	1.0961	1.1256	2.69
30	0.9954	1.0224	2.72
31	0.8196	0.8408	2.58
32	0.7732	0.7928	2.54
33	0.7221	0.7398	2.46

Table A3 presents the percentage errors obtained from the comparison of single-phase-to-ground short-circuit currents between PowerFactory and Python. Compared with the three-phase fault case, the errors are slightly higher at some buses, reaching a maximum value of approximately 3.64%. This behavior is associated with the greater complexity of unbalanced fault analysis, where positive, negative, and zero-sequence networks must be considered. In particular, the representation of the zero-sequence impedance has a direct influence on the differences observed between both simulation tools. Nevertheless, the errors remain below 4% and within acceptable limits for engineering studies, confirming the validity of the proposed Python-based model for the analysis of single-phase-to-ground faults.

Table A3. Comparison of single-phase-to-ground short-circuit currents (PowerFactory vs. Python).

Bus	PowerFactory [kA]	Python [kA]	Error [%]
1	9.1976	9.2554	0.63
2	8.0282	8.1545	1.57
3	4.0278	4.1509	3.06
4	2.8320	2.9256	3.30
5	2.1506	2.2247	3.44
6	1.3472	1.3944	3.51
7	1.1509	1.1863	3.08
8	0.7060	0.7289	3.25
9	0.5728	0.5921	3.37
10	0.4813	0.4981	3.50
11	0.4690	0.4854	3.49
12	0.4473	0.4629	3.49
13	0.3667	0.3786	3.25
14	0.3396	0.3501	3.10
15	0.3174	0.3270	3.02
16	0.2946	0.3033	2.96
17	0.2552	0.2622	2.74
18	0.2402	0.2467	2.69
19	5.6982	5.8126	2.01
20	1.4593	1.4955	2.48
21	1.1844	1.2117	2.30
22	0.8797	0.8979	2.07
23	2.5625	2.6363	2.88
24	1.4490	1.4864	2.58
25	1.0109	1.0358	2.46
26	1.2464	1.2904	3.53
27	1.1279	1.1682	3.57
28	0.8016	0.8301	3.56
29	0.6581	0.6821	3.64
30	0.5982	0.6196	3.57
31	0.4944	0.5105	3.25
32	0.4669	0.4817	3.16
33	0.4367	0.4498	3.00

References

1. Abdul-Lateef, A.O. Adaptive overcurrent distribution protection scheme coordination in the presence of distributed generation using artificial neural network. *J. Eng. Sci. Res.* **2024**, *30*, 7–21. [\[CrossRef\]](#)
2. Ke, H.; He, H. A Method of Distribution Network Protection and Application with Penetration of Renewable Generation. In Proceedings of the China International Conference on Electricity Distribution (CICED), Changsha, China, 7–8 September 2022; pp. 1473–1476. [\[CrossRef\]](#)
3. Javed, M.; Khan, L.; Muhammad, Y.; Mahmoudi, A.; Kahourzade, S.; Zafar, A. Optimizing Over-Current Relay Coordination: The Role of Entropy Evolution in Gravitational Search Strategy. In Proceedings of the 2025 IEEE 16th International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Nanjing, China, 22–25 June 2025. . [\[CrossRef\]](#)
4. Mohammed, J.; Viswambaran, V. Performance Analysis of Overcurrent Protection Schemes in Power Systems. In Proceedings of the 2024 Advances in Science and Engineering Technology International Conferences (ASET), Abu Dhabi, United Arab Emirates, 3–5 June 2024. [\[CrossRef\]](#)
5. Khan, A.U.; Hong, Q.; Booth, C. Performance Analysis of the Overcurrent Protection for the Renewable Distributed Generation Dominated Microgrids. In Proceedings of the 2020 IEEE Region 10 Symposium (TENSYP), Dhaka, Bangladesh, 5–7 June 2020.
6. Saldarriaga-Zuluaga, S.D.; López-Lezama, J.M. Hybrid Harmony Search Algorithm Applied to the Optimal Coordination of Overcurrent Relays in Distribution Networks with Distributed Generation. *Appl. Sci.* **2021**, *11*, 9207. [\[CrossRef\]](#)
7. Jimenez, S.; Vázquez, E.; Gonzalez-Longatt, F. Methodology of Adaptive Instantaneous Overcurrent Protection Setting. *Electronics* **2021**, *10*, 2754. [\[CrossRef\]](#)

8. Kordowich, G.; Jaworski, M.; Lorz, T.; Scheibe, C.; Jaeger, J. A Hybrid Protection Scheme Based on Deep Reinforcement Learning. In Proceedings of the IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe), Novi Sad, Serbia, 10–12 October 2022. [\[CrossRef\]](#)
9. Reddy, B.K.; Singh, A.K. Reactive Power Management and Protection Coordination of Distribution Network with High Solar Photovoltaic Penetration. In Proceedings of the 2021 12th International Renewable Engineering Conference (IREC), Amman, Jordan, 14–15 April 2021. [\[CrossRef\]](#)
10. Darabi, A.; Gharaveisi, A.; Gharaveisi, G. Highly Accurate Directional Overcurrent Coordination via Combination of Rosen’s Gradient Projection–Complex Method with GA-PSO Algorithm. *IEEE Syst. J.* **2020**, *14*, 1171–1182. [\[CrossRef\]](#)
11. Pujiantara, M.; Lystianingrum, V. Overcurrent Relay Coordination Setting on Distribution Power System Using Grasshopper Optimization Algorithm. In Proceedings of the International Seminar on Intelligent Technology and Its Application (ISITIA), Surabaya, Indonesia, 26–27 July 2023; pp. 804–809. [\[CrossRef\]](#)
12. Aminifar, F.; Teimourzadeh, S.; Shahsavari, A.; Savaghebi, M.; Golsorkhi, M.S. Machine Learning for Protection of Distribution Networks and Power Electronics-Interfaced Systems. *Electr. J.* **2021**, *34*, 106886. [\[CrossRef\]](#)
13. Cui, Q.; Weng, Y. An Environment-Adaptive Protection Scheme with Long-Term Reward for Distribution Networks. *Int. J. Electr. Power Energy Syst.* **2021**, *127*, 106350. [\[CrossRef\]](#)
14. Wu, D.; Zheng, X.; Kalathil, D.; Xie, L. Nested Reinforcement Learning Based Control for Protective Relays in Power Distribution Systems. *arXiv* **2019**. [\[CrossRef\]](#)
15. Wu, D.; Kalathil, D.; Begovic, M. Deep Reinforcement Learning-Based Robust Protection in DER-Rich Distribution Grids. *IEEE Open Access J. Power Energy* **2022**, *9*, 537–548. [\[CrossRef\]](#)
16. Muñoz-Arango, G.; Mora-Flórez, J.; Pérez-Londoño, S. Optimal Data-Driven Adaptive Overcurrent Relay Coordination for Active Distribution Networks. *Electr. Power Syst. Res.* **2024**, *228*, 110078. [\[CrossRef\]](#)
17. Narváez-Franco, J.; Herrera-Orozco, A.; Mora-Flórez, J. Optimal Coordination of Directional Overcurrent Relays in Active Distribution Networks with High Penetration of Distributed Energy Resources Using a Data-Driven Strategy. *Results Eng.* **2026**, *29*, 108629. [\[CrossRef\]](#)
18. Li, Q.; Lin, T.; Yu, Q.; Du, H.; Li, J.; Fu, X. Review of Deep Reinforcement Learning and Its Application in Modern Renewable Power System Control. *Energies* **2023**, *16*, 4143. [\[CrossRef\]](#)
19. Dong, R.; Du, J.; Liu, Y.; Heidari, A.A.; Chen, H. An Enhanced Deep Deterministic Policy Gradient Algorithm for Intelligent Control of Robotic Arms. *Front. Neuroinform.* **2023**, *17*, 1096053. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Águila Téllez, L.O.A.; González, D.; Gutiérrez, G. Ubicación y dimensionamiento óptimo de generación distribuida fotovoltaica en redes de distribución usando PSO. *Rev. Científica* **2022**, *18*, 50–68. [\[CrossRef\]](#)
21. IEC 60909-0:2016; Short-Circuit Currents in Three-Phase a.c. Systems—Part 0: Calculation of Currents. International Electrotechnical Commission: Geneva, Switzerland, 2016.
22. Pandey, R.; Bose, S.; Dwivedi, P. DDPG Algorithm for Power Optimization and Control of Solar PV-Integrated DFIG Wind Energy Systems. *Sci. Rep.* **2025**, *15*, 39212. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Alaei, P.; Amraee, T. Optimal Coordination of Directional Overcurrent Relays in Meshed Active Distribution Network. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 416–422. [\[CrossRef\]](#)
24. Pratiwi, R.A.; Pujiantara, M.; Priyadi, A. Optimization of Time Multiplier Setting Overcurrent Relay Using Cuckoo Search Algorithm Considering Inrush Current and Motor Starting. In Proceedings of the 11th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), Semarang, Indonesia, 29–30 August 2024; pp. 128–132. [\[CrossRef\]](#)
25. Uma, U.U.; Nmadu, D.; Ugwuanyi, N.; Ogah, O.E.; Eli-Chukwu, N.; Eheduru, M.; Ekwue, A. Adaptive Overcurrent Protection Scheme Coordination in Presence of Distributed Generation Using Radial Basis Neural Network. *Prot. Control Mod. Power Syst.* **2023**, *8*, 63. [\[CrossRef\]](#)
26. IEC 60255-151:2009; Measuring Relays and Protection Equipment—Part 151: Functional Requirements for Over/Under Current Protection. International Electrotechnical Commission: Geneva, Switzerland, 2009.
27. Luo, F.; Wang, S.; Lv, Y.; Mu, R.; Fo, J.; Zhang, T.; Xu, J.; Wang, C. Domain knowledge-enhanced graph reinforcement learning method for Volt/Var control in distribution networks. *Appl. Energy* **2025**, *398*, 126409. [\[CrossRef\]](#)

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