A Novel Algorithm to Mitigate Protection Challenges in a Distribution System Integrated with Inverter-Based Distributed Energy Resources

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Abstract*—To overcome global warming challenges due to fossil-fuels based generation, renewable distributed energy resources (DERs) like inverter based DERs (IBDERs) have been significantly integrated into distribution systems. Due to inverter controls, fault current values from IBDERs are considerably lower than that of conventional synchronous generators. The low fault current causes sensitivity issues in the overcurrent relay of IBDER which can create protection challenges. To overcome this issue, a new way of implementing machine learning based algorithm named Radial Basis Function Neural Network (RBFNN) will be proposed. This method will use the time series data to detect fault current contribution from IBDER fast and accurately. A distribution system case study with a recloser on the feeder between a feeder breaker and an IBDER breaker, is analyzed in this paper. The desired outcome is that the feeder breaker and recloser trip for faults between them. As such, the overcurrent relay at the IBDER should not operate for those faults to avoid any unnecessary outages to the customers between the recloser and IBDER. The proposed solution is to implement an RBFNN-based algorithm for both the recloser and the IBDER relay to allow for secure, sensitive, reliable, and fast operation. The RBFNN-based algorithm will trip the recloser instead of the IBDER breaker for any faults between the feeder breaker and recloser. However, this algorithm will block recloser operation for faults between the recloser and IBDER. PSCAD simulations were performed for the distribution system case study described, providing fault scenarios to demonstrate the benefits of this algorithm. This paper also shows the coordination of RBFNN algorithms between the recloser and IBDER for faults between the feeder breaker and recloser to avoid miscoordination.

Keywords— IBDER; RBFNN; Protection; Recloser; Fault

I. INTRODUCTION

The usage of DERs such as Solar Photovoltaics (P.V.), Wind Turbines, Fuel Cells, etc., has increased significantly recently. They are small generation units and storage technologies that provide electric capacity wherever it is needed and may help in reducing the cost of power system augmentation [1]. As such, transmission and distribution systems will be experiencing impacts due to the high penetration of DERs [2].

Rapid development of power electronics technologies has led to significant growth of Inverter Based DER or IBDER [3]. Using IBDER is more economical and has the environmental benefits of reducing greenhouse gas emissions [4]. However, they create protection challenges in a distribution system due to low shot-circuit fault current contribution [5]. The fault current fed from IBDER is only 1.2 to 1.5 times its rated current [6], compared to the 5 times rated current of conventional synchronous generation. IBDER's low fault current can be less than the desired pickup setting of an overcurrent relay. Therefore, it can create protection sensitivity issues leading to protection challenges [7]. Even if the fault current of IBDERs is higher than the pickup setting, the inverse time overcurrent relay operation will be slow due to the low fault current [8]. Therefore, the fault can remain on the system for a long time, cause significant damage to the costly electrical equipment [9], and be a safety hazard to nearby populations.

Due to the protection sensitivity issue in IBDER relay, this paper proposes a new way of implementing a machine learning based algorithm: Radial Basis Function Neural Network (RBFNN). This artificial neural network uses the time series current signal to detect a fault in the system. Its accuracy depends on how the algorithm is programmed in the training period. This paper studies the algorithm applied in a distribution system where a protective recloser is connected between the feeder breaker and IBDER. Ideally, the overcurrent element of the feeder breaker relay and protective recloser should operate to trip during the fault occurrence between them. An RBFNN algorithm programmed and implemented in the IBDER relay could trip before the protective recloser for any faults in the feeder creating outage issues for the customers between protective recloser and IBDER. To prevent such miscoordination, this paper proposes an RBFNN algorithm for both the recloser and IBDER protective relay. The algorithms are programmed so that it trips the feeder breaker and protective recloser for any faults between them. However, if a fault occurs between the protective recloser and IBDER, the RBFNN algorithm associated with the recloser should not operate. In this case, the overcurrent element should trip the recloser to clear the fault. For faults between the feeder breaker and the protective recloser, the overcurrent element of the utility feeder breaker and the RBFNN algorithm of the recloser should operate to clear the fault. However, since the RBFNN algorithm is also implemented in the IBDER relay, the miscoordination between the IBDER and protective recloser can still exist. To resolve this issue, a delay is recommended for the trip logic of the IBDER allowing the protective recloser to operate before the IBDER.

The distribution system with feeder breaker, protective recloser and IBDER was modeled and simulated using PSCAD software. The IBDER is modeled as a grid tied inverter. The RBFNN algorithm was implemented for the protective recloser and IBDER relays using Python programming language. The code was written in PyCharm code editor.

II. Modelling and Description of a Distribution System with IBDER

The distribution system has been designed in PSCAD simulation software as per the schematic shown in Fig. 1. It contains a feeder breaker (CB1) from a 12.47kV source, a feeder (6 miles in length), a protective recloser, an IBDER breaker (CB2) and an IBDER which is a grid-tied photovoltaic inverter (P.V. inverter) of around 300kW. In this model, the P.V. inverter shown in Fig. 2 comprises a P.V. array, a boost converter, and an inverter. The P.V. array transforms solar power to D.C. power by solar cells using semiconductor material electronics characteristics of P-V conversion [10]. Its operation depends on the weather condition mainly, temperature and illumination [11]. The P.V. array is connected to a DC/DC boost converter, which converts low D.C. power to a high D.C. power required by the load [12]. The output of a P.V. array is an unregulated D.C. power due to fluctuation in temperature and radiation [13]. Therefore, a boost converter regulates and controls the D.C. power to meet the desired regulated result [14]. The output of a boost converter is connected to an inverter, which tracks the maximum D.C. power that can be extracted from the P.V. array [15]. The inverter is used to interconnect renewable energy and the grid and converts D.C. power produced by renewable energy sources into A.C. power used in domestic and residential areas [16]. To supply power to residential areas without energy, grid-tied inverter facilitates utility power pulling from the grid [17]. As the inverter is used to interconnect renewable energy to the A.C. utility grid, the harmonics of current flowing into the grid increases. Therefore, LCL filter is used to reduce the total harmonic distortion.

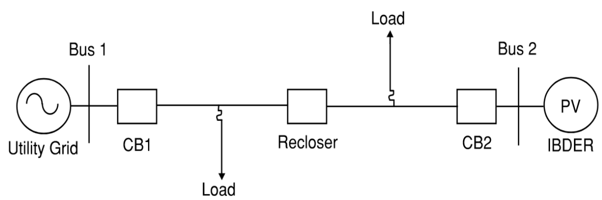

Fig. 1: Schematic of Distribution Network with IBDER

The inverter is controlled by a dual-loop control strategy where the outer loop controls the output D.C. voltage of boost converter, and the inner loop controls the current flowing into the grid.

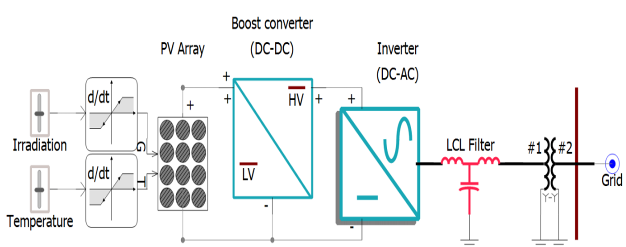

Fig. 2: PSCAD Modelling of P.V. Inverter

III. Impact of IBDER on Distribution Protection

The current control design of the inverter lowers the short circuit fault current to protect the semiconductor devices in the inverter [18]. However, it affects the protection sensitivity of the protective device during various fault scenarios. In the schematic shown in Fig. 3, the feeder breaker CB1 is controlled by a protective relay R1, a microprocessor-based controller controls the recloser, and another protective relay R2 controls the IBDER breaker CB2. There are fused loads to both sides of the recloser.

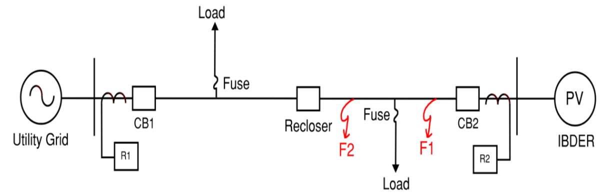

Fig. 3: Schematic of Distribution Network showing faults between recloser and IBDER

If faults like F1 and F2 occurs between the recloser and IBDER shown in Fig. 3, the overcurrent element of a recloser relay should operate to trip the recloser. However, the fault current fed from IBDER's circuit breaker CB2 could be less than the pickup setting of the overcurrent element of relay R2 due to the control design of the inverter. Therefore, the relay R2 might not operate, and the fault might remain in the system. In the PSCAD model of a distribution feeder with IBDER, simulations were performed for various faults. In this model shown in Fig. 4, a single-line-to-ground fault is created between the recloser and the IBDER at 5 sec for a duration of 2 sec.

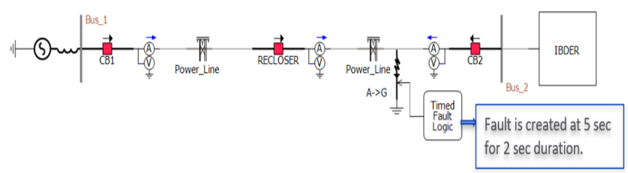

Fig. 4: PSCAD Model of Distribution Feeder with IBDER

The short circuit fault current from IBDER plotted in Fig. 5 shows that it is around 1.27 times the rated current.

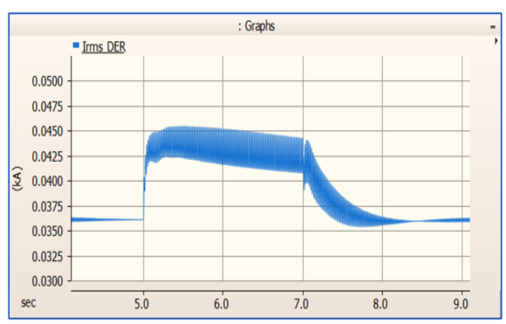

Fig. 5: Fault Current from IBDER

IV. Radial Basis Function Neural Network

The low fault current from IBDER creates sensitivity issues in IBDER relay R2. Therefore, a Machine Leaning

(ML) method was studied to overcome this problem. ML is a type of Artificial Intelligence (AI) which creates algorithms to imitate the way that humans learn, gradually improving its accuracy. It can be used in speech recognition, image recognition, computer vision, data classification etc. Artificial neural networks (ANNs) are a subset of ML whose name and structure are inspired by the human brain. It mimics the way the neurons provide signal to one another. In this paper, an artificial neutral network named Radial Basis Function Neutral Network (RBFNN) was implemented to improve the sensitivity of IBDER relay by using the time series data. RBFNN is a feed-forward neutral network which has three layers (shown in Fig. 6): input layer, hidden layer, and output layer [19, 20]. The input layer provides data to the neurons in the hidden layer, the hidden layer has neurons with radial basis function and the output layer consist of data which are linearly classified [21].

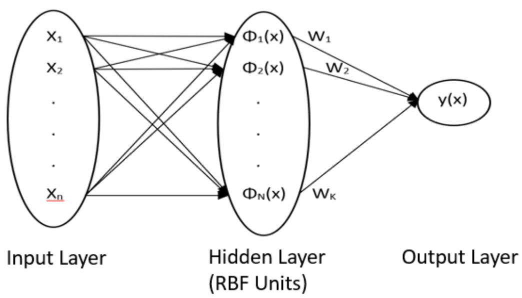

Fig. 6: Structure of RBFNN

The RBFNN uses the linear combination of radial basis functions. There are various RBF functions which can be utilized but we have used Gaussian function in our work due to its high efficiency. The Gaussian function depends on the Euclidean distance between the input and the centers.

A. RBFNN Matrix and Weight Calculation:

The RBFNN algorithm using Gaussian function, $\Phi(x, \mu)$ can be expressed as:

$$\Phi(||x - \mu||) = \exp(-\beta||x - \mu||^2) \quad (1)$$

Here, x is the input, μ is the center and β is the adjustment factor (β is 1 by default) in the algorithm.

The output of the algorithm, y is expressed as:

$$y_n = \sum_{k=0}^{K} W_k\, \Phi(||x_n - \mu_k||) \quad (2)$$

Here, y is the output, W is the weight, N is the number of sample and K is the number of centers of the algorithm.

The RBFNN matrix is expressed as:

$$\underbrace{\begin{pmatrix} y_1 \\ y_2 \\ . \\ . \\ y_n \end{pmatrix}}_{y} = \underbrace{\begin{pmatrix} \exp(-\beta||x_1 - \mu_1||^2 & .... & \exp(-\beta||x_1 - \mu_K||^2 \\ \exp(-\beta||x_2 - \mu_1||^2 & .... & \exp(-\beta||x_2 - \mu_K||^2 \\ & . & \\ & . & \\ \exp(-\beta||x_n - \mu_1||^2 & .... & \exp(-\beta||x_n - \mu_K||^2 \end{pmatrix}}_{\Phi} \underbrace{\begin{pmatrix} W_1 \\ W_2 \\ . \\ . \\ W_K \end{pmatrix}}_{W} \quad (3)$$

The weight of RBFNN, W is calculated as:

$$W = (\Phi^T\Phi)^{-1}\Phi^T y \quad (4)$$

B. Training of RBFNN Algorithm:

The RBFNN network is first trained offline. During the training period, from the recorded data of current, both healthy and faulty rms current data of IBDER are collected within 2 sec intervals from PSCAD model. Statistical features like of Mean Value, Standard Deviation, Skewness and Kurtosis are calculated from the electrical current data and fed into the algorithm.

(i). Mean (M): Average of all the values in the data set.
(ii). Standard Deviation (SD): Measure of degree of dispersion of data in relation to the mean.
(iii). Skewness (S): Measure of symmetry, or more precisely, the lack of symmetry.
(iv). Kurtosis (K): Measure of shape of the data to determine whether the data are heavy tailed, or light tailed relative to a normal distribution.

We have trained the network and created an algorithm using data from fault simulations F1 and F2, and from simulations of healthy system conditions - H1 and H2. Hence, the inputs of the algorithm are:

$$x_1 = (M_{F1}, SD_{F1}, S_{F1}, K_{F1}) \quad (5)$$

$$x_2 = (M_{F2}, SD_{F2}, S_{F2}, K_{F2}) \quad (6)$$

$$x_3 = (M_{H1}, SD_{H1}, S_{H1}, K_{H1}) \quad (7)$$

$$x_4 = (M_{H2}, SD_{H2}, S_{H2}, K_{H2}) \quad (8)$$

The centers of the algorithm can be either chosen from the inputs or any point close to the inputs (neigboring points). Here, we have considered x_2 and x_4 as the two centers.

$$\mu_1 = x_2 \quad (9)$$

$$\mu_2 = x_4 \quad (10)$$

The number of weights in the matrix equals the number of centers. Since the number of centers is two in this case, the weights of the algorithm can be considered as W_1 and W_2. As there are four inputs in the algorithm, there will be four outputs. For data labeled as a fault condition, the output (y_1, y_2) is set as '1'; for data labeled as system healthy, the output

(y_3, y_4) is set as ‘0’. Knowing the algorithm’s inputs, centers and outputs allows us to calculate the weights using the training data and the matrix method shown in equation (11).

$$\begin{pmatrix} \Phi(x_1,\mu_1) & \Phi(x_1,\mu_2) \\ \Phi(x_2,\mu_1) & \Phi(x_2,\mu_2) \\ \Phi(x_3,\mu_1) & \Phi(x_3,\mu_2) \\ \Phi(x_4,\mu_1) & \Phi(x_4,\mu_2) \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{pmatrix} \quad (11)$$

Features (P.U)	**Training Data (Approximate Range)**			
	F1	**F2**	**H1**	**H2**
Mean	(1.2 - 1.45)	(1.2 - 1.45)	(0.95- 1.05)	(0.95- 1.05)
Standard Deviation	(0.1 - 0.15)	(0.1 - 0.15)	(0.01 - 0.03)	(0.01 - 0.03)
Skewness	(-2.5 - -0.5)	(-2.5 - -0.5)	(-0.1 - 0.2)	(-0.1 - 0.2)
Kurtosis	(2 - 6)	(2 - 6)	(-3 - -1)	(-3 - -1)
Label (Output)	1 (Trip Operation)	1 (Trip Operation)	0 (No operation)	0 (No operation)

Table I: Training Data of RBFNN for IBDER Relay

Table I shows the training data of the RBFNN algorithm in the IBDER relay. The convention in this table, is to trip the IBDER breaker for an output labelled as ‘1’ but to refrain from tripping when labelled ‘0’.

C. Testing of RBFNN Algorithm:

After calculating the weights of the algorithm during the training period, this neural network can be tested using the calculated weights and any random current data (both faulty and healthy) to know its efficiency. Suppose the algorithm’s output is not showing the desired result during the testing period (i.e., output is not ‘1’ during fault). The adjustment factor β can be calculated using the computed weights and the desired output. The newly calculated β value can then be used in the testing period to redetermine the algorithm’s output. This step can be repeated until the desired result is achieved for both faulted and unfaulted (healthy) scenarios. The flow chart of the RBFNN algorithm is shown in Fig. 7.

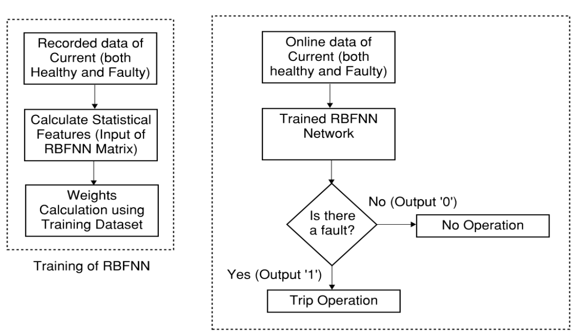

Fig. 7: RBFNN Algorithm

V. COORDINATION ISSUE BETWEEN IBDER AND RECLOSER

For faults like F3 and F4, occurring between the feeder breaker and the recloser as shown in Fig. 8, the desired outcome is that the overcurrent element of feeder breaker relay R1 and protective recloser relay should operate to trip circuit breaker CB1 and the recloser respectively.

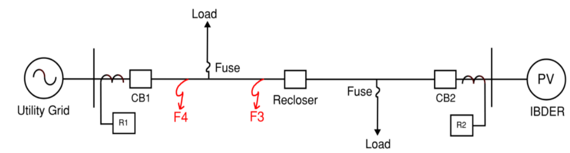

Fig. 8: Schematic of Distribution Network showing faults between feeder breaker and recloser

However, due to the implementation of the RBFNN algorithm in the IBDER relay and low fault current flowing through the recloser, the relay R2 may operate very fast and trip circuit breaker CB2 before the recloser relay can operate. This creates a coordination issue between the recloser and the IBDER, that may cause unnecessary outages to customers between them. The RBFNN algorithm can be implemented for both recloser relay and IBDER relay to mitigate this problem and instead trip only CB1 and recloser faults like F3 and F4. On the other hand, the algorithm in the recloser relay should be blocked for any faults (forward fault) between the recloser and IBDER. For faults F1 and F2 (Fig. 3), the overcurrent element of the recloser should operate. In the PSCAD model shown in Fig. 9, the study is done for a single-line-to-ground fault between the feeder breaker and the recloser.

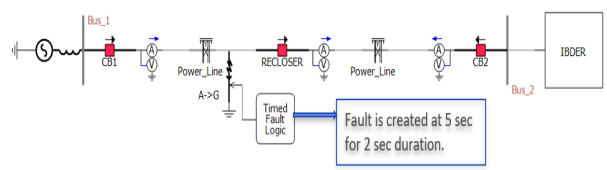

Fig. 9: PSCAD Model of Distribution Feeder with IBDER

The short circuit fault current from the recloser plotted in Fig. 10 shows a very low fault current for faults like F3 and F4.

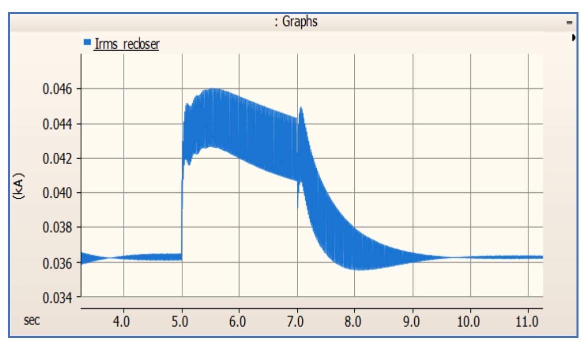

Fig. 10: Fault Current from Recloser

Fig. 11 shows the RBFNN matrix of both IBDER and recloser. These matrices show that the IBDER relay is tripping as expected for data simulated under fault conditions, while the recloser relay is tripping only for reverse faults (F3 and F4).

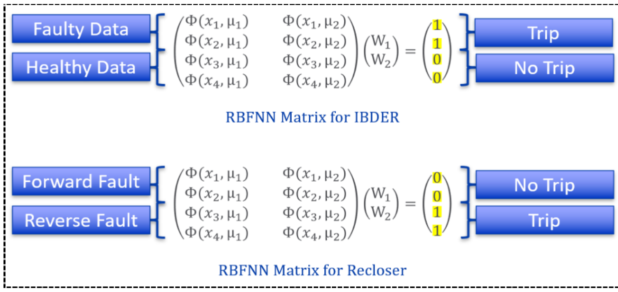

Fig. 11: RBFNN Matrix of IBDER and Recloser

If the RBFNN algorithm is implemented in both the recloser and the IBDER relays, there could be a race or coordination issue between them for faults F3 and F4 of Fig. 8. Therefore, a few cycles of delay can be implemented in the trip logic of the RBFNN algorithm in the IBDER relay to allow the recloser to operate before the IBDER relay. Delaying a trip will allow the P.V. to supply power to the customers between the recloser and IBDER after CB1 and reclosers have tripped.

VI. Conclusion

Renewable distributed energy resources like IBDERs have been significantly integrated into the distribution systems. However, during fault conditions, the low fault current contribution from an IBDER can create protection sensitivity issues in overcurrent elements that might allow the fault to remain in the system longer than desired. An artificial neural network named Radial Basis Function Neural Network (RBFNN) has been shown to overcome this protection challenge. This algorithm used the time series data to make the IBDER relay fast and accurate. This neural network is first trained using the simulated electrical current from a PSCAD model during faulted and healthy conditions. It is then tested using electrical current data from randomly sampled simulations to see the desired result. The RBFNN algorithm is also implemented for a recloser relay in the system to clear faults which are between feeder breaker and recloser to prevent outages to the customers between IBDER and recloser. However, this algorithm should not operate to allow overcurrent element to trip for faults between recloser and IBDER. The coordination issue between IBDER relay and recloser relay has been described for faults between feeder breaker and recloser. The delay logic can be implemented at the output of RBFNN algorithm of IBDER to resolve this issue. The system is modelled in PSCAD and the RBFNN algorithms are programmed using Python Language.

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