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INTELLIGENT FAULT DETECTION AND CLASSIFICATION IN OVERCURRENT PROTECTION SYSTEMS BASED ON ARTIFICIAL NEURAL NETWORKS

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Abstract

An ANN-based intelligent overcurrent relay is proposed for simultaneous fault detection and fault-type classification in a selected subsection of the IEEE-9 bus transmission system (Bus-7–Bus-8). Two neural network modules are implemented: the first performs fault detection and directly issues the trip command based on three-phase current features, while the second classifies the fault types into AG, BG, CG, AB, BC, CA, and ABC categories. Fault current signals are generated in MATLAB/Simulink under diverse operating conditions, including variations in fault resistance, location, and inception angle. The detection network achieved a correlation coefficient of $R \approx 0.993$, whereas the improved classification network achieved $R \approx 0.998$, demonstrating a substantial enhancement in accuracy and generalization. Time-domain tests demonstrated consistently faster tripping performance compared with the conventional inverse-time relay namely, improvements of 0.6 ms (AG), 0.7 ms (BG), 1.25 ms (CG), 0.6 ms (AB), 1.5 ms (BC/BC-G), 1.6 ms (AC/AC-G), and 0.5 ms (ABC/ABC-G). These results confirm the superior dynamic response and adaptability of the proposed intelligent relay, highlighting its suitability for modern protection applications and its potential as a foundation for next-generation smart-grid relaying systems.

Keywords: intelligent overcurrent relay, fault detection, fault classification, ANN, power system protection, adaptive protection

List of Symbols/Acronyms

Artificial Neural Network –ANN;
Double Line-to-Ground Fault–LLG;
Line-to-Line Fault–LL;
Mean Squared Error–MSE;
Overcurrent Relay –OCR;
Single Line-to-Ground Fault–SLG;
Three-Phase Fault–LLLG;

1. INTRODUCTION

The reliability of modern power systems depends strongly on the effectiveness of their protection schemes. Although conventional OCRs are simple and cost-effective, their performance is significantly affected by fault resistance, network parameter variations, and system disturbances. Moreover, they are inherently unable to classify fault types, which limits their ability to support fast and selective protection strategies. (OCR) play a fundamental role in power transmission systems, serving either as main protection devices or as backup relays[1]. Global technological progress, particularly in developing countries, have increased the requirement for electrical energy. For that reason, new power plants, substations, and transmission lines are developed each year, which in turn contributes to higher levels of power system failures [2]. In power systems, electrical networks may experience a wide range of disturbances, most especially short-circuit events like SLG, LL, LLG, and LLLG faults [3]. Among several protection devices, (OCRs) play a crucial role in protecting transmission lines, transformers, and distribution networks resisting excessive current conditions that can lead to severe apparatus damage or large-scale blackouts [4]. The integration of spread generation further complicates relay management, as differing fault current levels may lead to longer operating times and ineffective coordination. The integration of distributed generation significantly alters fault current levels, which complicates relay coordination and may increase the operating time of conventional (OCR) [5]. Adaptive protection strategies automatically adjust relay settings to dominant system conditions, overcoming the weaknesses of fixed coordination in networks with distributed generation [6]. The consistency, security, and fast response of ANN-based (OCRs) show great promise for enhancing power system protection [7].

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It's one of the most significant artificial intelligence technologies in recent history, this technology is crucial to the development of a powerful system for controlling power system failures [8]. ANNs have demonstrated impressive abilities in recognizing structural patterns, converting them into vectors, and dealing with complex data, all of which make them ideal for detection of faults and classification of abnormalities. The output of the ANN can be considered the new duration of operation [9]. By isolate the faulty component, the influence of the disturbance on the remainder of the system is greatly restricted. For example, if a fault occurs in each part of the grid, this error should be isolated as quickly as possible to avoid the propagation of this error to other parts of the grid [10].

Recently, artificial intelligence (AI) and machine-learning have been more frequently utilized to enhance the reliability of power systems. ANNs, in particular, have demonstrated exceptional abilities in pattern recognition, nonlinear transformation, and adaptive decision making, all of which make them ideal for the detection of faulty behavior and the classification of abnormal behavior [11]–[3]. Several modern studies (2021-2024) have documented significant enhancements in protection performance through ANN-based and hybrid intelligent relaying strategies, this is indicative of a growing trend towards the use of data to enhance the protection of smart grids.

Additionally, recent research has augmented the use of ANN-based detection methods for electrical systems other than permanent magnets, such as synchronous motors that are used in agriculture. These devices have a high degree of mechanical complexity, which necessitates the use of deep-learning methods to identify both electrical and mechanical errors [12].

Despite these improvements, the majority of existing ANN-based security schemes have primarily focused on either detection or classification alone, and have been tested only in the presence of idealized fault conditions. Additionally, limited attention has been devoted to the influence of fault resistance, inception angle, and location on the relay's response within larger communication networks.

To remove these boundaries, intelligent protective strategies based on artificial intelligence have been proposed. In particular, ANNs patterns show recognition, non -linear mapping and strong abilities to make adaptive decisions, making them suitable for mistakes and classification. Unlike the threshold-based relay, N-based plans can learn the relationship between current signature and error types, enabling adaptive and intelligent operations.

This work addresses the gap between conventional (OCR) and the demands of modern power systems by developing a hybrid ANN-based framework. Two ANN models are designed: (i) an intelligent relay model that detects the occurrence of a fault and (ii) a fault classification model that identifies the fault type. If accurate error placement is determined by the use of smart security systems, the performance of these networks can increase significantly [13]. The models are trained and validated using fault current data simulated in MATLAB/Simulink under diverse operating conditions. The proposed approach is evaluated against conventional OCRs in terms of accuracy and response time [14].

This study makes the following principal contributions:

1. Development of an ANN-based intelligent (OCR) protection scheme capable of performing both fault detection and fault-type classification within transmission systems.
2. Demonstration of improved detection speed and classification accuracy compared with conventional inverse-time (OCRs) under various operating conditions.
3. Provision of a scalable and adaptable methodology that can be extended to other types of protection relays and applied to larger and more complex power-system networks.

2. LITERATURE REVIEW

(OCRs) have always been used as protection devices in transmission and distribution systems. The simple construction, reliability, and cost-effectiveness of conventional OCRs particularly IDMT relays make them more preferable

A MATLAB/Simulink model for an inverse-time (OCR) based on IEC and IEEE standard curves was developed by Mehta and Makwana [15]. The simulation results showed that the error between the operation times is less than 2.7% with a high correlation (≈0.97) to theoretical IDMT characteristics hence proving again how effective under laboratory tested conditions Conventional OCR performs Hybrid intelligent methods have also been researched so as improve performance.

Yadav et al. [16] created a MATLAB/Simulink model for the analysis of both symmetrical and unsymmetrical faults in transmission lines. The simulation result registered a maximum fault current of about 43 A for three-phase short circuit at t = 0.0166 s, with more than 95 % agreement achieved between theoretical calculations and results obtained confirming the reliability of transient fault analysis using MATLAB in protective-relay design genetic algorithm (GA)-based optimization methods have been used to improve renewable-rich systems by bettering coordination and reducing time delays in operation [17].

However, hybrid tactics/programs demonstrated /included significant accuracy innovations /improvements, they also included/int reduced higher programmatic complexity which may real-time deployment

Saeed et al. [18] designed an instantaneous (OCR) using MATLAB/Simulink with logical blocks which include RMS converters, relational operators and S–R flip flops. The relay picked up for a current of 0.3e4 A within almost 0.1 s from the inception of fault current as theoretically expected and matched results by more than 98% to prove the reliability of instantaneous protection logic implemented in their model. Their method was intelligent but still rule-based. This paper proposes the application of artificial neural networks to the relaying scheme making it more adaptive and intelligent under various operating conditions.

Alnaib et al. [19] proposed a hybrid method that combines two-port network theory with artificial neural networks for detecting and classifying several simultaneous faults on the IEEE-14 bus system. Their work considered fault scenarios usually ignored in most previous works, such as synchronous faults and open conductor faults. The proposed method used two-port network theory for localization while ANN was employed both for type classification as well as location appraisal; hence high usefulness is demonstrated by results were Scaled Conjugate Gradient training algorithm attained very small (MSE=1.5e-17) value (for fault classification) and (MSE=6.1e-13) value (for location) thereby confirming robustness under different faulty conditions

Al-Jawady et al. [20] propose an intelligent ANN-based (OCR) for the protection of a 100km Terco transmission line. A back-propagation neural network (BPNN) is trained using MATLAB/Simulink to issue a trip signal within 4.4ms from fault inception with miscoordination time fifteen to twenty percent less than that of conventional relays, thereby demonstrating high speed and reliability under different fault conditions.

Sam et al. [3] also implemented an ANN-based model for the detection and classification of short-circuit faults on the Nigerian 330 kV transmission network. The system performed reliably with a slight deviation in classification of less than 3.07 % on line one and three but deviated more, up to 20.33 % on line two while detecting triple phase (ABC) faults. This shows that there is high accuracy in ANN based protection under most operating conditions however further optimization is needed for generalization over a network.

The results of Abawi et al. [11] showed near perfect fault detection and classification accuracies using the Levenberg–Marquardt algorithm, with extremely low MSE values (10e-3_10e-29) under a highly idealized simulation environment. The values themselves speak well for excellent numerical convergence achieved during training.

However, the experiments were conducted under limited and highly controlled operating conditions. In contrast to this, ANN based protection has been tested in this study under more diversified conditions which include variations of fault resistance and location together with timing of trip signal. Though comparative error values achieved are higher but proposed model possesses better generalization capability that adapts real situations where it can be practically implemented in modern protection systems.

The ANN-based relay offers better robustness and practical consistency under varying fault resistances, locations, and network conditions. Previous works reported lower numerical errors in ideal or simplified simulation environments. The present work focuses on a more realistic environment within the IEEE-9 bus system incorporating practical robustness, faster trip response with reliable fault classification thereby emphasizing the bridging of that gap between theoretical accuracy and real-world applicability.

3. SYSTEM MODELING AND DESCRIPTION

In this work, an intelligent (OCR) is developed and tested using a selected portion of the IEEE-9 bus standard power system. The protection scheme is applied specifically to the transmission line connecting Bus-7 and Bus-8, which represents a typical medium-length line in the original IEEE benchmark. As illustrated in Fig. 1, the studied subsection is highlighted within the overall IEEE-9 bus test system to indicate the portion under investigation. The IEEE-9 bus was chosen as a validated benchmark allowing transparent parameter control and faster simulation; however, the approach is scalable to larger systems such as IEEE-30 and IEEE-33.

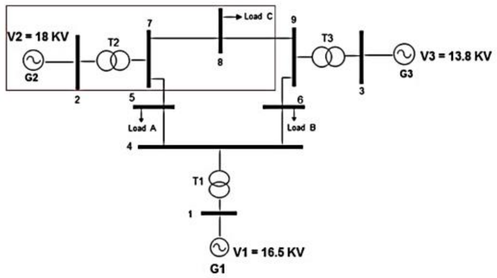

Fig. 1. Single-line diagram of the IEEE-9 bus test system highlighting the protected section between Bus-7 and Bus-8

The simplified model incorporates a synchronous generator at Bus-7, a step-up transformer for interconnection, a short transmission line section, and a load connected at Bus-8. The parameters of the generator, transformer, transmission line, and load used in the IEEE-9 bus subsystem (Bus-7 to Bus-8) are illustrated in Table 1.

These parameters are extracted from the standard IEEE-9 bus system and were used as the basis for developing and testing the intelligent (OCR). The conventional (OCR) is initially designed by selecting appropriate pickup current and time-dial settings based on the parameters of the IEEE-9 bus system. This traditional relay serves as a reference model and is then upgraded to an intelligent relay by employing ANN tools. ANN perform exceptionally in various tasks Classification, prediction, filtration, optimization, pattern recognition and function, including connection [21].

Table 1. Parameters of the power system (IEEE-9 subsystem Bus-7 to bus-8)

Parameters	Value
Generator G2	192 MVA, 18KV,60Hz
Transformer T2	100 MVA, 50Hz,18KV/230KV
[R1(pu), L1(pu)]	[1e-6, 0]
[R2(pu), L2(pu)]	[1e-6, 0.0625]
[Rm(pu), Lm(pu)]	[500,500]
T.L(7 ↔ 8)	100 km, 60Hz
[r1 r0](Ohms/km)	[0.044965 0.11241]
[l1 l0] (H/km)	[1.01e-3 2.02e-3]
[c1 c0] (F/km)	[7.471e-9 4.394e-9]
Load C	230KV,60Hz,100MW,35Mvar

The generator is modelled using its rated voltage and apparent power along with transient reactance data, while the transformer is adopted with its nominal MVA rating, turns ratio, and leakage impedance extracted from the standard IEEE-9 bus database. The transmission line parameters are included in terms of series resistance, inductive reactance, and shunt capacitance for each phase, representing the electrical characteristics of the protected line section between Bus-7 and Bus-8. A constant-power load is attached at Bus-8 to simulate the steady-state operating condition of the system under normal and fault scenarios. A neural network is generally composed of three types of layers represented by interconnected nodes: the input layer, one or more hidden layers, and the output layer [22].

Collected from simulation runs of the model under different fault conditions applied at various locations along the protected transmission line. The fault categories under Among the examined contingencies are SLG, LL, LLG, and LLL fault scenarios. These current signals are used to train two ANN-based modules developed using the Neural Network Toolbox (NF Tools). The general block diagram of the proposed ANN-based intelligent (OCR) integrated with the IEEE-9 bus subsystem is presented in Fig. 2.

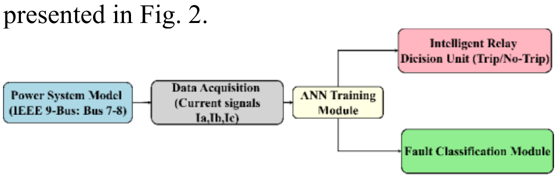

Fig. 2. General block diagram of the proposed ANN-based intelligent (OCR)

The first module replaces the decision-making function of a traditional (OCR), learning to issue a trip command directly from the measured currents under faulted conditions. The second ANN module performs intelligent fault classification by identifying the specific type of fault based on the same measured inputs.

The proposed intelligent relay operates online by continuously receiving the phase current measurements and simultaneously performing fault detection, trip decision making, and classification. The integration of the IEEE-9 bus sub-system with the ANN-based protection enhances system performance through faster response and more accurate decision-making compared with classical protection schemes. All simulation and training tasks are carried out in the MATLAB/Simulink environment.

4. PROPOSED METHODOLOGY

4.1. System overview

The proposed scheme is implemented on a selected portion of the IEEE-9 bus test system, focusing on the transmission line between Bus-7 and Bus-8. The simulated sub-system includes a synchronous generator connected to Bus-7, a step-up transformer, the transmission line section, and a constant-power load connected to Bus-8. A conventional (OCR) is initially applied to protect the line using standard inverse time-current characteristics.

4.2. Proposed intelligent protection scheme

In this work, an intelligent (OCR) is developed by emulating the tripping behavior of a traditional relay using ANN tools. Fault current signals (Ia, Ib, Ic) are generated for various scenarios, including (SLG), (LL), (LLG), and (LLLG), applied at random points along the transmission line between Bus-7 and Bus-8. These currents are collected and used to train two ANN modules: the first network predicts the relay trip/no-trip decision, and the second provides intelligent fault classification. Once the training is completed, the ANN models are integrated into the simulation to replace the standard relay and perform protection decisions online. The overall MATLAB/Simulink implementation of the proposed protection scheme is presented in Fig. 3.

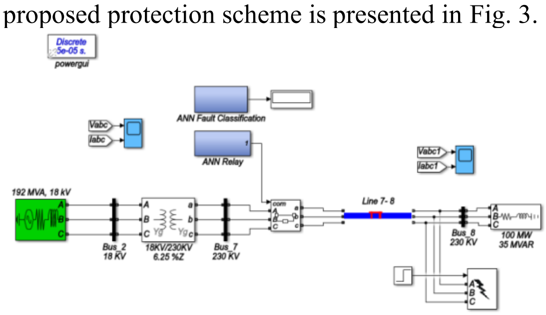

Fig. 3. MATLAB/Simulink model of the proposed intelligent overcurrent protection scheme

4.3. Flowchart of the Proposed Algorithm

The intelligent relay algorithm operates in real-time by continuously monitoring the three-phase currents, detecting abnormal conditions, and determining both the relay operation and the fault type. The proposed decision-making procedure is presented in the flowchart shown in Fig. 4.

4.4. Implementation Environment

All simulations and ANN training processes are conducted in MATLAB/Simulink (R2020a) using the Neural Network (NF) Toolbox. Due to their inherent parallelism, neural networks are capable of processing data more quickly than conventional methods [23]. The graphic mode that represents a result is the most effective remedy to express the study points [16].The proposed protection scheme is evaluated under a wide range of fault resistances and inception angles to assess its detection speed and classification accuracy. Results are later compared with those obtained from the conventional (OCR) under identical simulation conditions. At the end of this section, the proposed methodology is validated through several time-domain simulation tests under different fault scenarios, and the performance of the developed intelligent relay is presented in Section 6.

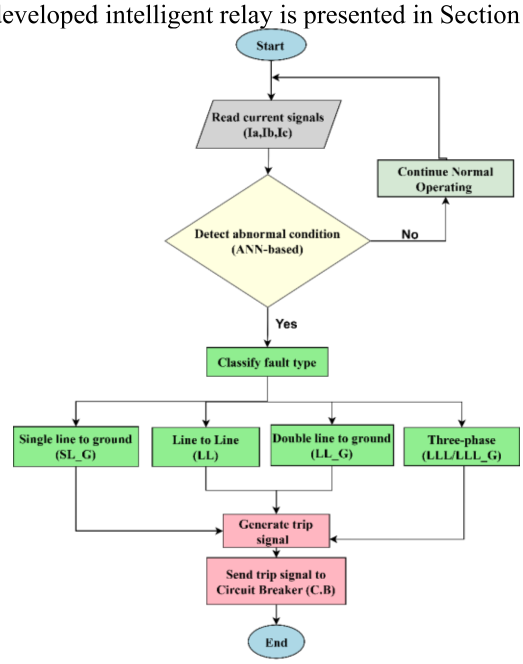

Fig. 4. Flowchart of the proposed ANN-based intelligent (OCR) algorithm

Challenges that were faced during implementation included achieving stable convergence of the neural network under highly resistive fault cases and trip timing synchronization within Simulink. These were solved by carefully preprocessing training data, reducing further the learning rate of the Levenberg–Marquardt algorithm, and retraining the model iteratively until consistent generalization was attained with minimal error on all datasets.

4.5.1. ANN-Based Relay Training

The intelligent ANN using (OCR) was developed and trained in MATLAB Neural Network Toolbox. The current signals collected under different fault conditions have been pre-processed and split into three sets: training 70%, validating 15%, and testing 15%. Among all training methods, the Levenberg-Marquardt backpropagation algorithm is the best choice in terms of speed of convergence and good generalization performance.

Input neurons of three-phase current features, hidden layer with ten neurons, and single output neuron for trip/no trip decision. Fig. 5 presents a block diagram of the ANN relay architecture developed.

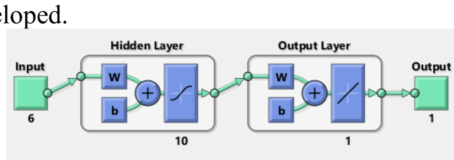

Fig. 5. Network architecture of the ANN-based intelligent (OCR) (6–10–1)

The performance of the training process was evaluated through an error histogram and regression analysis. The error histogram (Fig. 6) shows that the majority of prediction errors are centered around zero, indicating high training accuracy. The maximum error magnitude is approximately ±0.03, and more than 95 % of the samples fall within this range, which confirms that the ANN outputs are very close to the target values and that the network achieved precise and stable convergence during training.

Fig. 6. Error histogram of the ANN relay training process

Furthermore, the regression plots presented in Fig. 7 demonstrate a strong linear correlation between the ANN output and the target trip decision across all datasets. The obtained correlation coefficients (R = 0.99277 for training, R = 0.99276 for validation, R = 0.99371 for testing, and R = 0.99291 overall) indicate that the developed model achieved excellent consistency between predicted and actual responses. This high degree of correlation confirms that the ANN-based relay can reliably identify abnormal current patterns and issue the trip command with minimal deviation, reflecting superior learning and generalization capability during both training and testing phases.

4.5.2. ANN Fault Classification Training

The ANN fault classification module was designed and trained using MATLAB's Neural Network Toolbox (NFTool). Three current-related features were used as inputs to the classifier, and the fault type was encoded as a single scalar code (1–7). Fig.8 shows the selected architecture. It has 3 input neurons, 10 hidden neurons, and 1 output neuron.

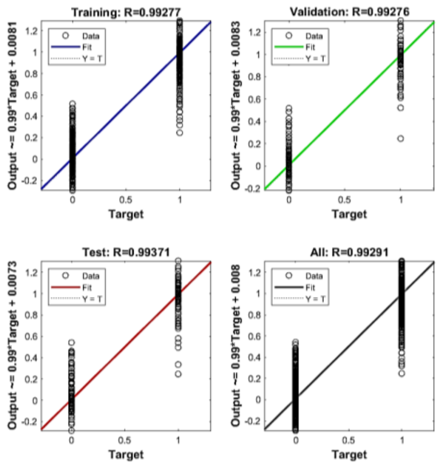

Fig. 7. Regression plots of the ANN relay showing strong correlation between target and output

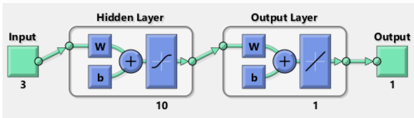

Fig. 8. Network architecture of the ANN-based fault classification module (3–10–1)

To check how well the training went, an error chart was made for the training, checking, and testing data sets. As seen in Fig. 9 most guess errors stay close to zero with a small and even spread showing that the network reached very good learning with low left-over error. The biggest change is about ±0.1 and more than 95% of all samples are within this range. This tight group near the zero-error line shows strong learning steadiness and great generalizing ability over all parts of the data.

Fig. 9. ANN Fault Classification Error Histogram

The regression analysis, as depicted in Fig. 10, proves the robustness of the proposed classifier since it gives correlation coefficients of R = 0.99831 (training), R=0.99802 (validation), R=0.99761 (testing), and R=0.99816(overall). This practically infers a perfect linear relationship between network outputs and target fault codes whereby apparently it can be presumed that the said classifier has learned mapping effectively current features to fault types. The ANN will output continuous values which will later be rounded or post-processed into integer codes within a range from 1 up to 7 for representing different categories of faults (AG, BG, CG, AB, BC, AC, ABC) .It proves ,henceforth ,that this very ANN based classifier developed here is capable enough to correctly as well as consistently identify any kind of faults under multifarious conditions with great amount precision accompanied by reliability besides generalization capability.

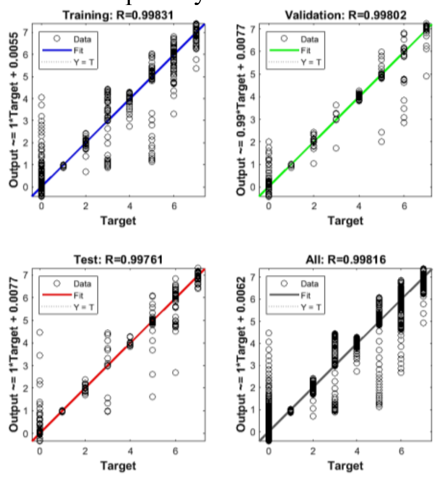

Fig. 10. Regression plots of the ANN fault classifier (training/validation/testing/all)

To run within the Simulink setup, the net result was joined to a MATLAB Function block that handles post-processing. This function links the number codes (1–7) to their matching tags (AG, BG, CG, AB, BC, CA, ABC).

5. SIMULATION RESULTS AND DISCUSSION

In this section, the behavior of the proposed ANN-based intelligent relay is tested under healthy and faulty conditions. During healthy conditions, the relay remains stable and does not issue a trip command. It has been tested for its performance under faulted conditions for SLG, LL, LLG, and LLLG scenarios. For all these cases, the developed scheme successfully detected the fault and generated an appropriate trip signal including correct classification of the type of fault. A simulation time of 0.3 s has been selected to have a clear view window around fault inception at 0.15 s with consideration for computational efficiency as well as dynamic response accuracy.

5.1. Performance of ANN Relay Under Normal (No-Fault) Conditions

The intelligent relay was first tested under good working conditions with no fault added. The run time for the test was 0.3 s during which the system kept working well. As seen in Fig. 11, Three step streams stay even and wave-like, the ANN-based fault check shows the state as "No Fault" and thus the trip signal does not turn on for any part of the time window. This proves that the suggested ANN relay does not cause unneeded tripping when things are normal.

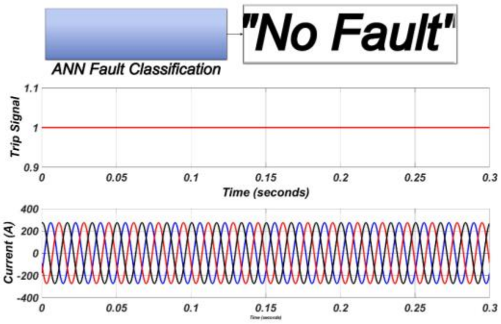

Fig. 11. Simulation results under normal operating condition

5.2.1. Response to Single Line-to-Ground Fault (A-G)

The A-G fault was applied at 0.15 s with a total simulation time of 0.3s to see how effective the proposed ANN relay would be in clearing the fault. As can be seen from Fig. 12, immediately when the fault occurs, there is large distortion and an increase in the magnitude of current in phase A while currents in phase B and C go to zero after the operation of the relay (i.e., after not more than 1ms). The ANN based classification module on which protection circuit decision making depends identifies the type of fault correctly as “AG” and hence relays generate trip signals right at the moment a fault has taken place ensuring quick isolation of a faulty line. In comparison with a conventional inverse-time relay, about 0.6 ms earlier tripping response for this A-G fault case can be obtained using the proposed ANN relay.

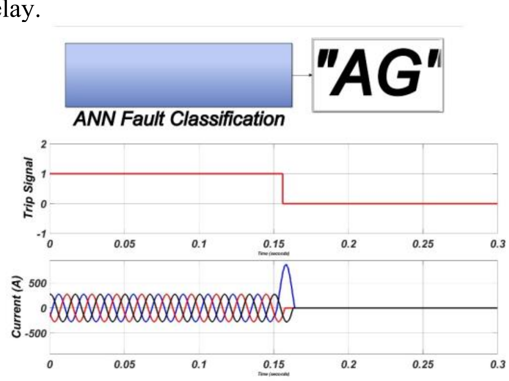

Fig. 12. Simulation results under A-G fault condition

5.2.2. Response to Single Line-to-Ground Fault (B-G)

The time of application of the B-G fault is 0.15 seconds up to 0.3 seconds. Results in Fig. 13 show that phase-B current rises sharply at the inception of the fault, while phases A and C do not register any change until the operation of the relay. The ANN-based classification module has accurately diagnosed this as a 'BG' fault, hence instant trip signal issuance by the relay. This proves the ability of intelligent relays to isolate single-phase-to-ground faults fast and accurately. The conventional inverse-time relay was beaten by almost 0.7 ms earlier tripping action in a B-G fault scenario; hence more dynamic responsiveness is reflected.

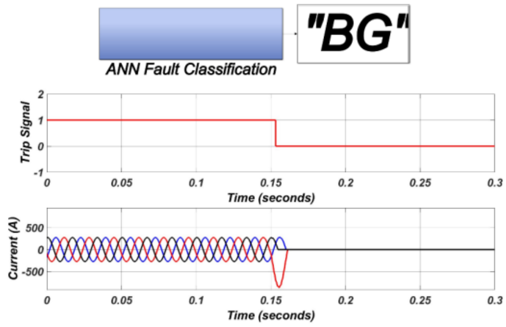

Fig. 13. Simulation results under B–G fault condition

5.2.3. Response to Single Line-to-Ground Fault (C–G)

A SLG (C–G) fault on phase C was applied at t = 0.15 s with a total simulation time of 0.3 s. It is seen in Fig. 14 that the phase-C current undergoes heavy distortion right from the instant of inception of fault, while the ANN-based intelligent relay successfully detects an abnormal condition. The classification module correctly identifies the type of fault as “CG” and hence immediate trip response from relay speaks strength of ANN-based scheme for accurate identification and clearance of SLG faults. The intelligent relay from the proposed system was above 1.25 ms faster in isolating the fault when compared with a normal inverse time relay, representing its speed as well as dependability under C-G fault conditions.

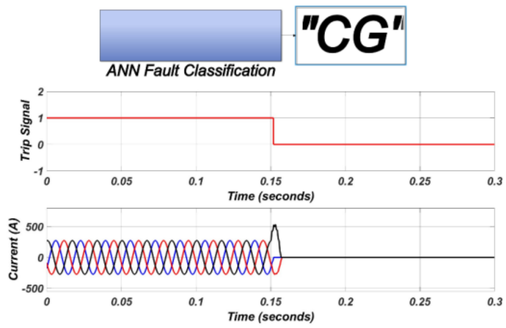

Fig. 14. Simulation results under C–G fault condition

5.2.4. Performance Under AB and AB-G Faults

At t = 0.15 s, AB and AB–G faults were initiated, with a total simulation time of 0.3 s. Phases A and B current disclosed a very high distortion while phase C did not disclose any significant effect up to the time of tripping. The relay based on ANN as in Fig. 15 accurately classifies disturbances as ‘AB’ and ‘AB-G’ and immediately issues trip signals; hence, speed and reliability are confirmed.

In reference to the conventional inverse-time relay, practically 0.6 ms tripping time for the AB/AB–G fault cases was realized by the ANN-based protection system, thereby validating further its rapid fault-clearing capability.

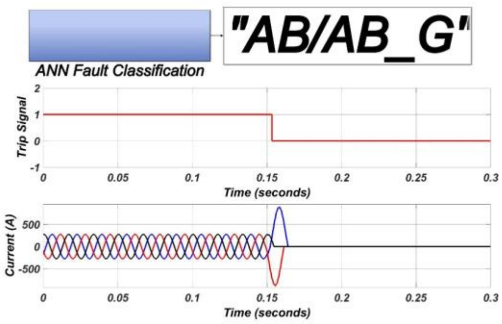

Fig. 15. Simulation results under AB/AB-G fault condition

5.2.5. Performance Under BC and BC-G Faults

At t = 0.15 s, a BC and BC-G fault is created that lasts for 0.3 seconds in total. Currents observed in figure 16 show great distortion and high magnitude of phase B and C currents after the inception of the fault while phase A remains unperturbed up to relay operation. The condition has been correctly identified by the ANN based classifier as “BC/BCG” and simultaneously a trip signal has been generated immediately by the intelligent relay corresponding to condition recognition. Intelligent relay response time was found to be approximately 1.5 ms less than conventional relays under identical conditions, thus confirming earlier tripping action as well as faster fault isolation under similar operating scenarios. The proposed scheme proves its accuracy in detecting unsymmetrical line faults during isolation.

5.2.6. Performance Under AC and AC-G Faults

An AC and AC–G fault was initialized at t = 0.15 s for a total simulation time of 0.3 s. In Fig. 17 it is seen that phases A and C acquire massive distortion and large magnitude increase immediately after the inception of the fault, whereas phase B remains as stable as before till tripping occurs. The ANN-based classification module detected this condition successfully as “AC/ACG” and intelligent relay issued trip signal in time also. In this case, the intelligent relay operated about 1.6 ms earlier than the conventional relay thus proves its dynamic response better and isolation capability faster under unsymmetrical fault condition. The results show how much reliable can be the developed approach in identifying unsymmetrical faults and clearing them with high accuracy.

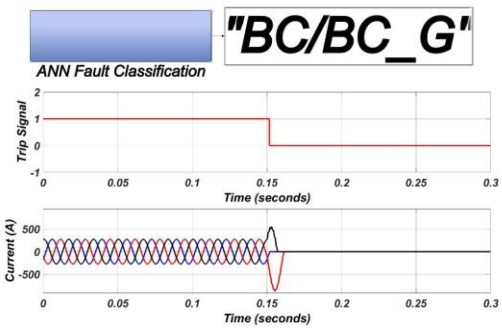

Fig. 16. Simulation results under BC/BC–G fault condition

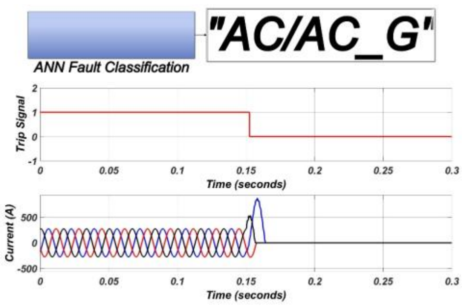

Fig. 17. Simulation results under AC/AC–G fault

5.2.7. Performance Under Three-Phase and Three-Phase-to-Ground Faults

At 0.15 seconds, both an ABC fault and an ABC–G fault were applied, and the overall simulation was conducted for 0.3 seconds. As shown in Fig. 18, the currents in all three phases exhibit severe distortion and magnitude increase immediately after the fault inception. The ANN-based classification module correctly recognized the condition as “ABC/ABCG” and the relay instantly generated a trip signal. It is observed that the intelligent relay initiated the tripping action about 0.5 ms earlier than the conventional relay, confirming its faster fault-clearing capability under symmetrical fault conditions. These results demonstrate the robustness of the proposed ANN-based relay in handling symmetrical faults and ensuring rapid isolation of the faulty section.

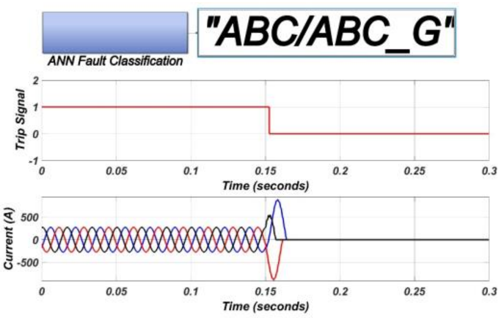

Fig. 18. Simulation results under ABC/ABC-G fault

6. QUANTITATIVE RESULTS, CONCLUSION, AND RECOMMENDATIONS

Presented in this paper is a new OCR based on ANN, intelligent, for use in detection and classification of faults chosen IEEE 9-bus transmission system. Two neural network modules compose the proposed scheme; one for detection of faults and the other for fault type classification. Excellent reliability and accuracy were proved by simulation and training results from the developed model. Results have given a correlation coefficient value near about $R \approx 0.993$ for the detection network and $R \approx 0.998$ for the classification network indicating very high learning ability besides generalization performance of such an intelligent protection system as proposed. The ANN-based relay detected as well as classified all major fault categories precisely-sl (SLG), (LL), (LLG), and (LLLG) faults-under various operating conditions with discrimination falling at minimum delays.

The intelligent relay has been proven in the time domain to be faster than conventional inverse-time relays, the difference being approximately 0.6ms for AG, 0.7ms for BG, 1.25ms for CG, 0.6ms for AB, and about 1.5ms for BC/BC-G and AC/AC-G faults plus about 0.5ms for ABC/ABC-G faults. This is very important proof of much better dynamic performance possible with even faster isolation achievable through the ANN-based relay being proposed.

Results confirm that the intelligent protection scheme efficiently overcomes the conventional limitations associated with (OCRs), such as sensitivity towards fault resistance, sluggish coordination, and inability to recognize the type of fault. The proposed framework based on ANN proved robustness and adaptability for integration within contemporary applications falling under the domain of smart grids requiring high levels of reliability as well as rapid responses. Although the scheme proposed by ANN requires comparatively more computation during offline training, in real-time operation its speed is extremely fast (less than 2 ms) accompanied by a very high degree of reliability. Consequently, any marginal increase in training cost will be fully justified by an improvement in detection accuracy and response speed compared with conventional OCRs.

Simulation results do not reflect accuracy and speed challenges like so many practical issues that are involved, for example, measurement noise as well as communication delays and parameter variations in power network components. Such issues should be addressed via hardware-in-the-loop testing and adaptive calibration to make sure that the proposed intelligent relay is reliable when working in real grid environments.

In conclusion, the enhanced ANN-based smart (OCR) gives a strong basis for cutting edge security frameworks. By consolidating speed, exactness, and versatility it sets up a reasonable way towards data-driven and self-learning handing-off innovations equipped for fulfilling the needs of developing force systems.

7. FUTURE WORK

The future work objective is to take the proposed ANN-based intelligent [OCR] outside of simulation by performing experimental validation on either a real-time digital simulator [RTDS] or perhaps a microcontroller-based hardware setup. This will practically verify the model's performance under actual grid operating conditions together with different fault scenarios.

Also, more work will look at adding in a full-on number check with usual marks like mean square error (MSE), mean absolute error (MAE), how right the class pick is, how exact it is, and how long it takes to answer. These marks will make sure there is a fair and repeatable check of how well the new ANN-based way works compared to other smart or normal protection methods.

Another promising direction is the setup of an adaptive retraining mechanism whereby the relay can self-update its parameters based on real-time data streams on dynamic power networks. Online learning algorithms will make the model more robust about grid parameter variations and fault conditions that evolve.

Further work shall also consider hybrid protection schemes in which neural networks are combined with the optimization algorithms, e.g. GA or PSO, for even higher speeds and reliability of fault classification. In the end, making a generalization of this proposed framework so that it can acquire real-time data from smart grid communication infrastructures and distributed energy sources would make the intelligent relay more scalable and practically deployable in actual modern interconnected power systems.

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