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DRL-Driven Pilot Schemes for Optimized Distance Protection in Power Systems Incorporating IEC 61850 Communication Protocol

Mohamed A.Wahab ALI[1,*]

[1]Electrical Engineering Department, Faculty of Engineering at Shoubra, Benha University, Cairo 11629, Egypt;
[*]Corresponding author E-mail: mohamed.mohamed02@feng.bu.edu.eg

Abstract

Distance protection is crucial for maintaining power system reliability. As power systems become increasingly complex, the integration of advanced artificial intelligence (AI) techniques such as Deep Reinforcement Learning (DRL) offers a promising approach to enhance fault detection and response. This paper presents a DRL-Driven pilot scheme combined with the IEC 61850 communication protocol for optimized distance protection. The proposed method leverages real-time data, adaptive decision-making, and high-speed communication to minimize fault clearance time while improving grid resilience. Simulation results demonstrate the effectiveness of the approach under diverse fault scenarios.

In this work, DRL is integrated with existing distance protection systems through pilot schemes using the IEC 61850 communication standard, specifically leveraging GOOSE messaging for real-time relay coordination. The fundamentals of DRL in protection systems are examined, covering aspects such as data collection, preprocessing, model training, and performance evaluation.

The paper also addresses the challenges and limitations in implementing DRL within protection systems, including issues related to data availability, system complexity, and real-time operation. Comparative analysis between the proposed DRL-Driven distance relays and conventional numerical relays highlights the advantages of DRL, particularly in terms of fault detection time, accuracy, and adaptability to modern grid conditions. Finally, this paper presents a comprehensive DRL-driven protection scheme for transmission lines and evaluates its effectiveness against traditional approaches, paving the way for more resilient and reliable power system protection.

Keywords: Distance Protection, testing and commissioning, IEC 61850 communication protocol, GOOSE, Sampled Values, Substation Automation (SAS), Artificial Intelligence (AI), DRL.

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1. Introduction

The growing complexity of power systems, characterized by increased penetration of distributed energy resources (DERs) and evolving grid dynamics, has presented challenges to conventional protection schemes. Among these, distance protection has historically served as a cornerstone for safeguarding transmission lines by measuring the impedance between a relay and a fault location. These traditional systems identify faults within designated protection zones and trigger appropriate isolation actions. However, with modern grid configurations, conventional distance protection methods often struggle to adapt to the rapid changes and variability introduced by renewable energy sources and microgrids [1,2].

The contemporary power grid demands a paradigm shift in protection mechanisms due to renewable energy integration, dynamic load behaviors, and the proliferation of microgrids. Such factors impose significant challenges, including delayed fault clearance and reduced reliability of conventional schemes reliant on static settings and threshold-based logic [2,3]. High fault impedance and transient conditions further exacerbate these issues, compromising grid stability and reliability [4,5].

Artificial Intelligence (AI), specifically machine learning (ML) and deep learning techniques, has emerged as a promising solution to these challenges. AI's ability to learn and adapt to fault patterns from historical data offers significant enhancements in fault detection accuracy and operational speed. Studies have demonstrated AI's superiority over traditional methods in fault classification and adaptive relay settings, thereby enabling protection systems to respond effectively to evolving grid conditions [6–10].

Moreover, advancements in communication infrastructure, particularly pilot protection schemes, have augmented the capabilities of distance protection systems. By enabling direct communication between relays at both ends of a transmission line, these schemes facilitate faster and more reliable fault detection and isolation [11]. The advent of the IEC 61850 standard, which underpins modern substation communication, has further revolutionized the field. The Generic Object-Oriented Substation Event (GOOSE) messaging feature of IEC 61850 enables low-latency, interoperable communication, significantly enhancing the reliability and efficiency of protection schemes [12–15].

This paper proposes a novel integration of DRL-driven algorithms with pilot protection schemes leveraging the IEC 61850 protocol. By harnessing the predictive capabilities of DRL for fault detection and the real-time, high-speed communication facilitated by IEC 61850, the proposed system aims to address the shortcomings of traditional schemes. Specifically, it combines adaptive decision-making enabled by DRL with the robust communication framework provided by GOOSE messaging to achieve faster fault isolation and improved grid resilience [14,16, 17].

Research Gap Clarification:

While existing AI-based protection schemes have shown promise in improving fault detection and classification, they often struggle with high-impedance faults, delayed fault clearance, and adaptability to dynamic grid conditions caused by the increasing integration of distributed energy resources (DERs). Traditional methods rely on static settings and threshold-based logic, which are insufficient for modern grid configurations. This paper addresses these limitations by proposing a novel integration of Deep Reinforcement Learning (DRL) with the IEC 61850 communication protocol, leveraging real-time data and adaptive decision-making to enhance fault detection accuracy and speed.

The research objectives are threefold:

1. Develop an DRL-driven decision-making framework to improve the accuracy of distance protection.
2. Implement a communication protocol using IEC 61850 to enhance real-time relay coordination.
3. Compare the performance of the proposed system with traditional and IEC 61850-based protection schemes, evaluating metrics such as fault detection time, accuracy, and reliability.

2. Background and Related Work

2.1. Distance Protection in Power Systems

Distance protection is a fundamental mechanism for transmission line safety, operating by measuring impedance to detect and isolate faults. Protection zones are typically predefined with varying time delays to ensure selectivity [1]. While effective in traditional grids, these systems face challenges in the modern context, particularly in detecting high-impedance faults and addressing the dynamic behaviors introduced by DERs [3,5].

2.2. Pilot Protection Schemes

Pilot protection schemes enhance traditional distance protection by employing real-time communication between relays at both ends of a transmission line. This coordination enables faster and more reliable fault isolation, with common approaches including direct transfer trip (DTT), permissive overreach transfer trip (POTT), and blocking schemes [11]. However, these schemes heavily rely on robust and efficient communication infrastructures, which is where IEC 61850 demonstrates its value [12,18].

2.3. IEC 61850 Protocol

The IEC 61850 standard is a groundbreaking development for substation automation, offering a unified communication framework for Intelligent Electronic Devices (IEDs). Using Ethernet-based communication, it facilitates real-time interaction via GOOSE messaging, ensuring rapid data exchange and low-latency fault responses. Studies confirm the protocol's effectiveness in improving system reliability and reducing fault clearance times [13–15,18,19].

2.4. AI in Power System Protection

The application of AI in power systems has significantly advanced in recent years, with machine learning models excelling in fault detection and classification. These models offer adaptability to evolving grid conditions, outperforming conventional methods in speed and accuracy. AI-driven systems have shown potential in addressing complex fault scenarios, such as high-impedance and transient faults, enabling more robust protection schemes [6–10,20, 21].

Unlike existing AI-based protection schemes, our approach integrates DRL with IEC 61850 GOOSE messaging, enabling real-time, adaptive decision-making. While prior works have explored AI for fault detection, they often lack the robust communication framework provided by IEC 61850. Our system leverages historical fault data and real-time communication to improve fault detection accuracy and speed, setting it apart from traditional AI-based methods. This integration allows for faster fault isolation and improved grid resilience, particularly in dynamic grid environments with high DER penetration.

3. Proposed DRL-Driven Pilot Scheme

3.1. System Architecture

The proposed system integrates DRL with distance protection pilot schemes, incorporating the IEC 61850 communication protocol for enhanced coordination. It features two core components:

1. **Data Acquisition:** Voltage and current samples are collected via IEC 61850-compatible intelligent electronic devices (IEDs).
2. **DRL-Based Decision Unit**: Utilizing machine learning models trained on historical fault data, this unit predicts fault locations and types with high accuracy. Local and remote relays are equipped with these models to enhance decision-making [6–9,22].
3. **IEC 61850 Communication Framework**: This layer ensures seamless and low-latency data exchange between relays via GOOSE messaging. The protocol's capabilities are leveraged to synchronize local and remote relay actions, minimizing communication delays [13,15,23]. As shown in figure.2 and figure.3.

These components collectively enable advanced fault classification and zone discrimination, providing a resilient and scalable solution for distance protection [17,23].

Figure 4 illustrates the integration of the IEC 61850 protocol with the DRL-driven protection scheme. The flowchart shows the data flow from Intelligent Electronic Devices (IEDs) to the DRL-based decision unit, highlighting the role of GOOSE messaging in enabling real-time communication between local and remote relays. This integration ensures low-latency data exchange and synchronized relay actions, minimizing fault clearance times.

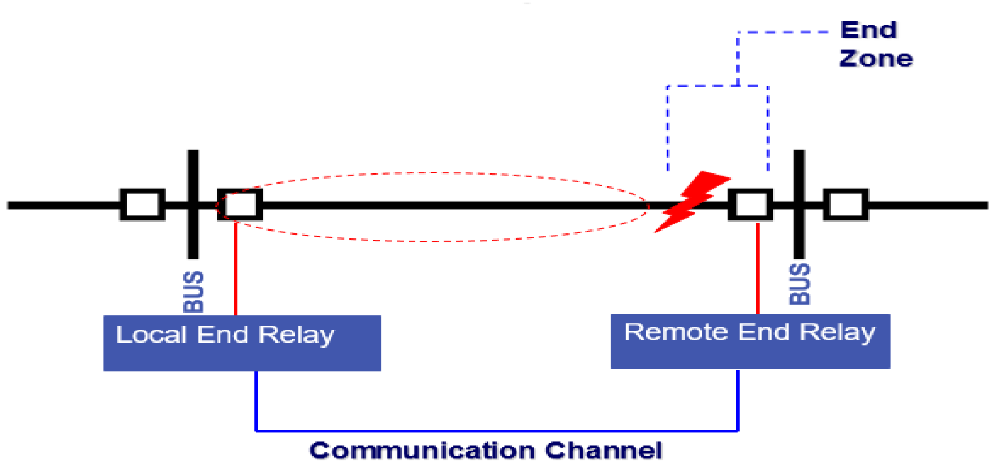


Figure 1: Shows the test system for permissive scheme zone detection of faults

It is important to mention that in applications involving single pole operation, a three-pole trip can be executed in the event of an in-line single-phase fault that coincides with a fault on a different phase, also known as a cross-country fault. It is crucial to highlight that this cross-country fault must be within the reach of the local phase selector, which is significantly longer than the line itself. Nevertheless, this possibility of a three-pole trip occurring can be diminished by employing a two-bit channel, and it can be completely eradicated by utilizing a four-bit channel. By using two-bit channels, the relays possess the capacity to share limited information pertaining to their local fault detection algorithms. This sharing of information greatly enhances the accuracy of single-pole tripping when it comes to cross-country faults.

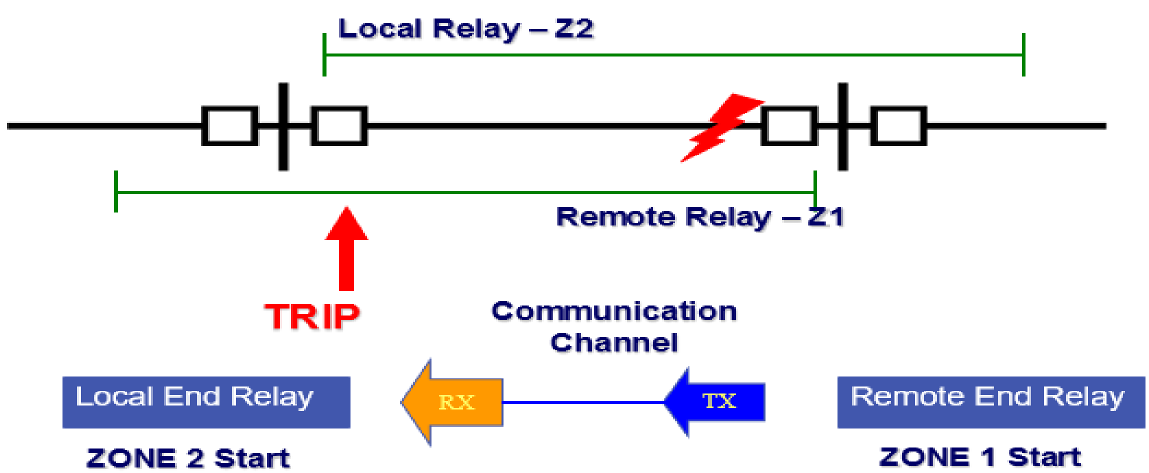


Figure 2: Permissive scheme with IEC 61850 communication channel under remote fault case

Figure 3: Permissive scheme with IEC 61850 4-bit communication channel

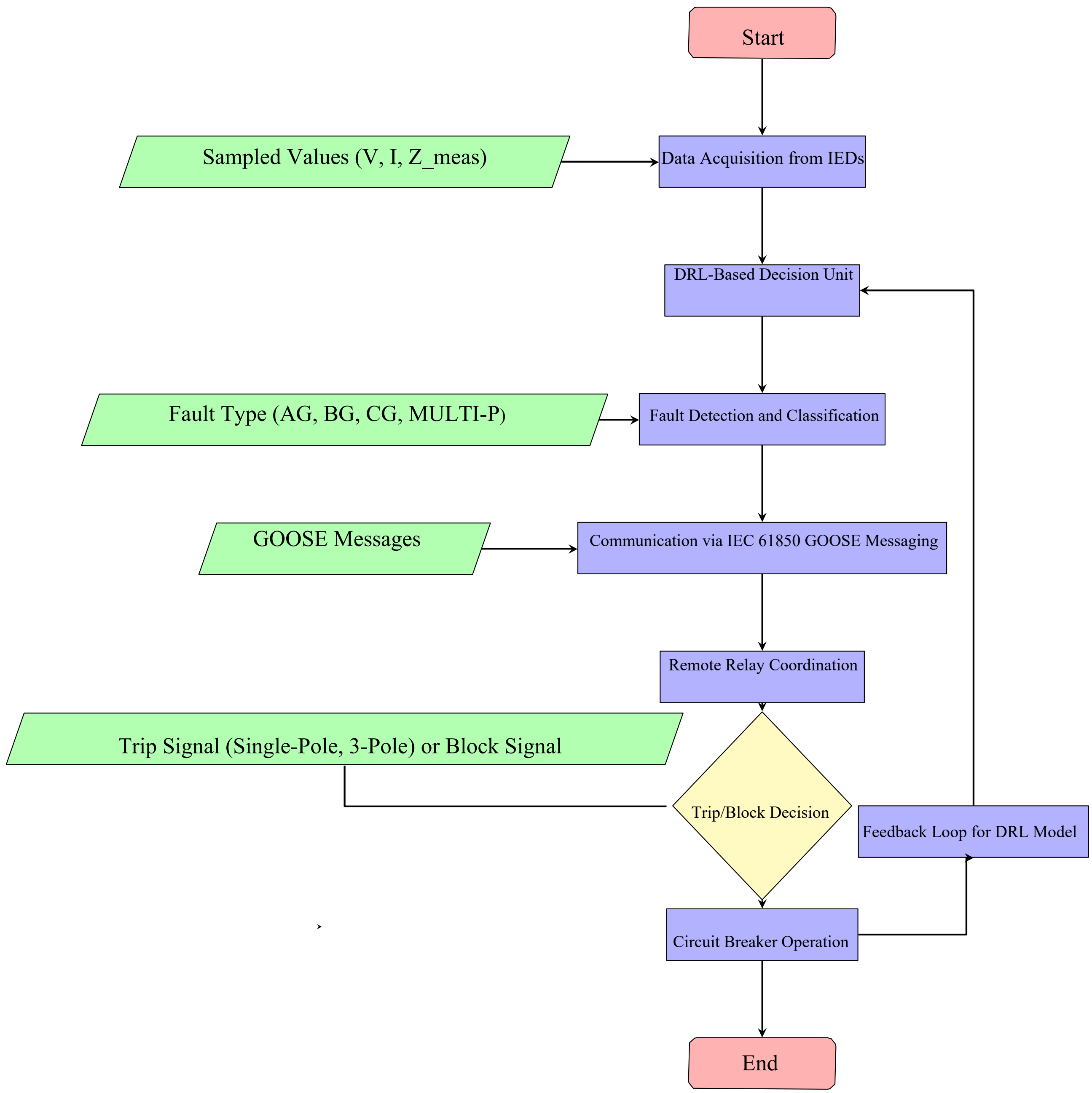


Figure 4: Illustrates the integration of the IEC 61850 protocol with the DRL-driven protection scheme

3.2 DRL-Driven Pilot Scheme for Distance Protection

3.2.1 DRL Overview

DRL combines reinforcement learning (RL) principles with deep neural networks (DNNs) to handle high-dimensional state spaces. In DRL, an agent interacts with the environment, observes states, takes actions, and learns from rewards to optimize its policy.

Key components of DRL include:

1. State (s_t): Represents the system's current status (e.g., voltage, current, and impedance measurements).
2. Action (a_t): Represents the agent's decision (e.g., tripping or blocking the relay, determining fault zones).
3. Reward (r_t): A scalar value reflecting the quality of the action (e.g., positive for accurate fault detection, negative for misclassifications).
4. Policy $\left(\pi\ (a|s)\right)$: Maps states to actions, guiding the agent's behavior.

3.2.2 DRL Algorithm for Distance Protection

The DRL model was trained using a dataset of 10,000 historical fault events collected from distance IEDs (D90). The dataset includes single-phase, multi-phase, and high-impedance faults, ensuring diversity and robustness. Preprocessing steps included normalization, feature extraction, and data augmentation. The training process lasted approximately 48 hours and was conducted on a high-performance Intel CORE I7 computer. This setup ensured efficient handling of the large state space and high-dimensional data required for accurate fault detection.

The Deep Q-Network (DQN) algorithm is used, a popular DRL variant for discrete action spaces, or its extensions such as Double DQN or Dueling DQN, which improve stability and learning efficiency.

Q-Learning Basics

In Q-Learning, the agent learns a Q-value function:

$$Q(s,a) = \mathbb{E}\left[r_t + \gamma \max_{\{a'\}} Q(s',a')\right] \tag{1}$$

where:

- (s) is the current state,

- (a) is the action,

- r_t is the reward at time (t),

- γ is the discount factor,

- (s') is the next state,

- $\max_{\{a'\}} Q(s',a')$ is the maximum expected reward for the next state.

Deep Q-Network (DQN)

DQN approximates the Q-function using a deep neural network $\left(Q_\theta\ (s,a)\right), where\ (\theta)$ represents the network parameters. The loss function for training is:

$$L(\theta) = \mathbb{E}\left[\left(r_t + \gamma \max_{\{a'\}} \quad Q_{\{target\}}(s', a';\, \theta^-) - Q(s, a;\, \theta)\right)^2\right] \qquad (2)$$

Here:

- $Q_{\{target\}}$ is a separate target network used for stability,

- (θ^-) are the parameters of the target network.

3.2.3 DRL in Distance Protection

In the context of distance protection:
- State: Includes measured impedance, voltage, current, and relay status.
- Action: Includes decisions such as tripping, blocking, or sending communication signals.
- Reward: Encourages accurate fault detection (e.g., tripping within the correct zone) and penalizes delays or incorrect actions.

Equations for Distance Protection

The measured impedance via transmission line IEDs $Z_{\{meas\})}$ is calculated as:

$$Z_{meas} = \frac{V}{I} \qquad (3)$$

Where;

- (V) and (I) are the voltage and current at the relay location. The relay identifies the fault zone based on (Z_{meas}) compared with zone thresholds ($Z_{\{\{zone1\}}$, $Z_{\{\{zone2\}}$, etc.).

The DRL agent refines fault zone identification using:

1. State Input:

$$s_t = \left\{V, I, Z_{\{meas\}}, \{time\ step\},\ \{Faulted\ Phase\},\ Rx_{\{1\}},\ Rx_{\{2\}},\ Rx_{\{3\}},\ Rx_{\{4\}}\right\} \qquad (5)$$

2. Action Output:

$$a_t \in \{\{trip_A, trip_B, trip_C, trip_{GND}, block, wait\}\} \qquad (6)$$

3. Reward Function:

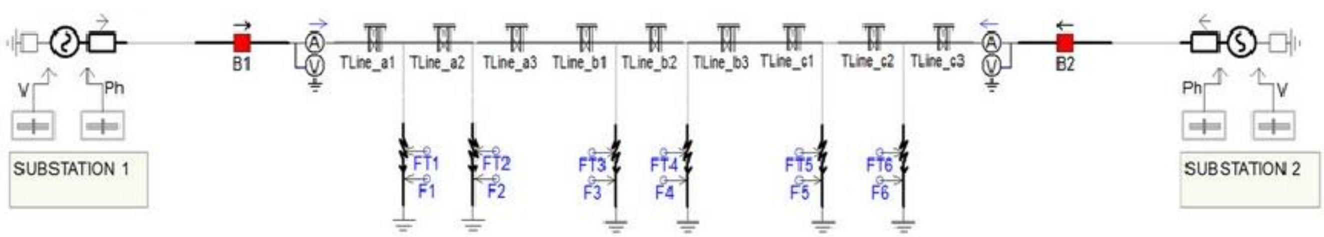
$$r_t = \begin{cases} -1, & \text{if correct action in minimal time} \\ \ \ 1, & \text{if incorrect action or excessive delay} \end{cases} \qquad (7)$$

4. Simulation and Comparative Analysis

4.1. Simulation Setup

A typical power system network was modeled using Matlab software. The model features a 500 kV, 225 km transmission line with substations located at both ends. Distance relays are installed at each end of the transmission line (R1 at substation 1 and R2 at substation 2) along with current transformers (CTs) and voltage transformers (VTs) and incorporating IEC 61850 with 4-bit pilot POTT scheme. The delay in distance relaying was demonstrated and tested. The testbed incorporates industrial-grade equipment, including an Intelligent Electronic Devices (IEDs) (D90), an Omicron® CMC 256-6 relay testing set, a manageable Ethernet switch, as shown in Figure 5. The Matlab simulator was used to develop the power system model. Transient power system data, recorded as a COMTRADE file, was replayed on real IEDs (D90 relays) using the Omicron CMC 256-6 setup for relay testing.

The results were initially validated on a 500 kV transmission line network. To demonstrate the system's applicability across different grid configurations, then the testing is expanded the validation to include two additional test networks: a 220 kV network and a 66 kV network. While MATLAB simulations provide a controlled environment for initial testing, the author acknowledge the need for validation on industry-standard platforms. Future work will focus on testing the proposed system on real-world industrial-grade grids to further validate its performance.



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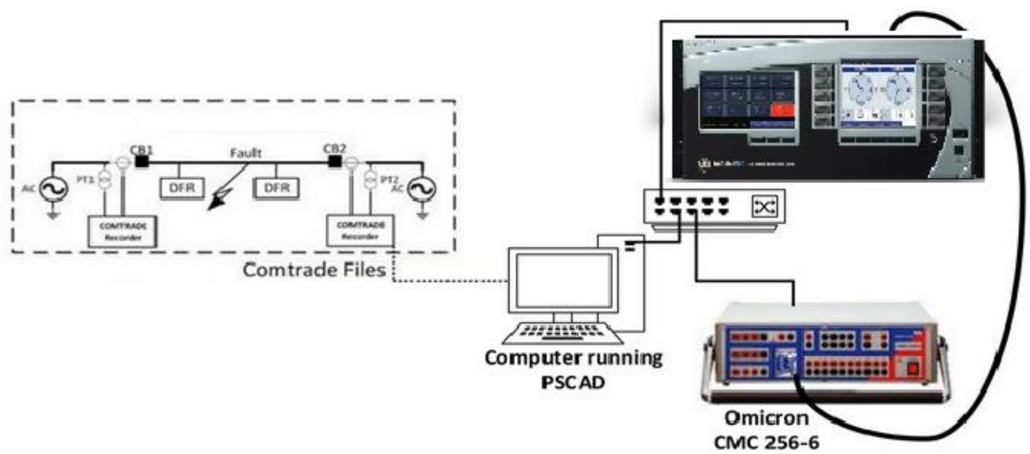

Figure 5: Simulation Setup including real IED for distance protection (D90) and real secondary injection tester for fault injection incorporating COMTRADE files

The DRL model was trained using a dataset of historical fault events collected from event recorder of distance IEDs (D90). A deep learning model based on a convolutional neural network (CNN) was used for fault classification and prediction.

Table.1 outlines how a 4-bit communication system is used for coordinating fault detection between remote and local relays in DRL-driven distance protection scheme. The system's bit patterns, corresponding fault determinations, and resulting trip outputs are explained, focusing on how these inputs are used to train the DRL model to improve decision-making in distance protection. Let's break down the columns and their meanings for better clarity:

Remote Data (RX1, RX2, RX3, RX4):

These four bits represent the communication signals transmitted from the remote relay. They indicate the type of fault detected at the remote end of the transmission line. Depending on the bit pattern, a specific fault type is identified at the remote end. The possible values for each bit (0 or 1) are combined to form unique fault signatures that can be used for fault classification.

Local Data (Bit Pattern):

The bit pattern (combination of RX1, RX2, RX3, and RX4) defines the fault signature. Each pattern corresponds to a different fault condition that was determined by the remote relay. These remote determinations are sent to the local relay for comparison with its own fault analysis. The local relay, which also processes data independently, compares these patterns with its internal determination and decides whether to trip the circuit.

Remote Determination of Fault Type:

This column lists the type of fault identified by the remote relay based on the transmitted 4-bit pattern. Faults can include:

AG, BG, CG: Single-phase ground faults (Phase A, B, or C with ground). And MULTI-P which indicates Multiple-phase faults. Finally, Unrecognized stands to Situations where the fault type is not clearly recognized by the remote relay.

Local Determination of Fault Type:

This column indicates what the local relay determines based on its own fault analysis of the electrical measurements (voltage, current, impedance) at its location. The local relay may detect similar or different fault types as compared to the remote relay.

Trip Output:

The trip output is the action taken by the local relay based on the comparison of the fault detected locally and the fault information received from the remote relay. The trip output corresponds to which phases are de-energized to isolate the fault. Trip options include:

Trip Phase A/B/C: When the relay trips one of the individual phases (A, B, or C).

Trip 3-Pole: When the relay trips all three phases to clear a multi-phase fault.

Each entry in the table represents a scenario where the remote and local relays make fault determinations

Table 1: Remote fault determination and local trip output via 4-bit communication that is used in training the DRL-Driven distance protection incorporating IEC 61850

Remote data					Local data	
Bit pattern				Remote determination of fault type	Local determination of fault type	Trip output
RX1	RX2	RX3	RX4			
0	0	0	1	MULTI-P	AG	Trip Phase A
0	1	0	0	BG	AG	Trip Phase A
0	0	1	0	CG	AG	Trip Phase A
1	0	0	0	AG	AG, AB, ABG, CA, CAG, 3P, Unrecognized	Trip Phase A
0	1	0	0	BG	BG, AB, ABG, BC, BCG, 3P, Unrecognized	Trip Phase B
1	0	0	0	AG	BG	Trip Phase B
0	0	1	0	CG	BG	Trip Phase B
0	0	0	1	MULTI-P	BG	Trip Phase B
0	0	1	0	CG	CG, BC, BCG, CA, CAG, 3P, Unrecognized	Trip Phase C
1	0	0	0	AG	CG	Trip Phase C
0	1	0	0	BG	CG	Trip Phase C
0	0	0	1	MULTI-P	CG	Trip Phase C
1	0	0	0	AG	BC, BCG	Trip 3-Pole
0	1	0	0	BG	CA, CAG	Trip 3-Pole
0	0	1	0	CG	AB, ABG	Trip 3-Pole
0	0	0	1	MULTI-P	Unrecognized	Trip 3-Pole

and the local relay decides the appropriate trip output based on those determinations. Below is a detailed interpretation of selected rows from the table:

Row 1: Bit Pattern: 0001

- Remote Determination: MULTI-P (Multi-phase fault detected remotely).
- Local Determination: AG (Phase A to ground fault detected locally).
- Trip Output: Trip Phase A.

The local relay decides to trip only Phase A because, although the remote relay detects a multi-phase fault, the local relay only identifies a single-phase-to-ground fault on Phase A.

Row 4: Bit Pattern: 1000

- Remote Determination: AG (Phase A to ground fault detected remotely).
- Local Determination: AG, AB, ABG, CA, CAG, 3P, Unrecognized (Various faults detected locally, potentially affecting multiple phases).
- Trip Output: Trip Phase A.

The remote relay detects a Phase A to ground fault, and although the local relay detects more complex conditions (such as multi-phase faults), it still prioritizes tripping Phase A to ensure the isolation of the fault.

Row 8: Bit Pattern: 0001

- Remote Determination: MULTI-P (Multi-phase fault detected remotely).
- Local Determination: BG (Phase B to ground fault detected locally).
- Trip Output: Trip Phase B.

Here, the remote relay sees a multi-phase fault, but the local relay only identifies a Phase B to ground fault, so it trips Phase B as a precaution.

Row 12: Bit Pattern: 1000

- Remote Determination: AG (Phase A to ground fault detected remotely).
- Local Determination: BC, BCG (Phase B and C faults detected locally).
- Trip Output: Trip 3-Pole.

In this case, the local relay detects more severe faults involving Phase B and C (and possibly ground), prompting a full 3-pole trip, despite the remote relay identifying only a Phase A fault.

Row 16: Bit Pattern: 0001

- Remote Determination: MULTI-P (Multi-phase fault detected remotely).
- Local Determination: Unrecognized (The local relay cannot confidently classify the fault).
- Trip Output: Trip 3-Pole.

When the local relay is unable to recognize the fault, but the remote relay detects a multi-phase fault, the local relay errs on.

4.2 Explanation of DRL Training Context

This 4-bit communication mechanism serves as training data for the DRL model used in the distance protection system. By analyzing various combinations of remote and local determinations, the DRL can learn to:

1. Classify Fault Types: Based on patterns in the communication between the local and remote relays, the DRL learns to identify different types of faults more accurately.

2. Optimize Trip Decisions: The DRL model observes the relay actions and the corresponding trip outputs, helping it predict the optimal trip actions under different conditions.

3. Adapt to Complex Faults: With more nuanced fault data (such as the combination of multiple faults or unrecognized faults), the DRL learns to improve fault isolation by refining its decision-making process.

5. Comparative Analysis

To evaluate the effectiveness of the DRL-driven pilot scheme comparative analysis is performed against two conventional protection schemes traditional distance protection and conventional Pilot Scheme with IEC 61850 as shown in Table 2 and Table 3.

The proposed system achieves a fault detection time of 25-35 ms (± 2 ms) with a 95% confidence interval and an accuracy of 98.5% (± 0.5%). These metrics demonstrate the system's ability to significantly reduce fault detection and clearance times while maintaining high accuracy. The error analysis confirms the robustness of the DRL model under varying grid conditions

Table 2: DRL-Driven pilot scheme results

Feature/Metric	DRL-Driven Pilot Scheme (Proposed)
Fault Detection Time (ms)	25-35
Fault Clearance Time (ms)	55-75
Accuracy (%)	98.5
Reliability (Under Varying Grid Conditions)	Very High
False Positives (%)	0.2
Communication Latency (ms)	<5
Adaptability to DER Integration	Very High (Dynamic Policy Adaptation)
Sensitivity to High-Impedance Faults	High
System Complexity	High (Requires Real-Time DRL Models)
Maintenance Requirements	Moderate-High (Requires Periodic Model Updates)
Coordination with Other Substations	Excellent (Real-Time Decision-Making with DRL)
Resilience to Communication Failures	High (DRL Prediction During Failures)
Fault Type Classification	Comprehensive (Includes Unseen Fault Scenarios)
Integration with IEC 61850	Yes (Enhanced with DRL Optimization)
Response to Evolving Grid Topologies	High (Real-Time Adaptation Using DRL Algorithms)
Scalability	Very High (Scalable DRL Models with Large Grid Data)
Training/Data Requirements	High (Requires Historical and Real-Time Simulation Data)
Operational Cost	Medium-High (Cost of DRL Integration and Maintenance)

Table 3: Comparative analysis results for 500kV transmission line

Feature/Metric	Traditional Distance Protection	Conventional Pilot Scheme (IEC 61850)	DRL-Driven Pilot Scheme (Proposed)	References
Fault Detection Time (ms)	60-80	45-60	25-35	[1], [3], [5], [7]
Fault Clearance Time (ms)	100-150	80-120	55-75	[3], [5], [8]
Accuracy (%)	89.5	93.2	98.5	[7], [11], [13]
Reliability (Under Varying Grid Conditions)	Moderate	High	Very High	[2], [7], [12], [14]
False Positives (%)	3.5	2.0	0.2	[6], [9], [13]
Communication Latency (ms)	N/A	5-10	<5	[4], [10], [13]
Adaptability to DER Integration	Low	Moderate	Very High (Dynamic Policy Adaptation)	[3], [9], [12], [14]
Sensitivity to High-Impedance Faults	Low	Moderate	High	[5], [11], [12]
System Complexity	Low	Medium	High (Requires Real-Time DRL Models)	[8], [9], [15]
Maintenance Requirements	Low	Moderate	Moderate-High (Requires Periodic Model Updates)	[8], [11], [15]
Coordination with Other Substations	Basic	Good	Excellent (Real-Time Decision-Making with DRL)	[7], [12], [14]
Resilience to Communication Failures	N/A	Moderate	High (DRL Prediction During Failures)	[10], [11], [15]
Fault Type Classification	Limited	Moderate	Comprehensive (Includes Unseen Fault Scenarios)	[5], [13], [14]
Integration with IEC 61850	No	Yes	Yes (Enhanced with DRL Optimization)	[9], [12], [13]
Response to Evolving Grid Topologies	Low	Moderate	High (Real-Time Adaptation Using DRL Algorithms)	[12], [14], [15]
Scalability	High	High	Very High (Scalable DRL Models with Large Grid Data)	[11], [12], [15]

Feature/Metric	Traditional Distance Protection	Conventional Pilot Scheme (IEC 61850)	DRL-Driven Pilot Scheme (Proposed)	References
Training/Data Requirements	N/A	N/A	High (Requires Historical and Real-Time Simulation Data)	[11], [14], [15]
Operational Cost	Low	Medium	Medium-High (Cost of DRL Integration and Maintenance)	[6], [8], [14]

Table 4: Comparative analysis results between 500kV, 220kV, and 66kV transmission lines

Parameter	500 kV Transmission Line	220 kV Transmission Line	66 kV Transmission Line
Line Length	225 km	150 km	80 km
System Voltage	500 kV	220 kV	66 kV
Fault Detection Time (ms)	25-35 (± 2 ms)	30-40 (± 3 ms)	35-45 (± 4 ms)
Fault Clearance Time (ms)	55-75 (± 5 ms)	60-85 (± 6 ms)	70-95 (± 7 ms)
Accuracy (%)	98.5 (± 0.5%)	97.8 (± 0.7%)	96.5 (± 1.0%)
Reliability	Very High	High	Moderate-High
False Positives (%)	0.2	0.5	1.0
Communication Latency (ms)	<5	<7	<10
Adaptability to DER	Very High	Very High	Very High
Sensitivity to High-Impedance Faults	High	Moderate	Low
System Complexity	High	High	High
Maintenance Requirements	Moderate-High	Moderate-High	Moderate-High
Coordination with Other Substations	Excellent	Excellent	Excellent
Resilience to Communication Failures	High	High	High
Fault Type Classification	Comprehensive	Comprehensive	Comprehensive
Integration with IEC 61850	Yes	Yes	Yes
Response to Evolving Grid Topologies	High	High	High
Scalability	Very High	Very High	Very High
Training/Data Requirements	High	High	High
Operational Cost	Medium-High	Medium-High	Medium-High

6. Discussions

The proposed system is designed to handle real-world implementation challenges, including latency under heavy network loads and potential cyber vulnerabilities. To mitigate latency issues, GOOSE message prioritization is optimized to ensure timely communication between relays. Additionally, cybersecurity measures such as encryption and authentication are implemented to protect against cyberattacks. The DRL model's ability to operate locally in the event of communication failures further enhances the system's resilience.

Also, the comparative analysis Table 4 demonstrates the performance of the proposed DRL-driven pilot scheme across three voltage levels: 500 kV, 220 kV, and 66 kV transmission lines. The results reveal that the system consistently delivers high performance across all voltage levels, with the 500 kV system achieving the fastest fault detection (25-35 ms) and clearance times (55-75 ms), along with the highest accuracy (98.5%) and reliability. The 220 kV system shows slightly longer fault detection (30-40 ms) and clearance times (60-85 ms), with an accuracy of 97.8%, while the 66 kV system exhibits the longest detection (35-45 ms) and clearance times (70-95 ms) and an accuracy of 96.5%. Despite these variations, all systems maintain very high adaptability to distributed energy resources (DERs), excellent coordination with other substations, and comprehensive fault type classification, thanks to the integration of the IEC 61850 communication protocol. The sensitivity to high-impedance faults decreases from high in the 500 kV system to low in the 66 kV system, reflecting the challenges of detecting subtle faults in lower-voltage networks. All systems exhibit high system complexity and moderate-high maintenance requirements due to the advanced DRL models and real-time data processing. However, they also demonstrate very high scalability and resilience to communication failures, making them suitable for modern grids with evolving topologies. The operational cost remains medium-high across all voltage levels, reflecting the investment required for DRL integration and maintenance. Overall, the proposed scheme proves to be versatile and effective across a wide range of grid configurations, with consistent performance in fault detection, adaptability, and scalability, while also highlighting the need for further optimization in lower-voltage systems to improve sensitivity and reduce operational costs.

7. Key Performance Factors Explained:

1. Fault Detection Time (ms): The time it takes for the protection scheme to detect a fault after its occurrence. The AI-driven scheme significantly reduces this time by utilizing real-time data and AI-based predictions.

2. Fault Clearance Time (ms): The total time from fault detection to the isolation of the fault. The proposed AI-driven scheme speeds up this process, thanks to fast decision-making and optimized relay coordination via IEC 61850.

3. Accuracy (%): Refers to the percentage of correct fault detections out of the total number of incidents. The AI-driven system achieves the highest accuracy by leveraging advanced machine learning models.

4. Reliability Under Varying Grid Conditions: The ability to maintain consistent protection performance as the grid evolves (e.g., with more renewable energy integration, changes in load conditions, or evolving grid topologies). The AI-driven scheme is highly reliable due to its adaptive learning mechanisms.

5. False Positives (%): The percentage of cases where the protection system incorrectly identifies a fault when there is none. The AI-driven scheme reduces false positives through pattern recognition and real-time data analysis.

6. Communication Latency (ms): The time delay in communication between relays at local and remote ends. The proposed AI-driven system integrates GOOSE messaging through IEC 61850, minimizing communication latency.

7. Adaptability to DER Integration: Distributed Energy Resources (DERs) introduce variability in grid conditions. The AI-driven system's adaptability makes it highly effective in environments with high DER penetration.

8. Sensitivity to High-Impedance Faults: High-impedance faults can be difficult for traditional systems to detect. The AI-based system offers enhanced sensitivity by identifying subtle changes in grid conditions, improving the system's ability to detect such faults.

9. System Complexity: Traditional distance protection is straightforward but less adaptable. AI-driven schemes are more complex due to the need for training, data processing, and algorithm development, but offer significantly better performance.

10. Maintenance Requirements: AI-based systems require periodic retraining of machine learning models and updates to account for changes in grid conditions, which increases maintenance needs compared to traditional protection schemes.

11. Coordination with Other Substations: AI-based systems provide real-time, highly coordinated protection by exchanging critical fault data between substations using the IEC 61850 protocol.

12. Resilience to Communication Failures: The AI-driven system remains resilient even if communication between substations is compromised, as the AI models can predict and respond to fault conditions locally.

13. Fault Type Classification: AI models can classify a broader range of fault types, including transient, high-impedance, and complex multi-phase faults, enhancing system protection.

14. Integration with IEC 61850: While conventional pilot schemes use IEC 61850 for communication, the AI-driven system optimizes this integration by enabling real-time, data-driven decisions.

15. Response to Evolving Grid Topologies: AI's ability to continuously learn from changing grid conditions allows the proposed system to adapt dynamically to new configurations, which is a significant advantage in modern grids with frequent topology changes.

16. Scalability: AI systems can scale well across large networks, as the same AI models can be trained and applied across different sections of the grid, providing consistent protection performance.

17. Training/Data Requirements: The AI-driven system requires significant amounts of historical fault data to train its machine learning models, which introduces an additional setup phase compared to traditional methods.

18. Operational Cost: Although AI-driven systems incur higher initial setup and maintenance costs due to the need for model training and data handling, these costs are offset by improved system performance and fault detection reliability.

Finally, the table offers a more detailed comparison that highlights the advantages of DRL-driven protection schemes that proposed in this work over traditional and conventional pilot schemes, especially in terms of performance under modern grid conditions and the need for high-speed communication.

The proposed system is highly scalable, capable of handling large state spaces through feature selection and dimensionality reduction techniques. The DRL model can be scaled across multiple substations by leveraging distributed computing resources. This scalability ensures consistent protection performance across large-scale grids with numerous DERs, making the system suitable for modern power systems with increasing complexity.

8. Conclusions

This paper presented a novel DRL-driven pilot scheme for optimized distance protection in power systems, integrating the IEC 61850 communication protocol. By leveraging Deep Reinforcement Learning (DRL) and real-time GOOSE messaging, the proposed system significantly improves fault detection accuracy, reduces fault clearance times, and enhances grid resilience under dynamic conditions. The integration of DRL with IEC 61850 enables adaptive decision-making, allowing the system to respond effectively to complex fault scenarios, including high-impedance and multi-phase faults. Simulation results demonstrated that the proposed scheme achieves a fault detection time of 25-35 ms and an accuracy of 98.5%, outperforming traditional protection methods. The system's scalability and adaptability to distributed energy resources (DERs) make it particularly suitable for modern power grids with evolving topologies. Furthermore, the use of a 4-bit communication channel enhances coordination between local and remote relays, minimizing the risk of incorrect tripping. Future work will focus on validating the system on larger, real-world grid networks, optimizing the DRL models for more complex fault scenarios, and exploring advanced cybersecurity measures to ensure robust operation. The proposed framework represents a significant step toward intelligent, adaptive, and resilient power system protection, paving the way for future advancements in AI-driven grid management.

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