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

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Presentation Overview

- Introduction to Distributed Energy Resources (DERs)
- Inverter Based Distributed Energy Resources (IBDERs)
- Impacts on Protection due to IBDERs
- Introduction to Machine Learning and Neural Network
- Radial Basis Function Neural Network (RBFNN)
- Training Dataset
- Analysis of a Distribution Network for various faults
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- Coordination Issue between Recloser and IBDER Relays
- Delay Logic of IBDER Relay
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Introduction to Distributed Energy Resources (DERs)

- Distributed Energy Resources (DERs) are smaller energy generation units and storage technologies that provide electric capacity wherever it is needed. They are usually located close to the load centers.

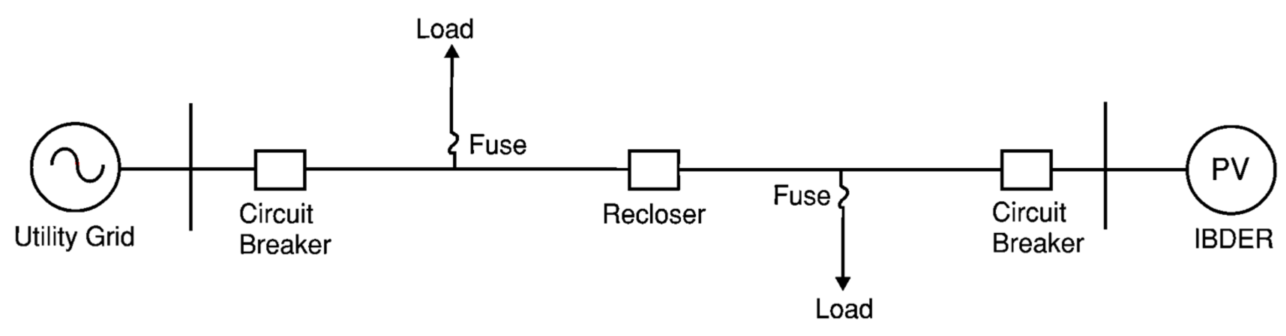
May be connected to local electric power grid or in stand-alone applications.

Technologies including Fuel Cells, Photovoltaics (PV), Wind Turbines, etc.

May help in reducing the cost of power system augmentation.

Inverter Based Distributed Energy Resources (IBDERs)

- To overcome the challenges on global warming due to fossil-fuels based generation, renewable DERs have been significantly integrated into distribution systems.
- These DERs can be integrated into the distribution system using power electronics-based inverters. They are called Inverter Based Distributed Energy Resources (IBDERs).



Schematic of Distribution Network with IBDER

Impacts on Protection due to IBDERs

- During a short-circuit fault, the current contribution from IBDER is very low due to strong control of the inverters, which differs from the conventional synchronous generators.

DERs	Fault current as a function of rated current
Synchronous Generator	5x
IBDER	1.5x

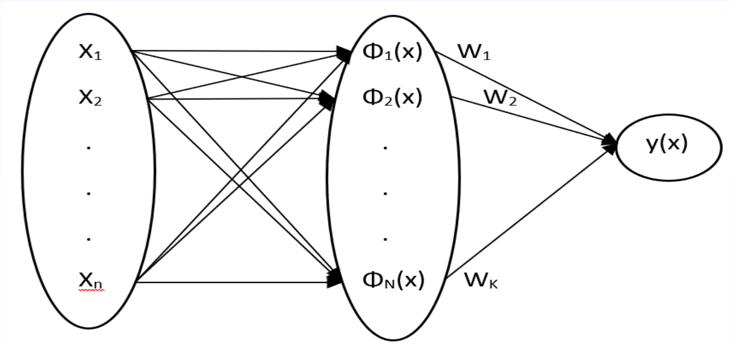
- The lower fault current from IBDER can be lower than the pickup current setting of an overcurrent element protecting an IBDER. This can create sensitivity issues which lead us to protection challenges.
- Even if the IBDER fault current is higher than the desired pickup setting, an inverse time overcurrent relay will operate slowly due to a very low fault current. Therefore, the fault can remain on the system longer than desired.
- Such protection challenges can cause significant damage to costly electrical devices.

Introduction to Machine Learning and Neural Network

- Machine learning (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.
- To improve the accuracy and efficiency of the neural network, training datasets are created to train the network.
- Once the network is well trained, they become a powerful tool in artificial intelligence which allows us to classify and cluster data at a high velocity.
- The types of neural network are: Radial Basis Function Neural Network (RBFNN), Recurrent Neural Network, Convolutional Neural Network etc.

Radial Basis Function Neural Network (RBFNN)

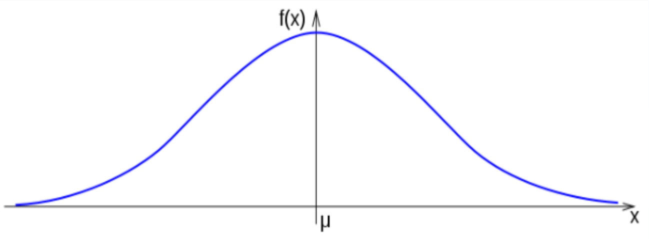
- To overcome this protection issue due to IBDERs, a new way of implementing machine learning based algorithm named Radial Basis Function Neural Network (RBFNN) will be proposed.
- This method will use the time series data to detect the fault current contribution from IBDER fast and accurately.
- RBFNN is a neural network which has three layers: Input Layer, Hidden Layer and Output Layer. It uses the linear combination of radial basis functions.
- The radial basis functions like Gaussian function depends on the Euclidean distance between the input and the centers.



Input Layer

Hidden Layer (RBF Units)

Output Layer



Gaussian Curve

RBFNN Matrix

RBFNN method using Gaussian function can be expressed as:

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

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

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

If $\Phi^T\Phi$ is invertible, $\boxed{W = (\Phi^T\Phi)^{-1}\Phi^T y}$

x ➡ Input
μ ➡ Center
β ➡ Adjustment factor
y ➡ Output
N ➡ Number of samples
K ➡ Number of centers
W ➡ Weight

Number of centers, K should always be less than number of samples, N.

Training Dataset

- In this neural network, a training dataset is generated for the offline training of the RBFNN.
- From the recorded data of current, both healthy and faulty data are collected within some time interval.
- Many statistical features (like Mean Value, Standard Deviation, Skewness and Kurtosis) can be used in the training dataset.
- Typically, the output of the RBFNN in the training dataset is labeled as ‘1’ for data classified as fault and ‘0’ for data classified as system normal/healthy.
- The RBFNN model is trained using a dataset generated in PSCAD to approximate the feature mappings of the current data in both normal and fault situations.
- The weights of this neural network are calculated based on the input and output data during the training dataset.
- After training, the network can be tested using healthy and faulty data to see whether a desired result is achieved or not.

Impact of Adjustment Factor, β on Network

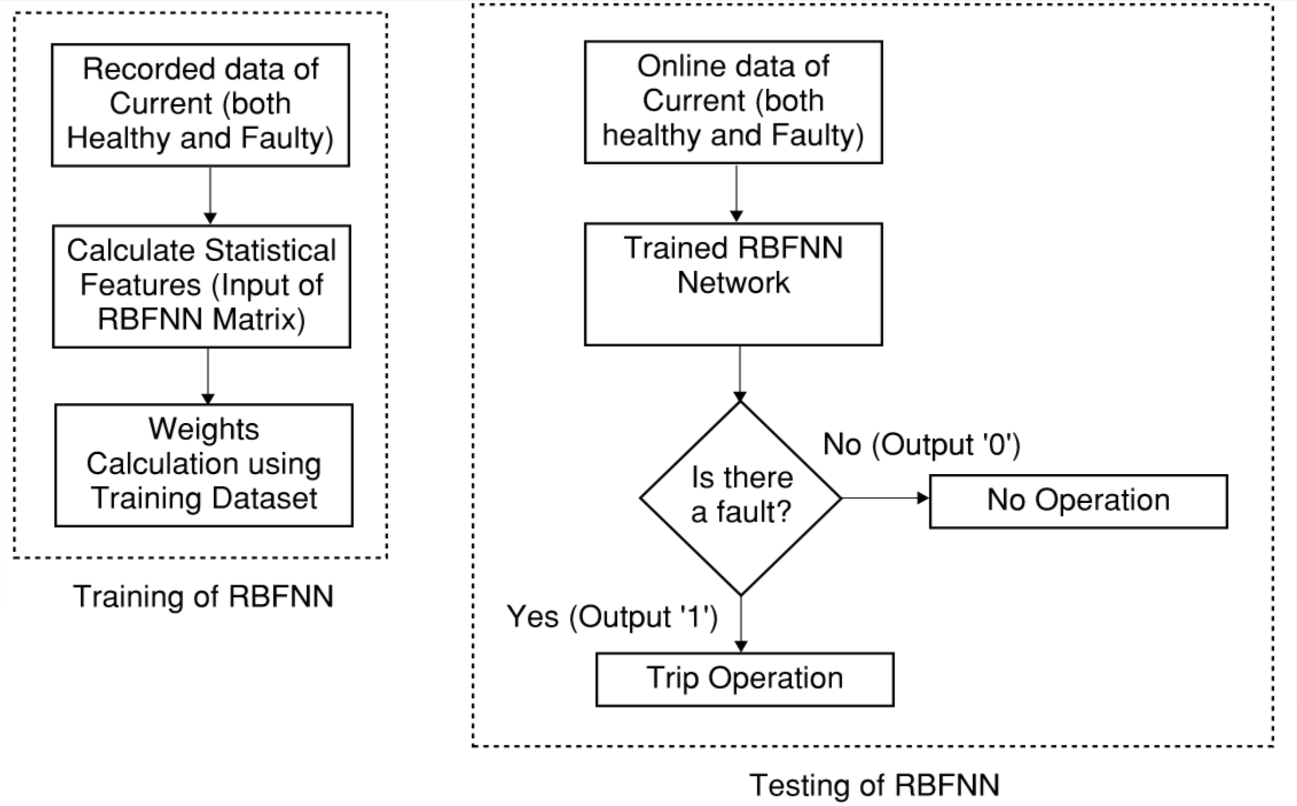
- The adjustment factor, β can be 1 (by default).
- In testing phase, if the output of the network during fault is not exactly 1 (like 0.8 or 0.9), then by using the weights (calculated in training phase) and ‘1’ as output, β can be calculated to converge the equation.

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

$$\boxed{y_n} = \sum_{k=0}^{K} \boxed{W_k} \exp\left(-\beta \boxed{||x_n - \mu_k||^2}\right)$$

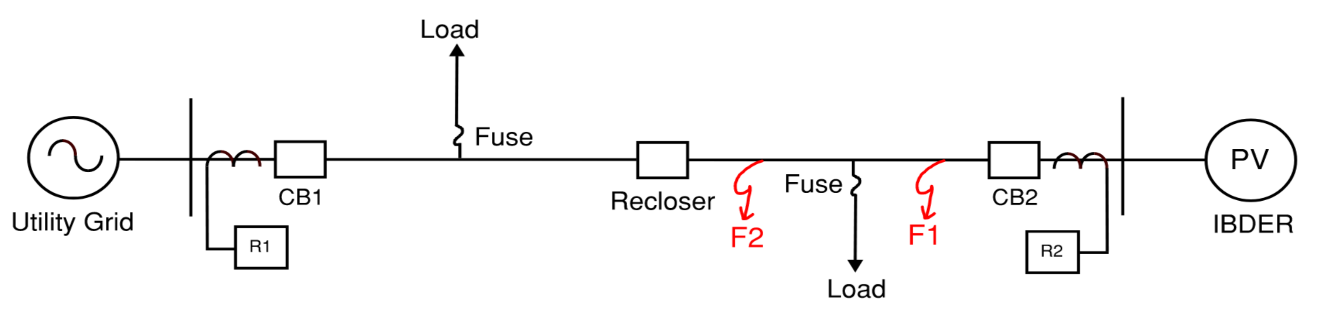
Calculate

Flow Chart of RBFNN Algorithm



Analysis of a Distribution Network for Faults F1 and F2

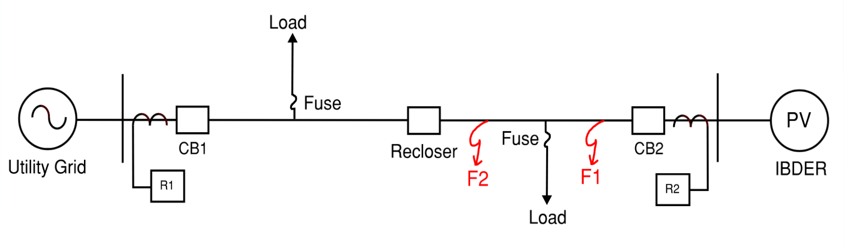
- For Faults F1 and F2, the overcurrent element of a recloser relay operates to trip the recloser.
- However, the fault current fed from circuit breaker CB2 could be less than the pickup setting of overcurrent element of relay R2. This challenges traditional protection methods.
- Therefore, the RBFNN algorithm can be applied for relay R2 (IBDER Relay).



Training Dataset of IBDER Relay R2 for Faults F1 and F2

- RMS Current for both healthy and faulty conditions are measured.
- For currents taken in both system fault and system healthy conditions, all the statistical features can be calculated.

Statistical Features	Training Data (Approximate Range)			
	Fault Current F1	Fault Current F2	Healthy Current H1 (Summer)	Healthy Current H2 (Winter)
Mean Value (p.u.) (M)	(1.3 - 1.45)	(1.3 - 1.45)	(0.95 - 1.05)	(0.95 - 1.05)
Standard Deviation (p.u) (SD)	(0.1 - 0.15)	(0.1 - 0.15)	(0.01 - 0.03)	(0.01 - 0.03)
Skewness (p.u) (S)	(-0.5 - -2.5)	(-0.5 - -2.5)	(-0.1 - 0.2)	(-0.1 - 0.2)
Kurtosis (p.u) (K)	(2 - 6)	(2 - 6)	(-3 - -1)	(-3 - -1)
Label (Output)	1 (Trip Operation)	1 (Trip Operation)	0 (No operation)	0 (No operation)



RBFNN Equations Using Statistical Features

- Inputs of the Equations:
  $x_1 = (M_{F1}, SD_{F1}, S_{F1}, K_{F1})$
  $x_2 = (M_{F2}, SD_{F2}, S_{F2}, K_{F2})$
  $x_3 = (M_{H1}, SD_{H1}, S_{H1}, K_{H1})$
  $x_4 = (M_{H2}, SD_{H2}, S_{H2}, K_{H2})$

- Centers (μ) are chosen from the inputs. Let's say x_2 and x_4 are the two centers. Therefore, $\mu_1 = x_2$ and $\mu_2 = x_4$.

- Number of weights are equal to the number of centers. Since the number of centers are two in this case, the weights can be W_1 and W_2.

- Since there are four inputs, there will be four outputs. For healthy data, the output is set as '0' and for faulty data, the output is set as '1'. Therefore, the outputs are:
  $y_1 = 1$, $y_2 = 1$, $y_3 = 0$ and $y_4 = 0$.

- The weights (W_1 and W_2) are calculated based on these data using Matrix method.

RBFNN Algorithm for Faults F1 and F2

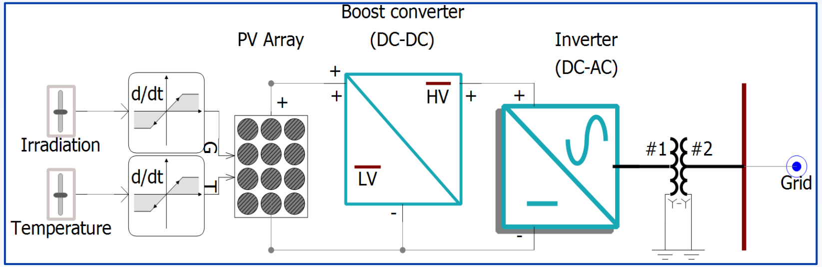
- The weights W_1 and W_2 are calculated using this matrix equation.

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

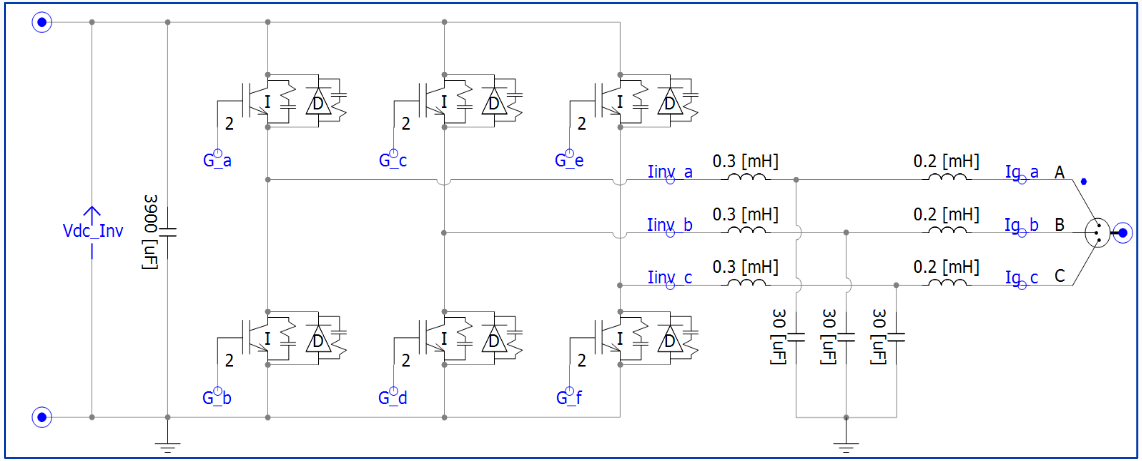
$$\begin{pmatrix} \Phi(x_1, \mu_1) & \Phi(x_1, \mu_2) \\ \Phi(x_2, \mu_1) & \Phi(x_2, \mu_2) \\ \Phi(x_3, \mu_1) & \Phi(x_3, \mu_2) \\ \Phi(x_4, \mu_1) & \Phi(x_4, \mu_2) \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

- After calculating the weights, the neural network can be tested using any random current data (both healthy and faulty) to know its efficiency.

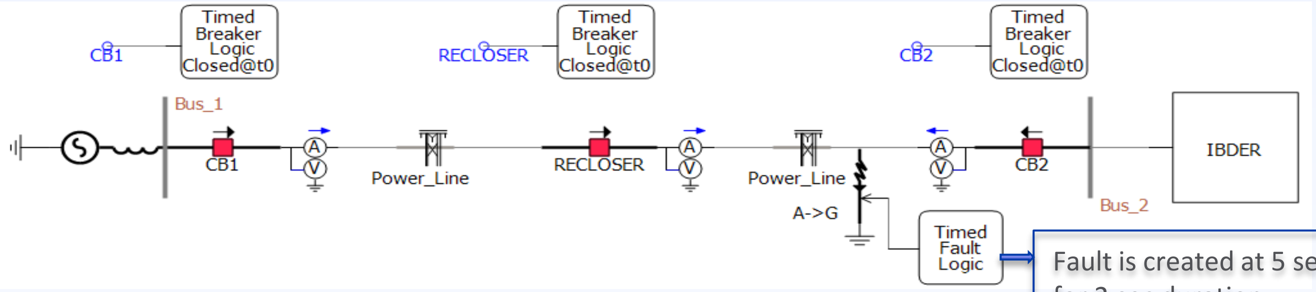
PV Inverter Model in PSCAD



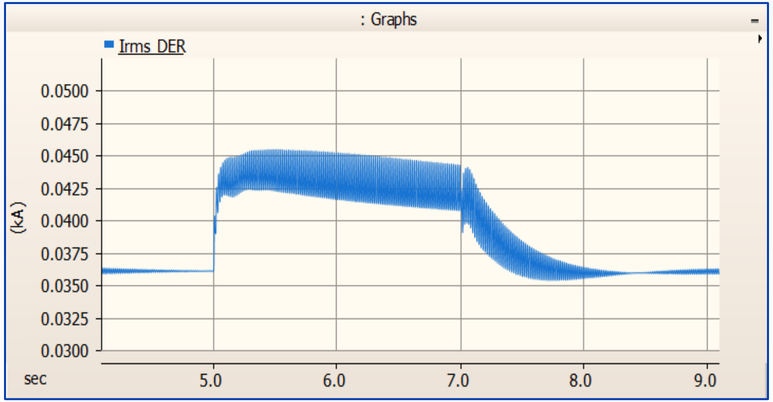
In this model, the PV Inverter is composed of a PV array, a boost converter, and an inverter with LCL filter.



PSCAD Study



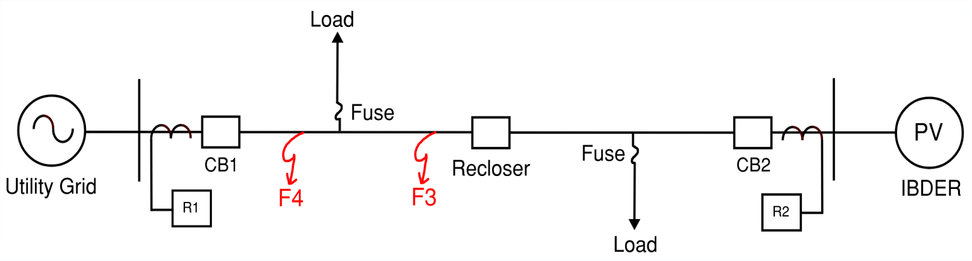
Fault is created at 5 sec for 2 sec duration.



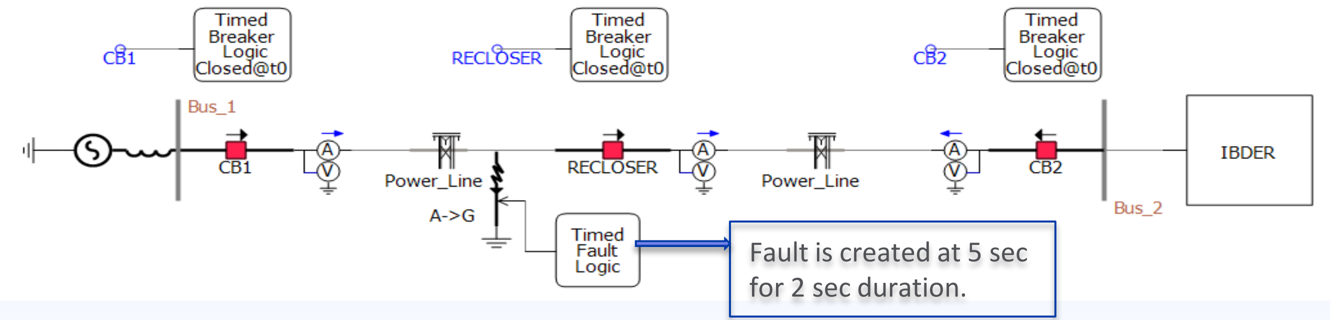
Fault current from the IBDER (around 1.3 times the rated current)

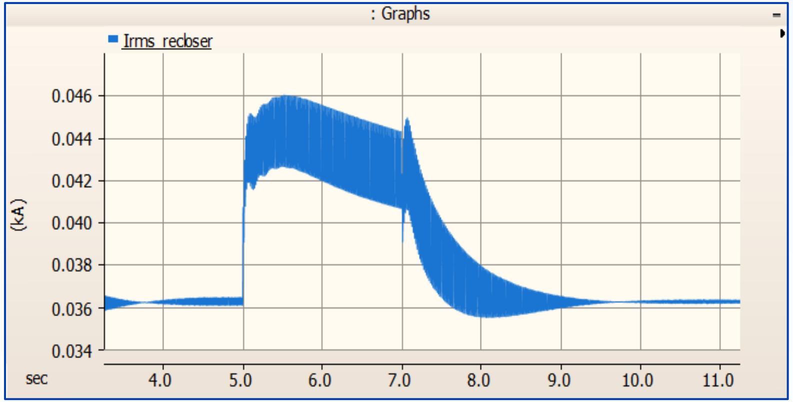
Analysis of a Distribution Network for Faults F3 and F4

- For Faults F3 and F4, ideally the overcurrent element of feeder breaker relay and recloser relay should operate to trip CB1 and recloser respectively.
- However, due to the implementation of RBFNN algorithm, the IBDER relay will operate very fast to trip CB2 before the recloser relay.
- This can cause unnecessary outages to the customers between recloser and IBDER.
- To avoid such operation, the RBFNN algorithm can be implemented for both recloser relay and IBDER relay such that for faults like F3 and F4, only CB1 and the recloser are tripped instead of CB2.
- The RBFNN algorithm of recloser relay will be blocked for any faults between the recloser and IBDER.



PSCAD Study





Fault current from the recloser

RBFNN Matrix for IBDER and Recloser

Faulty Data

Healthy Data

$$\begin{pmatrix} \Phi(x_1,\mu_1) & \Phi(x_1,\mu_2) \\ \Phi(x_2,\mu_1) & \Phi(x_2,\mu_2) \\ \Phi(x_3,\mu_1) & \Phi(x_3,\mu_2) \\ \Phi(x_4,\mu_1) & \Phi(x_4,\mu_2) \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

Trip

No Trip

RBFNN Matrix for IBDER

Forward Fault

Reverse Fault

$$\begin{pmatrix} \Phi(x_1,\mu_1) & \Phi(x_1,\mu_2) \\ \Phi(x_2,\mu_1) & \Phi(x_2,\mu_2) \\ \Phi(x_3,\mu_1) & \Phi(x_3,\mu_2) \\ \Phi(x_4,\mu_1) & \Phi(x_4,\mu_2) \end{pmatrix} \begin{pmatrix} W_1 \\ W_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 1 \end{pmatrix}$$

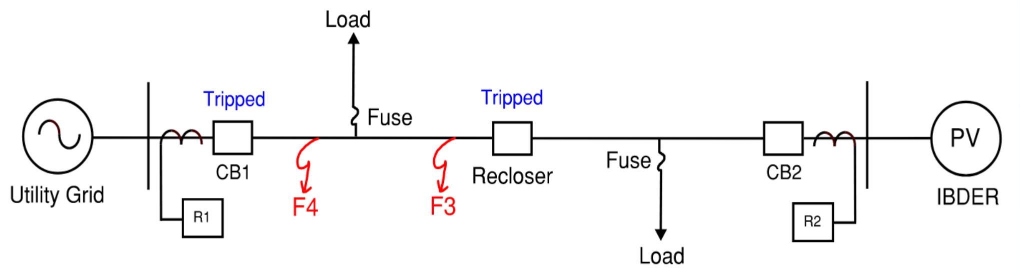
No Trip

Trip

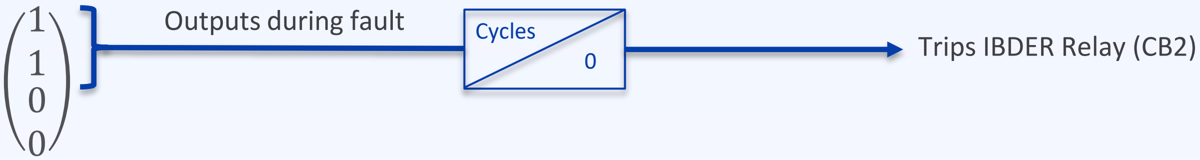
RBFNN Matrix for Recloser

Coordination Issue between Recloser and IBDER Relays

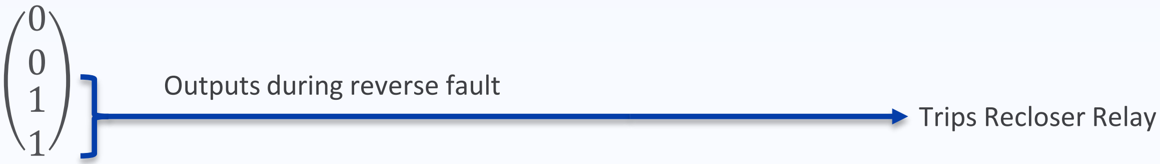
- If RBFNN algorithm is implemented in both recloser and IBDER relays, there could be a race or coordination issue between them for faults like F3 and F4.
- Therefore, a logic should be implemented to allow the recloser to operate before IBDER relay for such faults.
- A timer of few cycles can be added at the RBFNN output of IBDER relay which will make the IBDER relay to operate little slow compared to recloser relay.
- This will allow the PV to supply power to the customers between recloser and IBDER after CB1 and reclosers are tripped.



Delay Logic of IBDER Relay



IBDER Relay is Tripped after few cycles.



Recloser Relay is Tripped immediately for reverse faults.

Conclusions

- Renewable distributed energy resources (DERs) like inverter based DERs (IBDERs) have been significantly integrated into the distribution systems.
- The low fault current contribution from IBDER creates sensitivity issues in the overcurrent relay of IBDER which can cause protection failure.
- To overcome this issue, setting method inspired by the machine learning algorithm RBFNN has been proposed, with each RBFNN set according to the location as inspired by training methods used in ML.
- RBFNN algorithm uses the time series data to detect the fault current contribution from IBDER fast and accurately.
- The RBFNN network is first trained using statistical features and then tested using random current data (both healthy and faulty).
- The RBFNN matrix and equations for IBDER and Recloser relays has been shown.
- The coordination issue between IBDER relay and recloser relay has been described for faults between feeder breaker and recloser.
- The delay logic of IBDER relay can overcome the coordination issue.
- The system is modelled in PSCAD and the RBFNN algorithm is programmed using Python Language.

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Thank you Everyone.

Any Questions?