Chapter 5

FAULT EVENTS CLASSIFICATION USING ENSEMBLE & DEEP LEARNING TECHNIQUES

5.1 Introduction

The ensemble learning technique is an efficacious mechanism for enhancing the robustness and the precision of the base individual classifier models. The idea is to train multiple base models and then integrate the decisions of all models for making the final verdict. The deep learning technique which is an advanced branch of ML is also gaining grounds in various research applications due to its higher accuracy, generalization capability, and competency of handling large dataset. The application of ensemble and deep learning algorithms for fault events identification in series compensated transmission networks has been described in this chapter. Further, the viability and the robustness of the proposed ensemble and deep learning based fault ascertaining scheme is analyzed for different fault scenarios in the simulated test networks. The comparative analysis of the procured events categorization accuracy for different test cases by the proposed ensemble and deep classifier based scheme are summarized in the last section.

5.2 Ensemble Leaning

Ensemble systems simply train multiple classifier models to solve the same classification problem. In contrast to usual learning mechanisms which mainly build single learner model from the training dataset, ensemble system builds a set of multiple base classifiers and then superimposes the outcomes of all models for making the final judgment. It is also termed as committee-based learning system. The principle behind ensemble methodology is to weigh various individual classifiers and then integrate them to acquire a superior classifier that outperforms all individual classifier [103-105]. It is widely used to enhance the (classification, function prediction, etc.) functioning of a model, or mitigate the possibility of an unfortunate picking off a poor one. Ensemble techniques represent an effective perspective for handling the issue of mining huge datasets because of their better accuracy and competency of utilizing the divide and conquer procedure in parallel computing environments. Dietterich [106] have reported that the application of ensemble mechanism can effectively outperform the limitations of single classifier-based approaches. The generalization performance of any classifier model is totally depends on the diversity of the utilized training dataset. Hence, multiple data subsets have been created from the original dataset, for the training different base classifier modules. The main objective of applying dataset division mechanism is to enhance the diversity of the training. The mechanism of averaging the outputs of different base classifiers significantly mitigated the risk of poor selection. The partitioning of the original dataset into smaller subsets also enables the ensemble classifier to handle large training dataset. The sub datasets are created by applying resampling approaches, such as bagging and bootstrapping, where the data subsets are generated randomly, with replacement, from the original training set. Hence, for designing classifier with better generalization performance, the strategy of ensemble learning is utilized in which multiple base classifiers are trained with different subset of the training dataset and ultimately the outputs of all the base classifiers are combined for making the final decision. It comprehensively provides better generalization than that of individual base classifier model. The mechanism of ensemble learning is demonstrated in

Figure 5.1, where three base classifiers are trained with different sub dataset for acquiring the decision boundaries. In the end, the acquired decision boundaries are combined to obtain the final decision boundary which is precisely more accurate than that of individual classifiers [107].

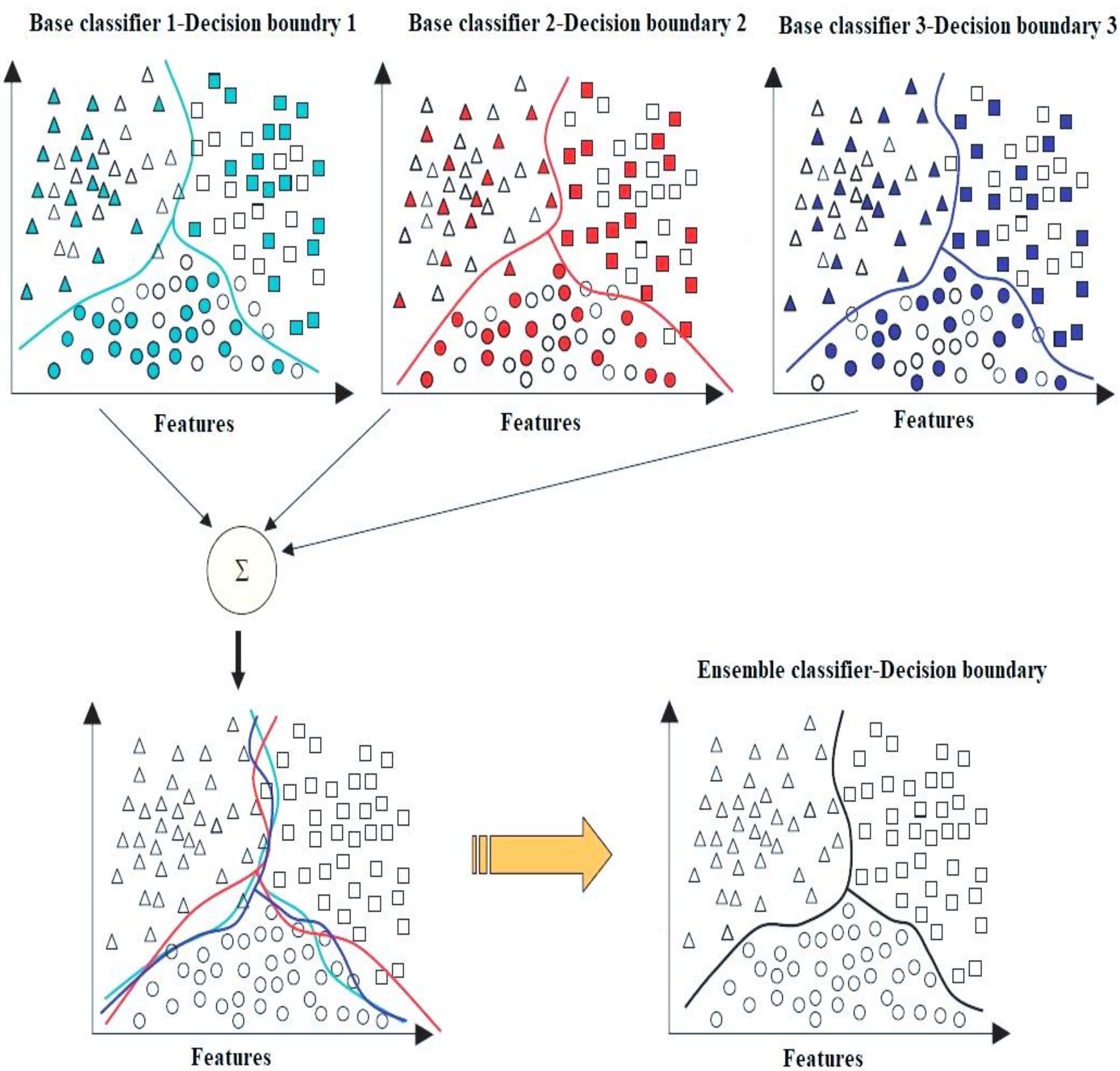


Figure 5.1 Ensemble Learning Mechanism

Designing of ensemble systems essentially requires two factors; firstly the selection of sub-dataset building mechanism, secondly is picking of particular strategy for combining the outputs of different base classifiers for making final decision. The following mechanisms are widely utilized for segregating the original datasets into different sub datasets-

1) Bagging
2) Boosting
3) AdaBoost
4) Stacked generalization

5.2.1 Bagging: It was formulated by Leo Breiman in 1994. Its name was evolved from "bootstrap aggregating". It effectively reduces the likelihood of over fitting of the classifier model and also detracted the complexity. It involves the building of various subsets of training data by using bootstrap. Random bootstrap sample is acquired by sub-sampling the training data with replacement, while the size of the sample is same as that of training data set. Each subset is used for learning of different individual classifiers and then combining them through model averaging method (regression) or majority voting (classification) for getting the predicted response of trained ensemble [108-109]. The bagging algorithm is given below-

---

Bagging Algorithm

---

1. Training phase:
    - Initialization of the training data set Ds
    - define the number of weak classifier (M)

- define type of weak learner and learning rate
    - For k =1, 2.....M; create new subset data for different individual classifiers of same size as that of Ds by replacement data sampling.
    - Start training of individual classifier using subset data.
    - Compound classifier is formulated on the basis of the aggregation output of every individual classifier.

2. Classification phase:
    - Run all individual classifier for new instances to be classified.
    - The particular class of new instances is decided on the basis of maximum number of votes by individual classifier.

5.2.2 Boosting: The boosting mechanism is based on the principle that the union of weak base classifier models can solve the classification task in a superior manner than that of the original base models. The boosting strategy of learning is introduced by Schapire in 1990. Apart from bagging, where samples are selected to train base models are bootstrapped replicas of the training set i.e., each sample has similar chance of being in every training set, in boosting mechanism the training set for individual subsequent base models progressively focuses on the samples wrongly identified by formerly learner models. Random sampling without replacement data processing mechanism has been utilized in boosting ensemble. For example, the boosting builds 3 base classifiers: the first model $C1$ is trained by a random subset of the training set. The training subset picked for the second model $C2$ is the most informative dataset, given $C1$. Hence, $C2$ is trained by the samples which are incorrectly identified by $C1$. Similarly, model $C3$ is trained by all the samples on which *C*1and *C*2 disagree. Ultimately, the union of *C1, C2,* and *C3* models based majority voting mechanism is applied for final decision. The boosting algorithm is demonstrated below-

---

Boosting Algorithm

---

1. Training phase:
   - Initialization of the training data set Ds of size N
   - define the number of weak classifier (M)
   - define type weak of learner and learning rate
     - ➢ Pick $N_1 < N$ samples without replacement for building subset S_1.
     - ➢ Train weak base model (C1) by S1.
     - ➢ Create another subset *S*2 the most informative dataset, given *C*1, such that half of *S*2 is truly identified by *C*2, and the other half is wrongly identified.
     - ➢ Train another base model *C*2 with *S*2.
     - ➢ Build subset *S*3 by picking those samples for which *C*1 and *C*2 disagree. Train model *C*3 by *S*3.
2. Testing phase: For given test samples R
   - ➢ Classify R by *C*1 and *C*2. If they give identical category, than the class is the final label.
   - ➢ If they disagree, select the category identified by *C*3 as the final decision.

5.2.3 AdaBoost: This ensemble strategy has been introduced Freund and Schapire in 1997. In contrast to Bagging or Boosting, an undemocratic voting mechanism (weighted majority voting) has been utilized in AdaBoost strategy. The principle behind it is to apply weighted version of training samples instead of randomly using sub data sets. Hence it is more efficient than the former boosting mechanism. In it, the models that have better performance during the training phase are awarded with higher voting weights than the others. There are two methods (AdaBoostM1 and AdaBoost M2) that have been frequently applied for classification and regression analysis. Initial one is mainly applied for binary classification applications, whereas AdaBoost M2 is utilized for multiclass categorization.

5.3 Proposed DWT and Ensemble Learning based Fault Events Classification Scheme

The structure of the proposed ensemble learning (Bagging) based scheme for ascertaining the fault events in a series compensated transmission network is shown Figure 5.2. The 3-phase post-fault current samples retrieved at the sending side of the power network are decomposed using Db5 mother wavelet. Thereafter, the fault characteristic features are extracted for each phases i.e. e_a, e_b, e_c in terms of norm entropy of the DWT detail coefficients. Later on, the realized feature vectors are applied to the ensemble learning based classifier models for ascertaining the categories of the fault events in the transmission network. In the training stage, the entire training dataset are segmented into multiple subsets but of similar size by applying the replacement mechanism. The different fragmented data subsets are utilized for the training of individual weak classifier models. Finally, a composite classifier model has been created by aggregating the outcomes of each individual weak classifier models. In the testing phase, the precise category of the test fault instances is decided on the basis of maximum number of votes gained by individual classifiers. The details of the simulated test networks, considered test scenarios, training and testing mechanism are thoroughly described in the coming sections.

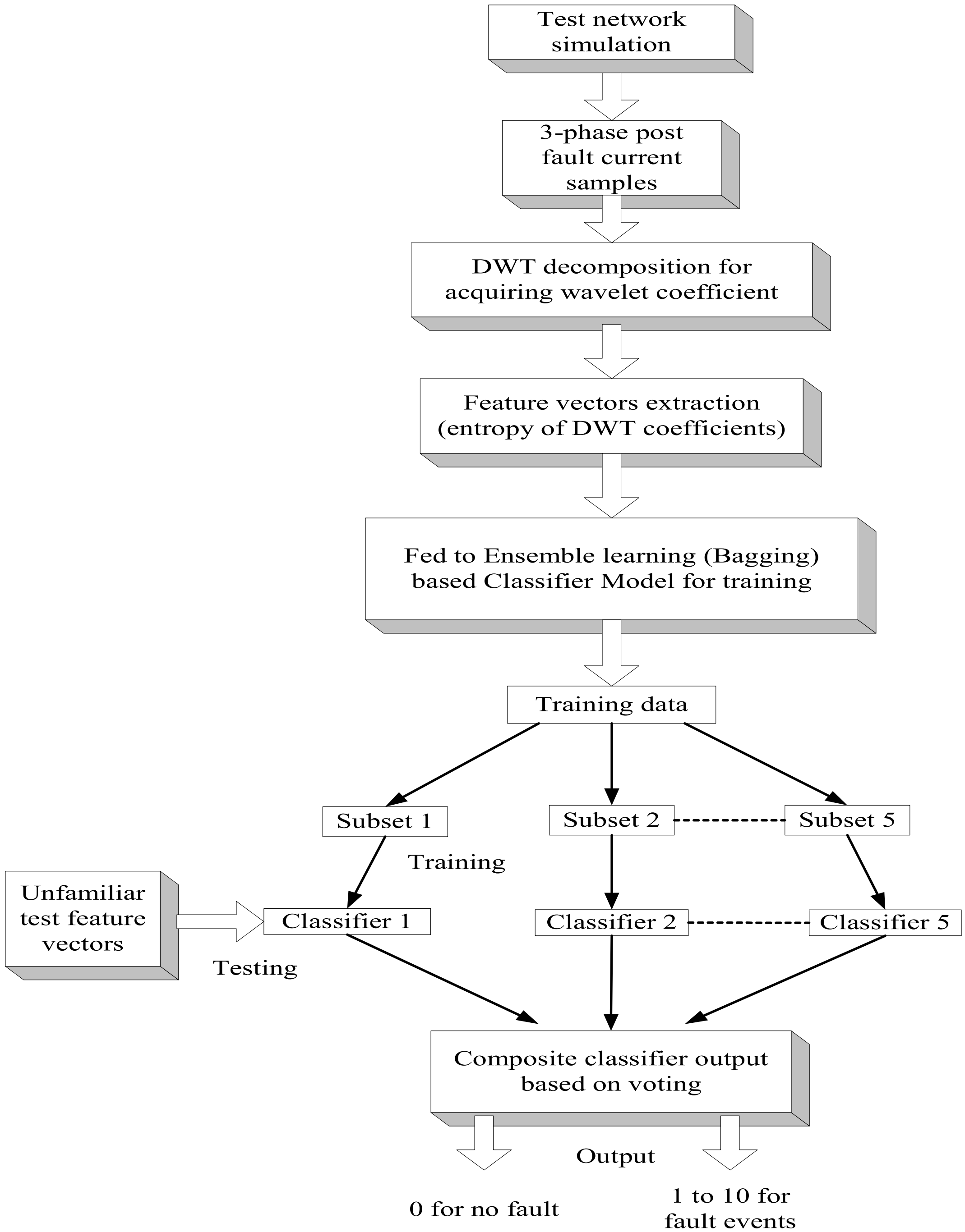


Figure 5.2 Flow-chart of Ensemble Learning (Bagging) based event classification scheme

5.3.1 Training and Testing Mechanism

In the proposed ensemble learning based events classification scheme, an elementary approach i.e. 'bagging technique' has been utilized. It simply segmented the training feature sets into different subsets by applying the bootstrap mechanism. Random bootstrap samples are formulated by sub-sampling the training dataset with replacement. However, the size of each subset is equal and identical to the training set. Once the extracted characteristic feature vectors corresponding to different training scenarios (as depicted in Table 5.1) are applied to the ensemble classifier models, it split the original dataset into different subset according to the number of weak learner models are utilized. In the present work, five different weak learners have been employed and the learning rate is kept as 1. Hence, five different training subsets are created by using bootstrap sub-sampling mechanism. The applied algorithm of bagging methodology already has been discussed in section 5.2. The details of the other specific parameter used in bagging based classifier model are depicted in Appendix. The different fault types in the transmission circuit are labelled in the similar manner i.e. normal operating mode- class 0, AG-class1, BG-class 2, CG-class 3, AB-class 4, AC-class 5, BC-class 6, ABG class 7, BCG-class 8, ACG-class 9, ABC-class 10. Individual formulated subsets are used for the training of different weak classifiers. Later on, the extracted feature vectors corresponding to new unfamiliar test events (as depicted in Table 5.1) are applied to the trained ensemble learning based classifier model. The individual classifier models identify the class of the test instance based on the trained pattern set. Eventually, the final category of the test instances has been decided on the basis of majority voting provided by individual weak classifier models. If the output is 0 it means normal operating conditions whereas if it lie between '1 to 10' then there is fault in the network of that type. The performance of the proposed approach is examined for three critical evolving fault situations and during CTs saturation conditions.

5.4 Case Study and Results

In order to figure out the feasibility and efficiency of the proposed ensemble learning based fault events ascertaining scheme, it has been also extensively analysed for various fault scenarios in the simulated test networks. Table 5.1 shows the details of the training and testing cases that are taken into consideration while evaluating the competency of the ensemble learning (bagging) based fault categorization scheme.

Table 5.1 Training and testing conditions considered on first test system

S. No	Parameters	Training cases	Testing cases
1.	Fault locations	Twenty different locations	Seven new unknown location (30 km, 50km, 110 km, 170 km, 190 km, 230 km and 250 km)
2.	Fault Resistance (ohms)	0.001, 20, 60	0.1, 0.5, 1, 5, 10, 50
3.	Fault inception angle (°)	0, 75, 150	30, 45, 60, 90, 120, 135
4.	Fault events types	No fault and all kinds faults events	Unknown no fault and all kinds of fault events
5.	Level of line compensation	35 % and 45 %	30 % and 40 %

5.4.1 Test Case I: Two-Bus Series Compensated Transmission Test Network

The viability of the proposed ensemble learning based fault events categorization scheme is assessed for all possible fault scenarios on the first simulated test network which is a 400 kV, 50 Hz, mid-point capacitor compensated transmission system shown in Figure 5.3 The ensemble learning based scheme is also validated for all sorts of shunt fault events, evolving fault events and cross-country fault events with varying circumstances in the simulated test network. Figure 5.4 represents the 3-phase post fault current samples retrieved during AG fault event at 30 km in the network from the sending side on different inception angles. The extracted fault feature vectors i.e. ea, eb, and ec are applied as the training and testing dataset to the ensemble learning (bagging) classifier models. The applied training datasets are divided into 5 different subsets using bootstrap mechanism so as to train the individual weak classifier models. During the testing, the corresponding segmented feature subsets are applied to the individual classifier models. Each model predicts the category of the test event according to the previously trained pattern set. Eventually, the final class of the particular test instance is assigned by weighing the majority voting provided by individual weak classifier models. The fault events classification accuracy percentage has been estimated by using the expression given below-

$$Classfication_{accuracy}\left(\%\right)=\frac{\left(\text{Total correct classified events}\right)}{\text{Total number of test events}}\times 100 \tag{5.1}$$

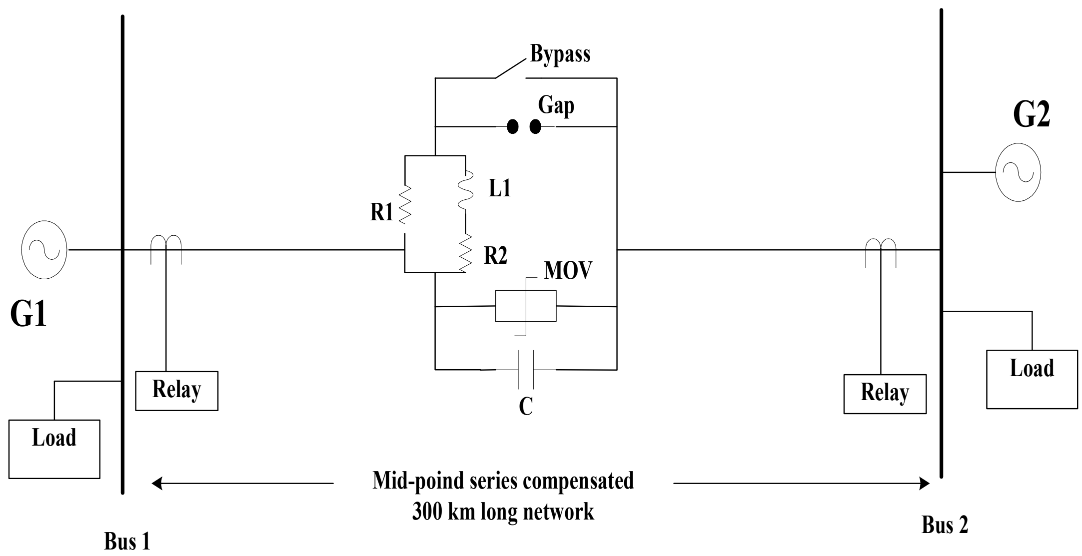
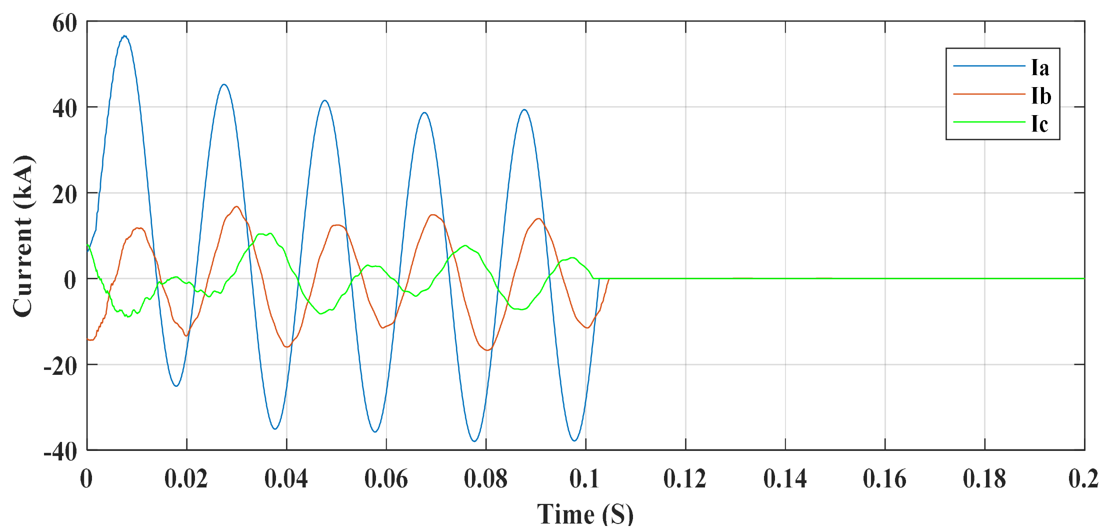
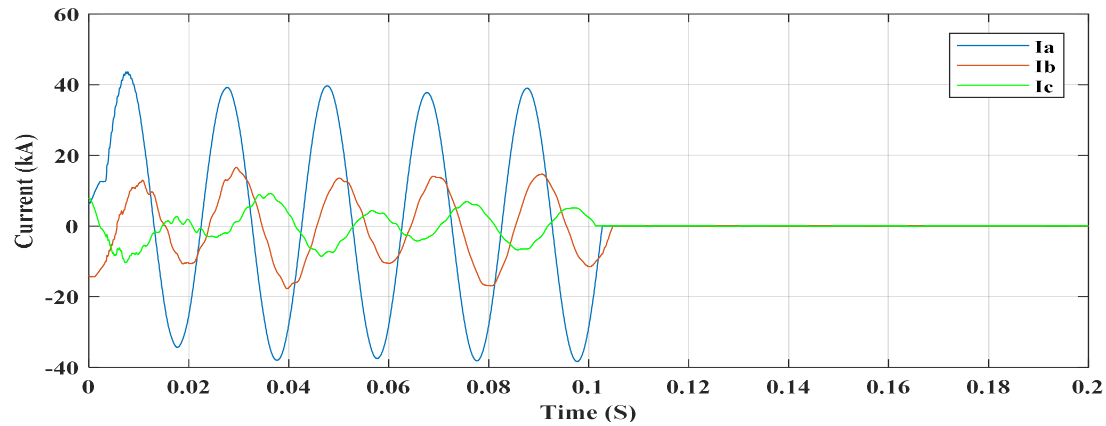


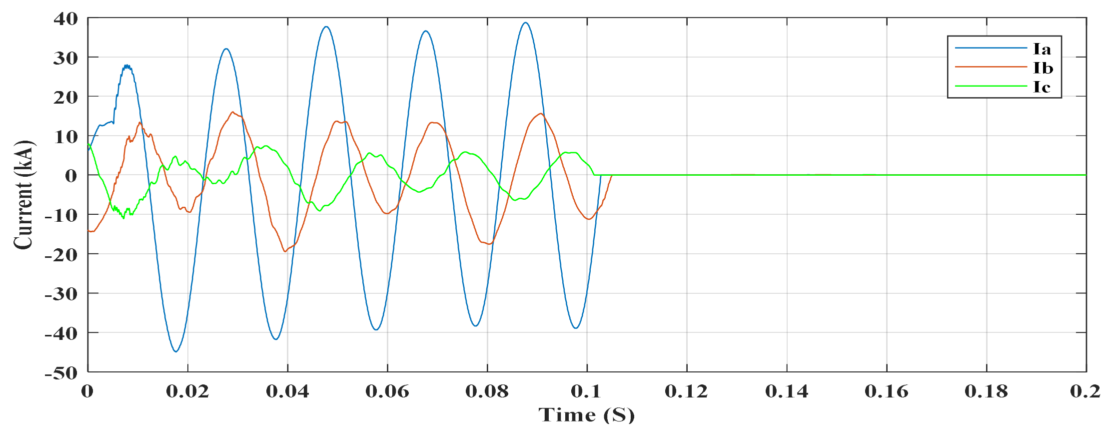
Figure 5.3 Two-bus mid-point compensated network (first test system)



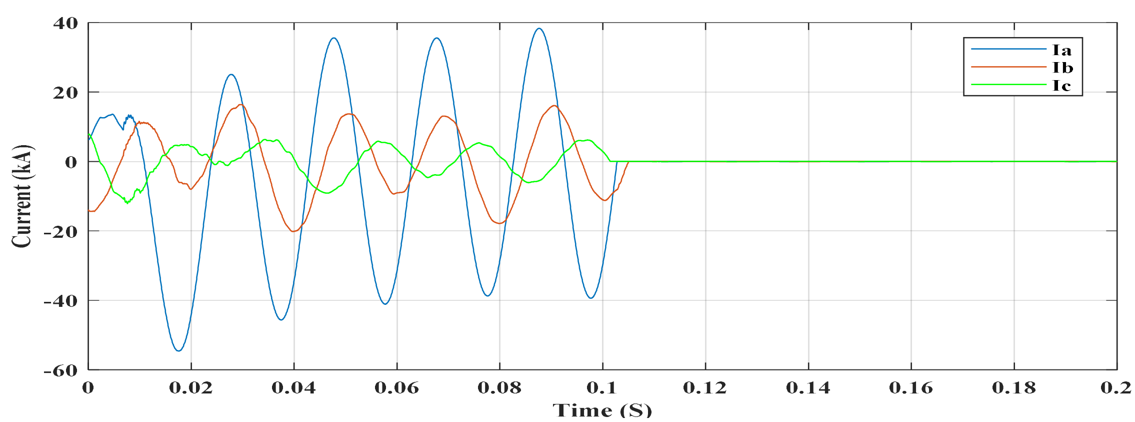
(a)



(b)



(c)



(d)

Figure 5.4 Three phase current signals during line to ground fault event at 30 km on different inception angles (a) 30 degree; (b) 60 degree; (c) 90 degree; (d) 120 degree

Table 5.2 represents the results of fault events classification obtained by bagging algorithm based scheme during testing. The bagging based events classification scheme also gives 100% classification accuracy for line to ground and 3-phase fault events in the simulated test network. The classification accuracy percentage provided for LL and LLG fault events are 98.412% and 98.941% respectively. The overall average fault events categorization accuracy obtained is 99.338%. Table 5.3 shows the corresponding confusion matrix obtained during testing of bagging based scheme. From the results depicted in Table 5.2, it has been reaffirmed that the proposed DWT combined with ensemble learning (bagging) based approaches is very effective in detecting and identifying the classes of the fault events in the compensated transmission networks with high accuracy percentage.

Table 5.2 Faults classification accuracy percentage obtained by ensemble learning (bagging) technique based scheme

Fault type	Number of test samples	Number of incorrect classification	Correct classification	Over all Accuracy (%)
Line to Ground	1512	0	1512	100.00
Line to Line	1512	24	1488	98.412
Double Line to Ground	1512	16	1496	98.941
3 phase (LLL)	504	0	504	100.00
Avg. Accuracy				99.338

Table 5.3 Confusion matrix for the ensemble learning based scheme (First test system)

Actual fault events	Sample size	Predicted fault events											
		AG	BG	CG	AB	AC	BC	ABG	BCG	ACG	ABC	No fault	Accuracy (%)
AG	**504**	**504**	0	0	0	0	0	0	0	0	0	0	**100**
BG	**504**	0	**504**	0	0	0	0	0	0	0	0	0	**100**
CG	**504**	0	0	**504**	0	0	0	0	0	0	0	0	**100**
AB	**504**	0	0	0	**493**	0	0	**11**	0	0	0	0	**99.2**
AC	**504**	0	0	0	0	**496**	0	0	0	**8**	0	0	**98.8**
BC	**504**	0	0	0	0	0	**499**	0	**5**	0	0	0	**99.4**
ABG	**504**	0	0	0	**4**	0	0	**500**	0	0	0	0	**98.4**
BCG	**504**	0	0	0	0	0	**3**	0	**501**	0	0	0	**99.4**
ACG	**504**	0	0	0	0	**9**	0	0	0	**495**	0	0	**97.6**
ABC	**504**	0	0	0	0	0	0	0	0	0	**504**	0	**100**
No fault	**10**	0	0	0	0	0	0	0	0	0	0	**10**	**100**

The time span taken by the proposed ensemble learning based scheme for detecting the fault events in the transmission network is depicted in Table 5.4. Table 5.5 provides the comparative analysis of the average events classification accuracy obtained by the proposed DWT and ensemble learning based scheme for different test circumstances with some already transcribed approaches in the literature [58, 39, 32, and 40]. From this analysis it can be concluded that the proposed ensemble learning based scheme provides better results in terms of average events classification accuracy percentage than the already reported schemes.

Table 5.4 Time of response of ensemble learning based scheme

S. No	Classifier Model Utilized	Time of response
(i)	Ensemble learning (Bagging)	1.438e-01 s

Table 5.5 Comparative analysis of average classification accuracy achieved by proposed scheme with previously reported approaches

Fault type	Ref. [58] (%)	Ref. [39] (%)	Ref. [32] (%)	Ref. [40] (%)	Ensemble learning (%)
Line to ground	97.23	97.447	100.00	99.449	100.00
Line to line	97.29	99.616	97.560	97.687	98.412
Double line to ground	97.84	98.611	98.788	99.314	98.941
3 phase (LLL)	97.68	100.00	100.00	98.565	100.00
Average accuracy	**97.51**	**98.918**	**99.087**	**98.753**	**99.338**

5.4.2 Test Case II: Modified IEEE 9-Bus Series Compensated Test Network

The practicality of the proposed ensemble learning based events classification scheme for compensated transmission circuit is also validated on an interconnected simulated test network i.e. WSCC – IEEE 9-bus second test system shown in Figure 5.5. All sorts of fault events with varying conditions (as depicted in Table 5.6) are simulated on the second test network while evaluating the proficiency of the proposed ensemble learning based events classification scheme. Figure 5.6 shows the 3-phase post fault current signal retrieved during phase 'A' to ground fault at 50 km from the sending side on different inception angles. The extracted feature vectors corresponding to different fault scenarios in terms of norm entropy of DWT coefficients are utilized as the training and testing dataset to the bagging classifier models. In testing phase, each classifier model predicts the types of test fault event according to the training pattern set. Eventually, the final class of the particular test instance is assigned by combining the voting provided by individual weak classifier models.

Table 5.6 Training and testing conditions considered on second test system

S. No	Parameters	Training cases	Testing cases
1.	Fault locations	Twenty different locations	Five new unknown location (50 km, 110 km, 170 km, 210 km and 250 km)
2.	Fault Resistance (ohms)	0.001, 15, 30	0.1, 1, 5, and 10
3.	Fault inception angle (°)	0, 75, 150	30, 45, 60, 90, and 120
4.	Fault events types	No fault and all kinds faults events	Normal operation mode and all kinds of fault events (unfamiliar)
5.	Level of line compensation	35 % and 45 %	30 % and 40 %

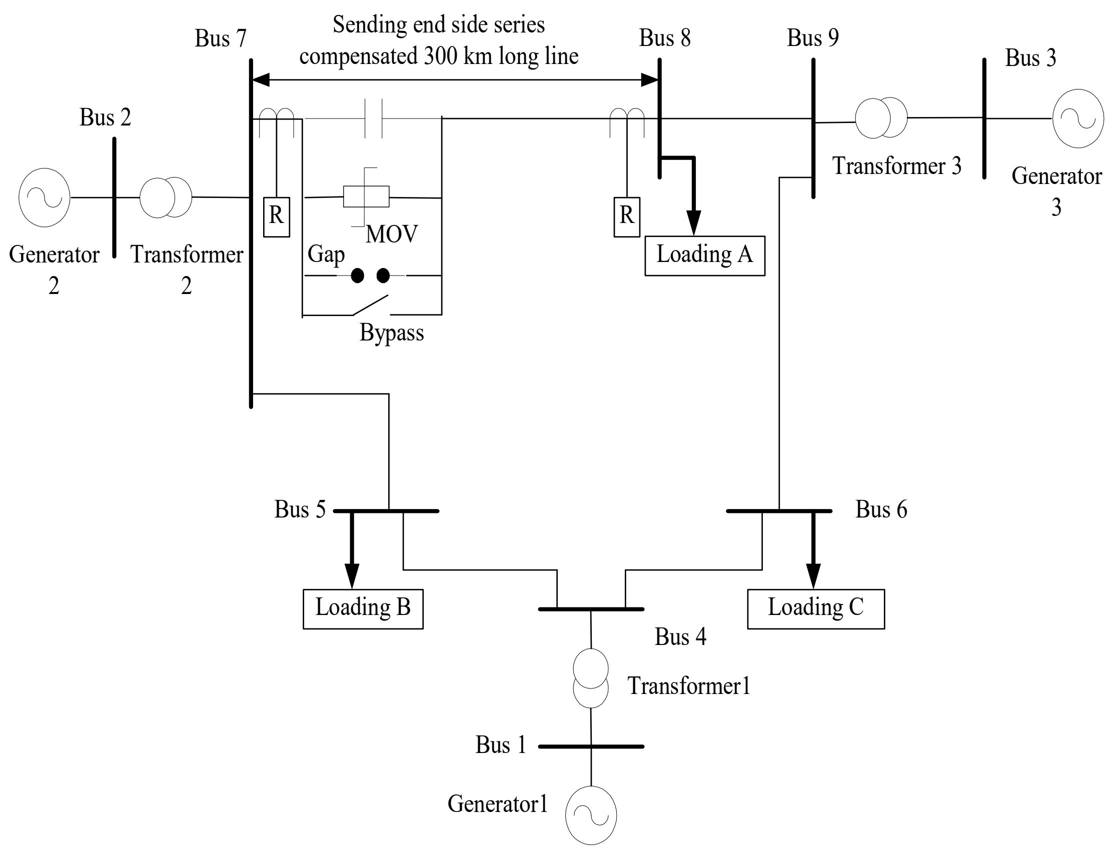
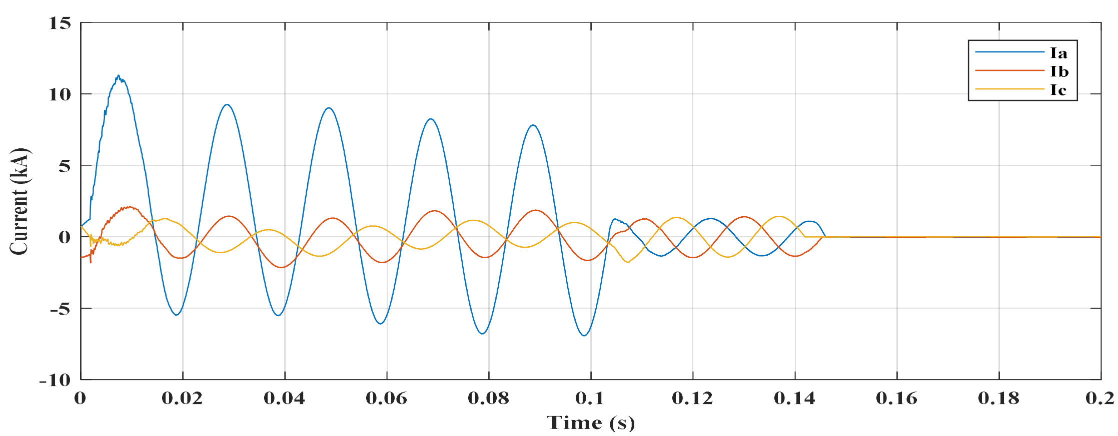
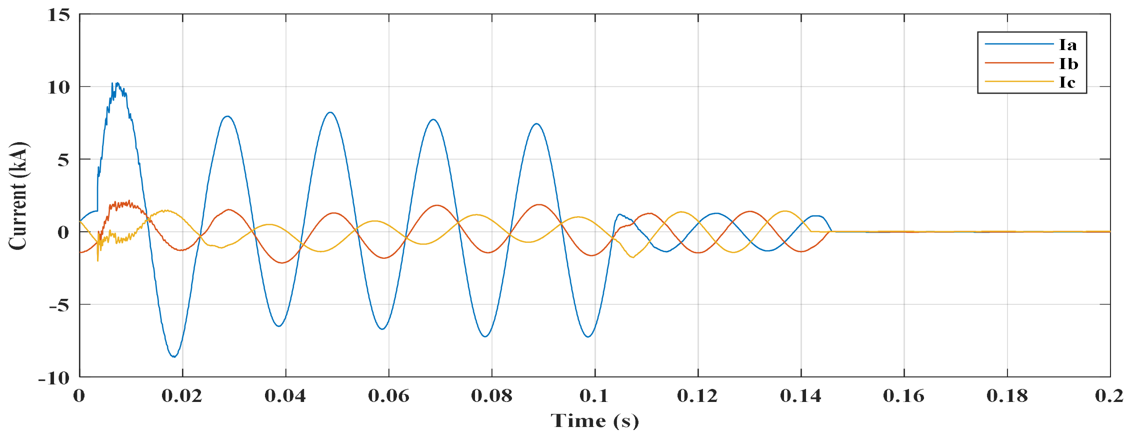


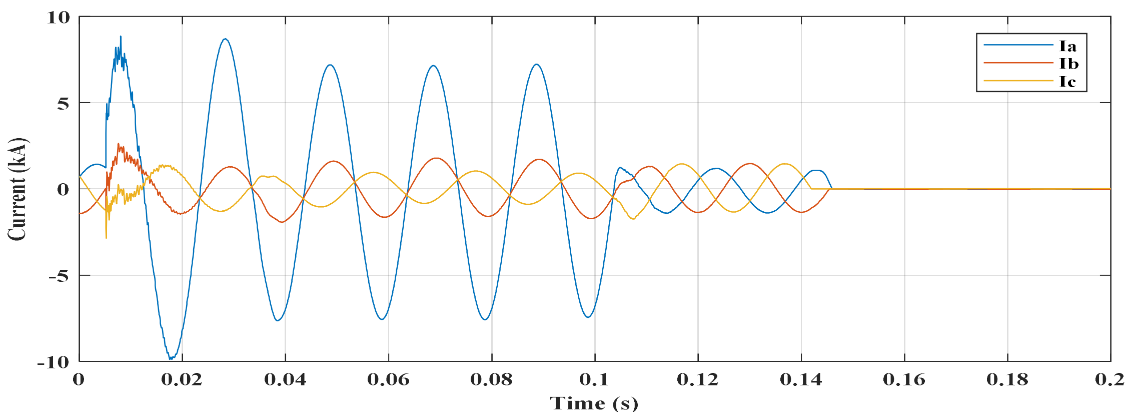
Figure 5.5 Second Test System



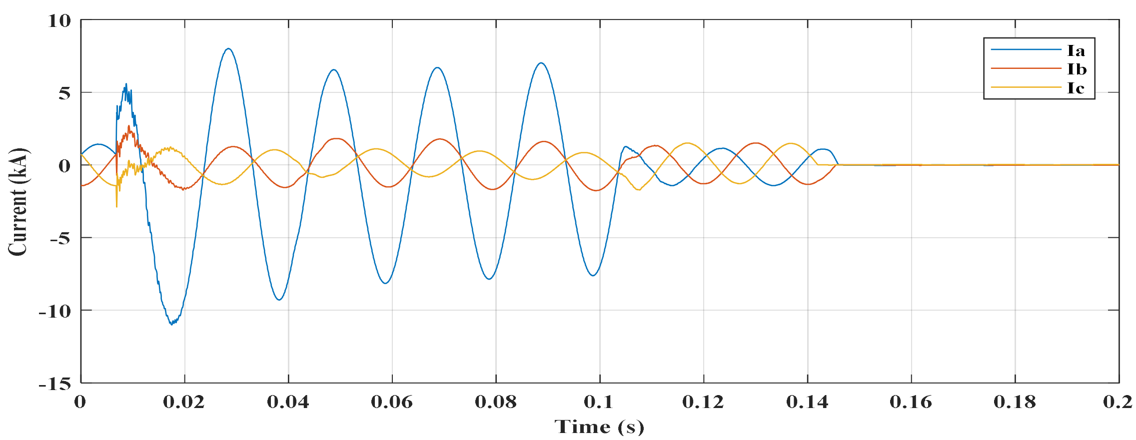
(a)



(b)



(c)



(d)

Figure 5.6 Three phase current signals during line to ground fault event at 50 km on different inception angles (a) 30 degree; (b) 60 degree; (c) 90 degree; (d) 120 degree

Table 5.7 presents the fault events classification accuracy percentage obtained by the proposed DWT and ensemble learning based scheme during the testing on the second test network. It has been noticed that ensemble learning based scheme gives 99.29% over all events classification accuracy during the testing. The associated confusion matrix for ensemble learning based scheme is shown in Table 5.8.

Table 5.7 Faults classification accuracy percentage obtained by bagging technique based scheme

Fault type	Number of test samples	Number of incorrect classification	Correct classification	Over all Accuracy (%)
Line to Ground	600	0	600	100.00
Line to Line	600	11	589	98.17
Double Line to Ground	600	6	594	99.00
3 phase (LLL)	200	0	200	100.00
Avg. Accuracy				99.29

Table 5.8 Confusion matrix for ensemble learning based scheme (second test system)

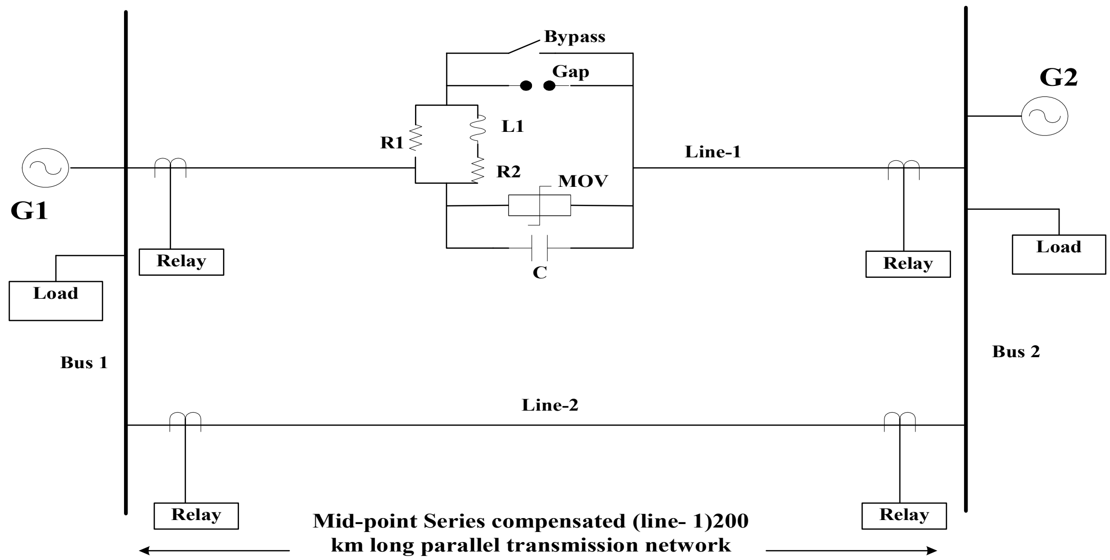
Actual fault events	Sample size	Predicted fault events											
		AG	BG	CG	AB	AC	BC	ABG	BCG	ACG	ABC	No fault	Accuracy (%)
AG	**200**	**200**	0	0	0	0	0	0	0	0	0	0	**100**
BG	**200**	0	**200**	0	0	0	0	0	0	0	0	0	**100**
CG	**200**	0	0	**200**	0	0	0	0	0	0	0	0	**100**
AB	**200**	0	0	0	**194**	0	0	**6**	0	0	0	0	**97.0**
AC	**200**	0	0	0	0	**197**	0	0	0	**3**	0	0	**98.5**
BC	**200**	0	0	0	0	0	**198**	0	**2**	0	0	0	**99.0**
ABG	**200**	0	0	0	**4**	0	0	**196**	0	0	0	0	**98.0**
BCG	**200**	0	0	0	0	0	0	0	**200**	0	0	0	**100**
ACG	**200**	0	0	0	0	**2**	0	0	0	**198**	0	0	**99.0**
ABC	**200**	0	0	0	0	0	0	0	0	0	**200**	0	**100**
No fault	**10**	0	0	0	0	0	0	0	0	0	0	**10**	**100**

5.4.3 Test Case III: Series Compensated Parallel Transmission Network (Third test system)

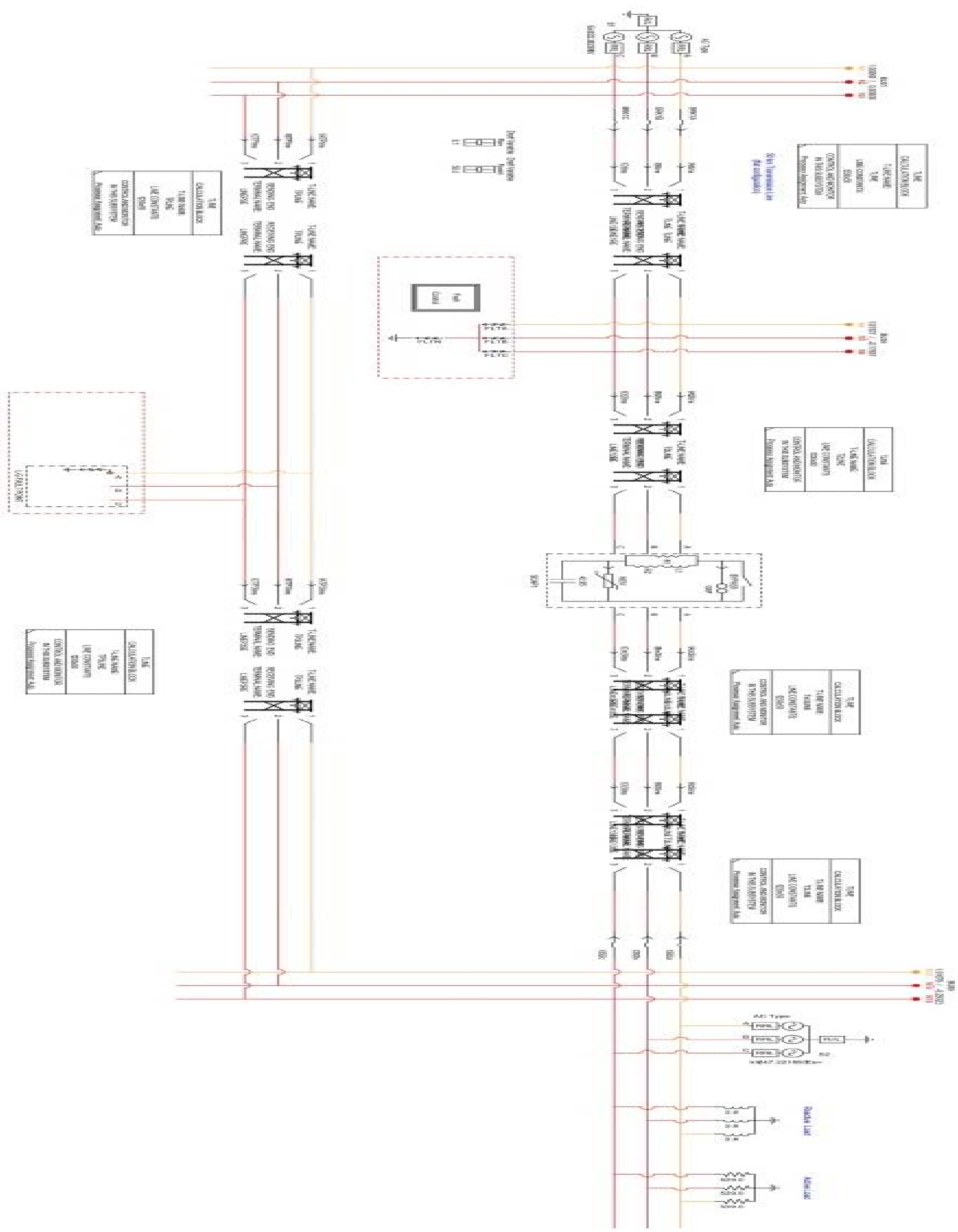
The strength and probability of the proposed DWT and ensemble learning based fault events categorization scheme is also validated on a parallel transmission network. A 230 kV, 200 km long mid-point capacitor compensated double circuit transmission network is simulated in real time digital simulator (RTDS) platform as third test system (shown in Figure 5.7). A series capacitor compensating unit is installed at the mid of the line one of the network. Two different compensation percentage levels i.e. 35 %. The details regarding the utilized network parameters are depicted in the appendix. Different types of fault events (as mentioned in Table 5.9) with different varying conditions are simulated on the third test system while estimating the efficacy of the proposed events classification scheme. Figure 5.8 shows the 3-phase post fault current signal retrieved during different fault events in the network at 30 km from the sending side on line in the simulated network. In the training phase, the extracted feature vectors i.e. e_a, e_b, and e_c corresponding to different fault scenarios are fed to the ensemble learning based classifier model as input training dataset. Thereupon, during testing the feature vectors associated with considered test cases are fed to the individual weak classifier models and each model predicts the particular class label of the applied test case on the basis of trained pattern set. Later on, the final category of the test case is decided by using majority voting obtained by individual classifier models. The classification accuracy percentage has been estimated similarly by using the expression given in equation 5.1.

Table 5.9 Training and testing conditions used on third test system

S. No	Parameters	Training cases	Testing cases
1.	Fault locations	Fifteen different locations	Six new unknown location (30 km, 50km, 70 km, 130 km, 150 km, and 170km)
2.	Fault Resistance (ohms)	0.001, 20, 60	Five unfamiliar fault resistances
3.	Fault inception angle (°)	0, 75, 150	Five unfamiliar inception angles
4.	Fault events types	No fault and all kinds faults events	Unknown no fault and all kinds of fault events
5.	Level of line compensation	35 %	35 %

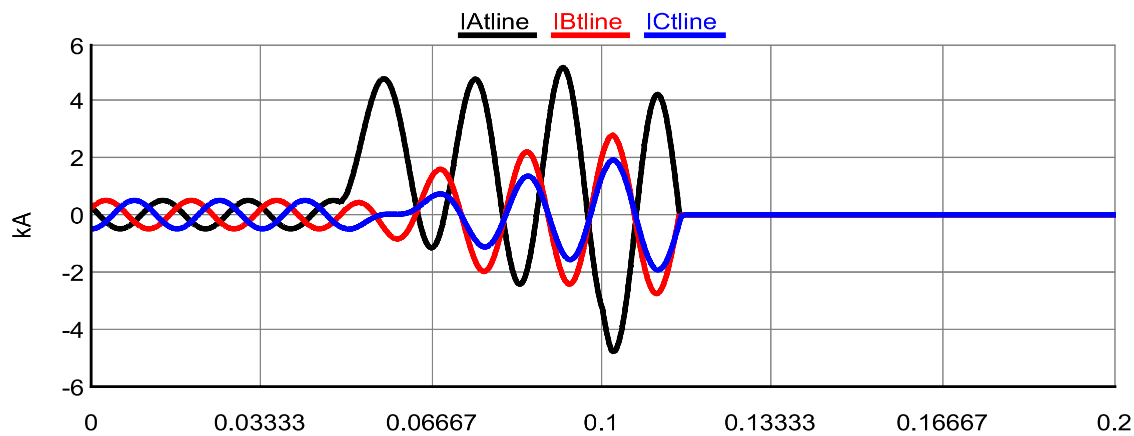

Bypass
Gap
G2
R1
L1
R2
MOV
Line-1
G1
Relay
Relay
Load
C
Load
Bus 1
Bus 2
Line-2
Relay
Relay
Mid-point Series compensated (line- 1)200
km long parallel transmission network

(a)

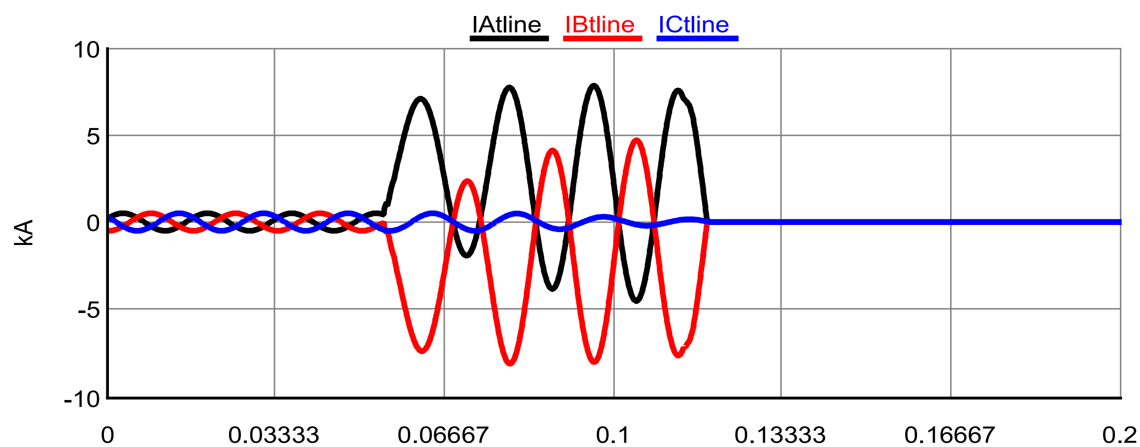


(b)

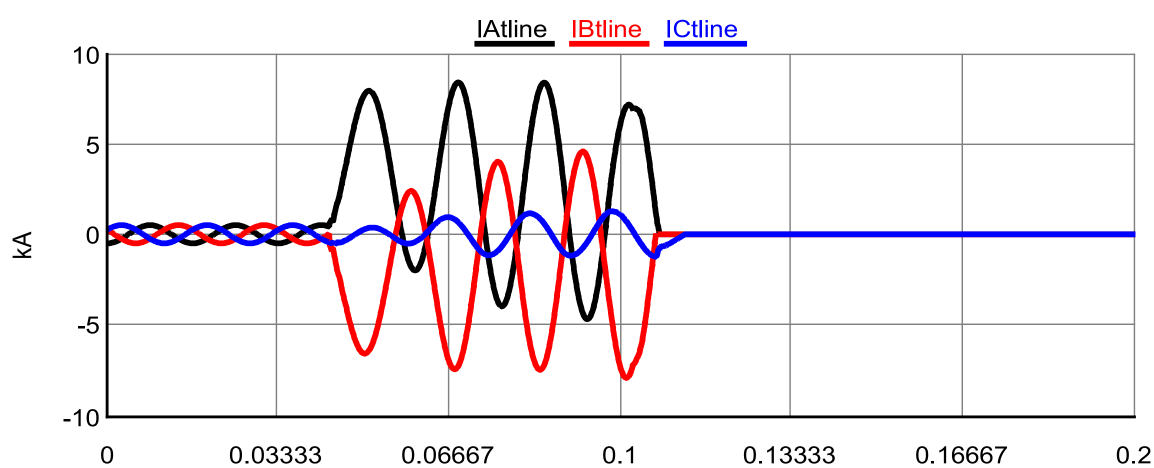
Figure 5.7 Simulated series compensated double circuit transmission (third test system) network; (a) single line diagram, (b) simulated test network in RTDS


IAtline IBtline ICtline
6
4
2
0
-2
-4
-6
kA
0
0.03333
0.06667
0.1
0.13333
0.16667
0.2

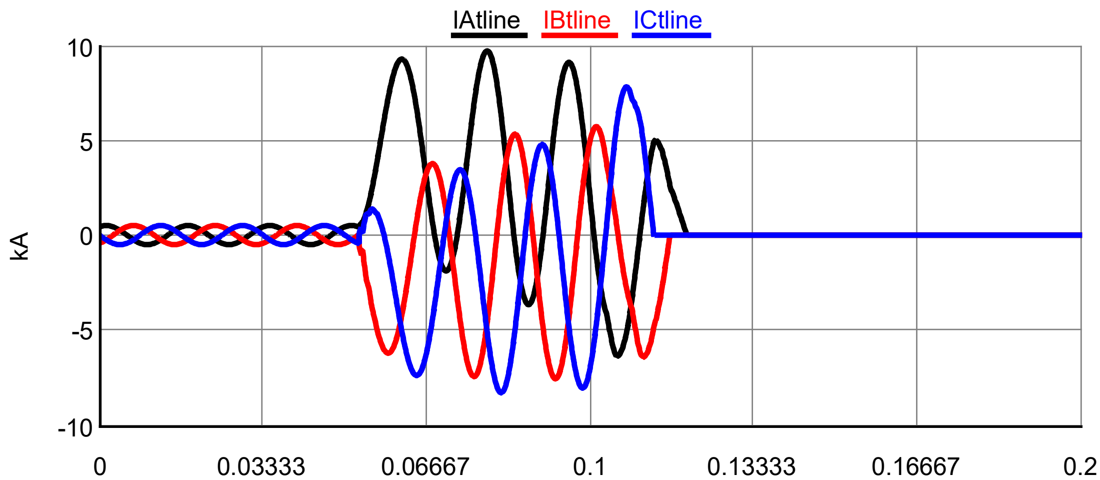
(a)


IAtline IBtline ICtline
10
5
0
-5
-10
kA
0
0.03333
0.06667
0.1
0.13333
0.16667
0.2

(b)


IAtline IBtline ICtline
10
5
0
-5
-10
kA
0
0.03333
0.06667
0.1
0.13333
0.16667
0.2

(c)



(d)

Figure 5.8 3-Phase current with respect to time (s) for different Fault events at 30 km (a) A-G event (b) A-B event (c) AB-G event (d) ABC event

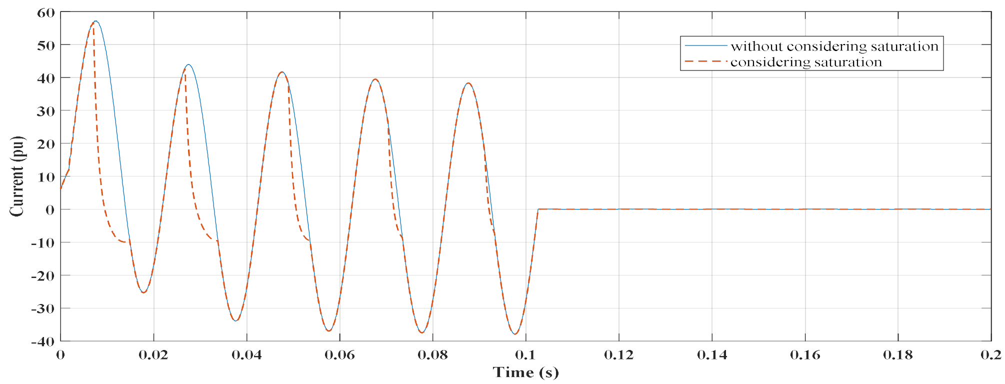
Table 5.10 shows the fault events classification accuracy percentage obtained by the proposed DWT and ensemble learning based scheme during the testing on the simulated parallel one line compensated transmission network. It has been noticed that ensemble learning based scheme gives 99.27% over all classification accuracy during the testing.

Table 5.10 Faults classification accuracy percentage obtained by ensemble learning based scheme

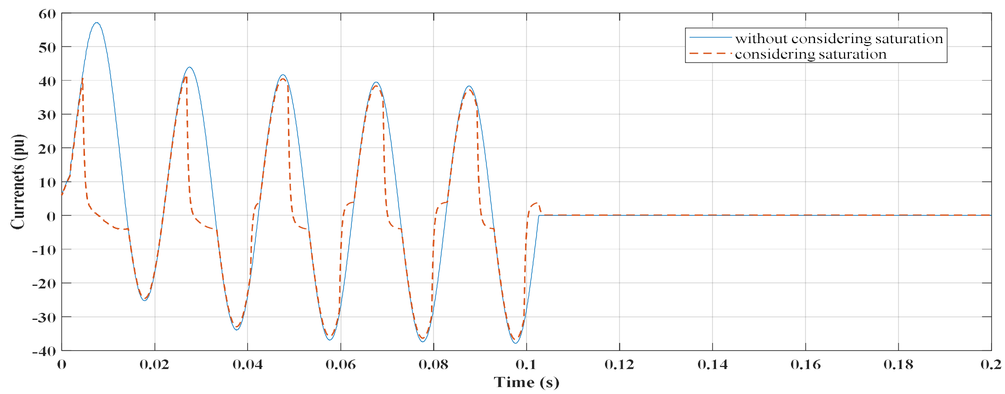
Fault type	Number of test samples	Number of incorrect classification	Correct classification	Over all Accuracy (%)
Line to Ground	450	0	450	100.00
Line to Line	450	9	441	98.00
Double Line to Ground	450	4	446	99.11
3 phase (LLL)	150	0	150	100.00
Avg. Accuracy				**99.27**

5.5 Performance of Ensemble learning Based Scheme During CTs Saturation

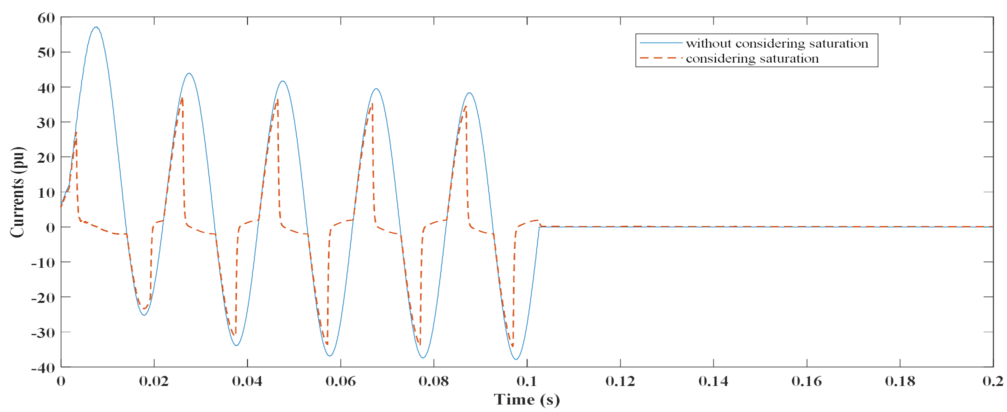
The suitability of the proposed ensemble learning based fault events categorization scheme in series compensated power network is evaluated during the case of CTs saturation. It is well known fact that CTs saturation eternally causes hindrances in distance relaying. Hence, in present work, the effect of CTs saturation on the performance of proposed ensemble learning based scheme has been comprehensively investigated. For exploring the impact of CTs saturation on the proposed scheme, various test cases have been considered with CTs saturation conditions. Three different burden resistance (2ohm, 5ohm and 10 ohm) cases are taken during CTs saturation analysis. Figure 5.9 shows the phase 'A' fault current signal with and without considering CTs saturation at 30 km from the sending terminals on varying conditions. Table 5.11 shows the results provided by the proposed ensemble learning based scheme in terms of particular fault identification during CTs saturation. It has been noticed that the proposed scheme is effective in identifying the fault events in the network irrespective of CTs saturation at different burden levels. However, the overall fault classification accuracy provided by the proposed scheme during the CTs saturation condition is comparatively less than during without considering the saturation phenomena.



(a)



(b)



(c)

Figure 5.9 Fault current signals at 40 % line compensation with and without considering CTs saturation((a) A-G at 30 km, with FIA 30 degree, FR 0.1 ohm, CT burden 2 ohm; (b) A-G at A-G at 30 km, with FIA 30 degree, FR 0.1 ohm, CT burden 5 ohm; (c) A-G at 50 km, A-G at 30 km, with FIA 30 degree, FR 0.1 ohm, CT burden 10 ohm)

Table 5.11 Performance of proposed classifier models during saturation at three different burden impedances

Simulated test parameters	Actual fault type	Output of the proposed ensemble learning based scheme
Five unknown fault locations with varying fault resistance, inception angle and level of line compensation	No fault	No fault
	LG event	LG
	LLG	LLG
	LL	LL
	LLL	LLL

5.6 Cross-Country Fault Events Identification using Ensemble Learning based scheme

Cross-country faults are one of the additional kinds of the abnormality that has been observed sometimes in the power transmission networks apart from commonly occurring shunt fault events. The cross-country faults (CCF) are defined as those faults that strike up at the same time but on different positions in the transmission network and can involve same or different phases. The occurrence of such faults in the transmission network significantly hampered the functioning normal distance relaying mechanism. The strength of proposed ensemble learning based scheme is also estimated for identifying the cross-country fault events in series compensated power network. Figure 5.10 shows the designed fault logic in RTDS for creating evolving and cross-country fault in the simulated test network (third test system). In the present work, six types of cross-country fault events at ten different locations in the third test system have been simulated. The initial fault is actuated in the first line like as AG fault is occurred at 30 km in the first line of the network, at the same time span BG fault event actuated at 100 km in the second line of the network. In the similar fashion all considered cases of the cross-country fault events have been simulated in the test transmission system. Figure 5.11 (a) shows the 3-phase current samples during ABG fault event in the line one of the network. Figure 5.11 (b) shows the fault current signals for phase ‘A’ to ground fault at 30 km in line one and at the same time another fault (BG) i.e. the cross-country fault case is occurred at 100 km in the second line of the network. For training, the extracted feature vectors associated with normal double line to ground events and CCF cases at five different locations are applied to the ensemble learning based classifier modes as input dataset. The normal double line to ground fault events and CCF are labelled as follows: ABG- class 1, BCG-class 2, ACG-class3, AG-bg-class 4, AG-cg-class 5, BG-ag-class 6, BG-cg-class 7, CG-ag-class 8, and CG-bg-class 9. During the testing, the feature vectors associated with new unknown cases of CCF and normal double line to ground shunt events are applied to the trained ensemble classifier model for discriminating the normal shunt events and CCF events. The classifier model predicts the class label of the test instance as its output. Table 5.12 represents the results obtained by the proposed scheme during identification of CCF events.

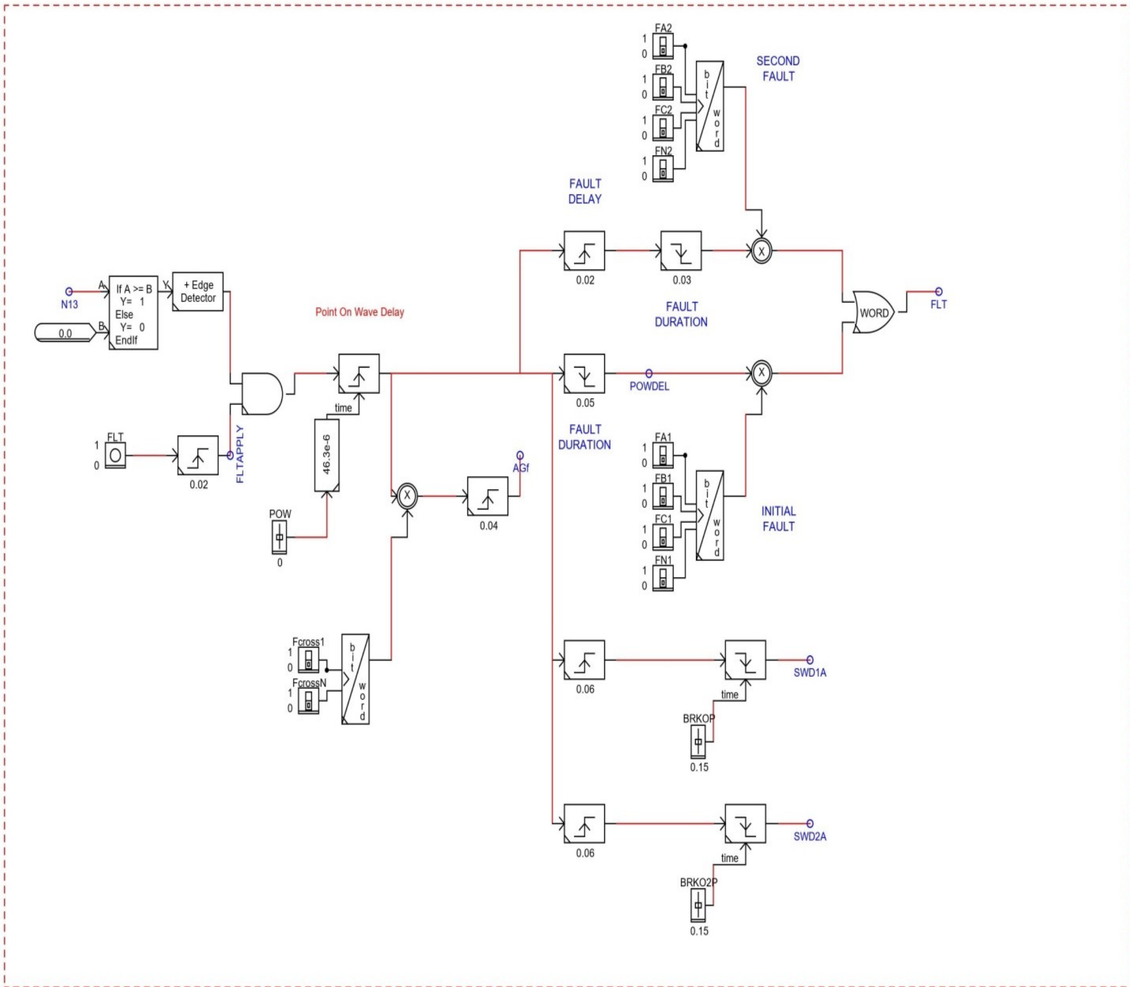
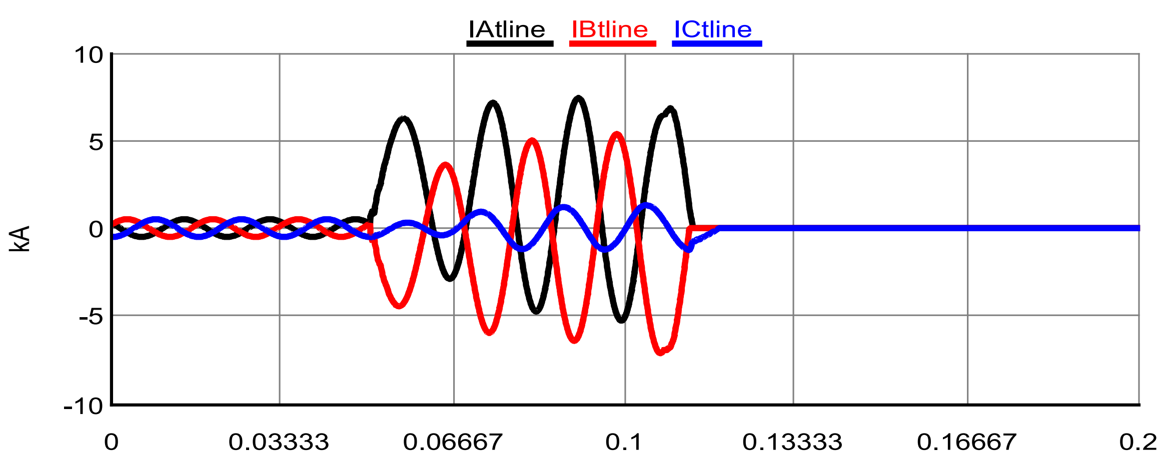
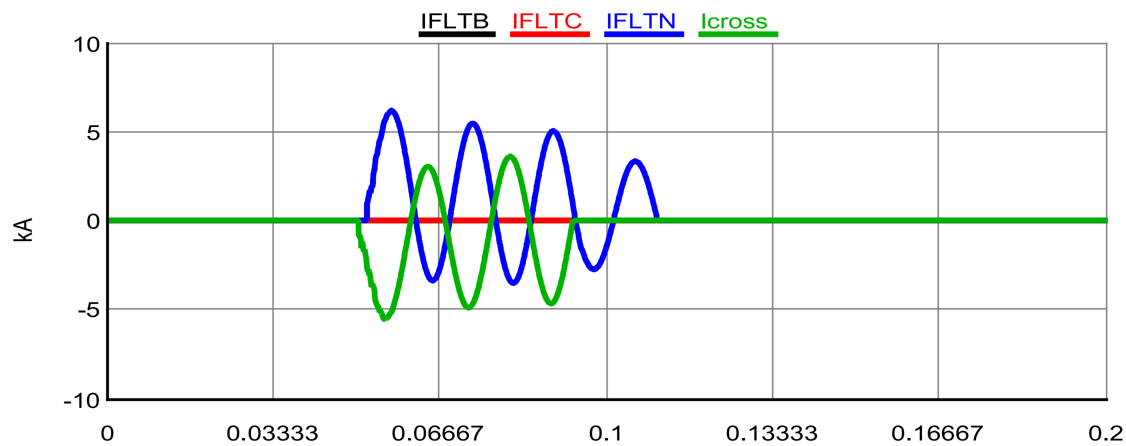


Figure 5.10 Fault logic for simulating evolving and cross-country faults



(a)



(b)

Figure 5.11 3-phase post fault current samples (a) ABG at 30 km; (b) Fault current during cross-country fault in the network i.e. AG (30 km) in line one and BG (100) at same time in line 2

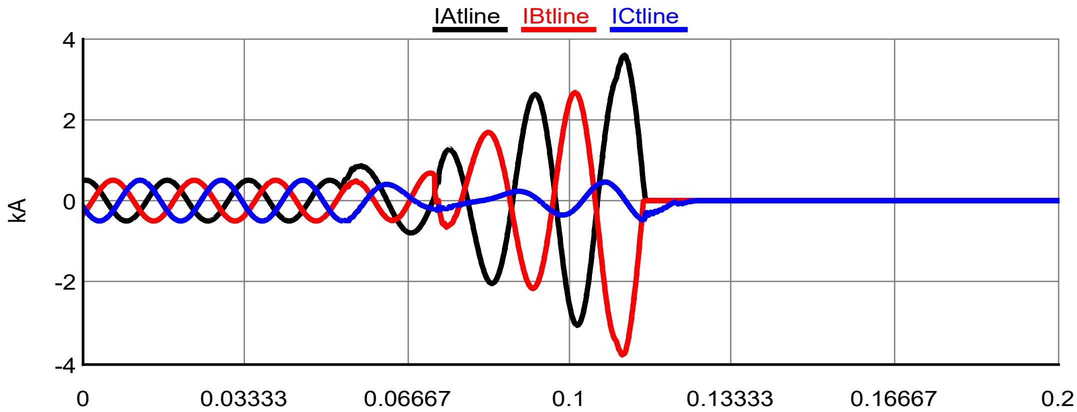
Table 5.12 Identification of CCF events using ensemble classifier models

S.No.	Cross-country fault type		Cross-country fault or not	Classifier output
	Initial fault (line-1)	CCF event (line-2)		
1.	ABG at 30 km	-	No	1
2.	AG at 30 km	bg at 50 km	Yes	4
3.	ACG at 30 km	-	No	3
4.	AG at 30 km	cg at 50 km	Yes	5
5.	BG at 30 km	ag at 50 km	Yes	6
6.	BCG at 30 km	-	No	2
7.	BG at 30 km	cg at 50 km	Yes	7
8.	CG at 30 km	ag at 50 km	Yes	8
9.	CG at 30 km	bg at 50 km	Yes	9
10.	ABG at 50 km	-	No	1
11.	AG at 50 km	bg at 100 km	Yes	4
12.	ACG at 50 km	-	No	3

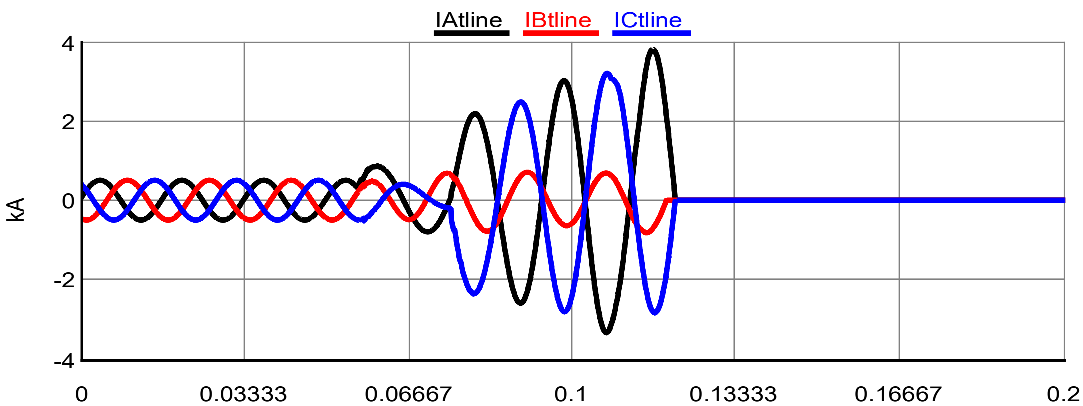
13.	AG at 50 km	cg at 100 km	Yes	5
14.	BG at 50 km	ag at 100 km	Yes	6
15.	BCG at 50 km	-	No	2
16.	BG at 50 km	cg at 100 km	Yes	7
17.	CG at 50 km	ag at 100 km	Yes	8
18.	CG at 50 km	bg at 100 km	Yes	9

5.7 Evolving Fault Events Identification Using Ensemble Learning based Scheme

The competency of the proposed ensemble learning based fault events ascertaining scheme in the compensated power network is also examined for evolving fault cases in the network. Two different cases of evolving fault at varying condition are simulated in the third test system. Firstly, the fault is initiated with phase 'A' in the network and subsequently after few milliseconds it extended to phase 'B' which ultimately makes it a double line to ground fault. Figure 5.12 show the 3-phase current samples during the case of evolving fault occurred in the network. The fault initially actuated in phase 'A' and within few milliseconds it gets spread to phase 'B'. The computed feature vectors in terms of entropy value of DWT coefficients of each phase i.e. e_a, e_b, and e_c are applied to the ensemble learning based classifier model as input dataset. Once the classifier models get trained, the feature vectors corresponding new unknown test cases are fed to the models for ascertaining the evolving faults in the transmission network. Table 5.13 provides the evolving fault classification results obtained by the proposed ensemble learning based scheme.



(a)



(b)

Figure 5.12 3-phase current samples during evolving fault in the third test network (a) AG-bg at 30 km, (b) AG-cg at 30 km

Table 5.13 Identification of evolving fault events using bagging classifier model

S.No	Primary fault type	Secondary fault type	Time interval (ms)	Evolving Fault or not	Classifier output
1.	AG	-	-	No	1
2.	ABG	-	-	No	2
3.	AG	bg	5	Yes	3
4.	ACG	-	-	No	4
5.	AG	cg	5	Yes	5
8.	AG	bg	10	Yes	3
9.	AG	cg	10	Yes	5
11.	AG	bg	15	Yes	3
12.	AG	cg	15	Yes	5

5.8 Deep Learning Mechanism

The idea of deep learning (DL) mechanism has been coined by Hinton et al. [110] in 2006. It is an advanced branch of ML also termed as representation-learning mechanism. Recently, it has been gaining ground in different research application in both medical and engineering fields. Deep learning mechanism has significant advantages such as multi-layer feature representation, better accuracy and generalization capability, and competency of handling large data set. Each layer is deeply connected to preceding layer and makes their verdicts based on the output fed by preceding layer. The deep connection or i.e. having lots of hidden layers considerably helps in representing a complex function in terms of simple functions [111]. Multiple definition of DL are reported in the literature such as-

- Definition 1: A sub-class of ML techniques that utilizes multiple linear and non-linear layers information representation for recognizing the pattern analysis of any data series.
- Definition 2: Deep learning is a sub-field of ML which learns in multiple levels, corresponding to various levels of abstraction. It usually uses artificial intelligence based network. Each consecutive connected layer uses the output of the former layer as its input. It realizes the feature pattern of the data series automatically.

On the basis of adopted learning mechanism it can be categorized in following types-

i) Supervised learning
ii) Un-supervised learning
iii) Semi-supervised learning
iv) Reinforcement learning

Supervised learning: In supervised learning methods, the model is primarily learned on a pre-acquired data set along with its corresponding labels. Thus, once the model understands the pattern of the known data set, it can be further applied for making the verdict about the unfamiliar data set.

Un-supervised learning: In un-supervised methods, the prior labels are not defined in the input dataset. In contrast, the algorithm itself tries to identify the specific similarities in the input dataset so that the original dataset can be categorized into identical categories. Clustering and self-organizing mapping methods are most common examples of it.

Semi-supervised learning: Semi-supervised methods, it lies between both supervised and un-supervised. The data set comprises of little amount of label data and larger content of undefined/ unlabeled data.

Reinforcement learning: This learning scheme lies in between supervised and unsupervised learning strategy. The algorithm gets informed if the prediction is incorrect, but does not information how to correct it. It has to search and make out different possibilities until it works out how to get the answer right. Sometimes it is also called learning with a critic because of this monitor that check the answer, but does not recommend the improvements.

Depending upon the architectures and applied training mechanism the DL networks [112-113] can be broadly classified as follows-

i) Convolution neural network (CNN)

ii) Recurrent neural network (RNN)

iii) Deep belief networks (DBN)

iv) Stacked Autoencoder

5.8.1 Convolution Neural Network: CNN is one of the well-known architecture of DNN. It usually consists of numerous layers, where every layer has two sections, one for convolution and other for pooling. The series of convolution/pooling layers is generally ended by a regression layer for recognizing the particular class label of the input data set.

5.8.2 Recurrent Neural Network: RNN works on the idea of using the output information of the layer and feeding it again to the input for acquiring the final outcome of the layer. It termed as recurrent because it execute the same task for each element of a sequence, with the output being depended on the previous computations. In RNN, the initial layer is similar to that feed forward neural network. Once the input is applied to the next layer, it computes the output by considering the information acquired in the previous time-step. In RNN, if the output is incorrect, than the learning rate or error correction can be added to make small changes so that it will gradually work towards making the correct prediction during the back propagation. It is usually applied in text detection. The structure of the RNN is shown in Fig. 5.13 and its unfolded architecture is provided in Figure 5.14.

.

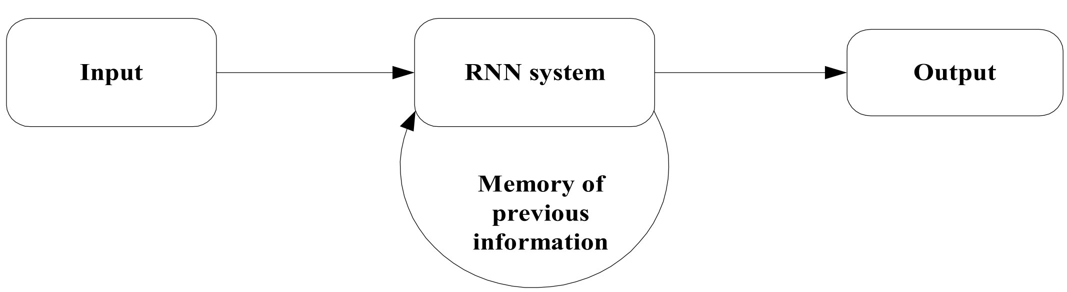


Figure 5.13 Structure of RNN

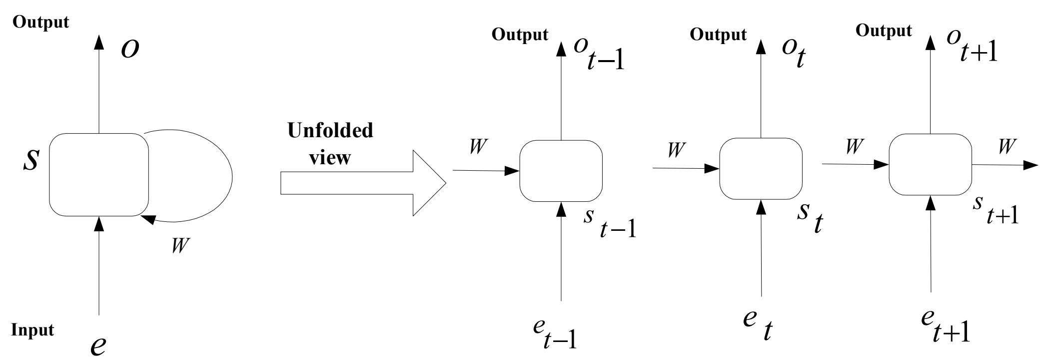


Figure 5.14 An unfolded (in time) structure of RNN

5.8.3 Deep Belief Networks: An elementary belief network is consists of different layers of stochastic binary units with associated connection weight. Its basic aim is to infer the states of unknown stochastic binary units and transforming the associated weights in the units so that the designed network can verdict same as the trained data set. The DBN are characterized as stack of multi-layered Restricted Boltzmann machine (RBM) system, where every RBM layer communicates with both the former and forthcoming layer. Each layer in any DBN system plays twofold function; it works as hidden layer for prior nodes and as visible layer to afterward nodes. The DBN is effectively trained by training the one RBM layer at a time. As the initial RBM layer is trained, the corresponding samples are forwarded by it and the output is obtained at its hidden layer that fed as input to the visible layer of subsequent RBM and so on. This mechanism of training is termed as layer wise pre training scheme. Fig. 5.15 shows the structure of RBM and Figure 5.16 represents the architecture of DBN system.

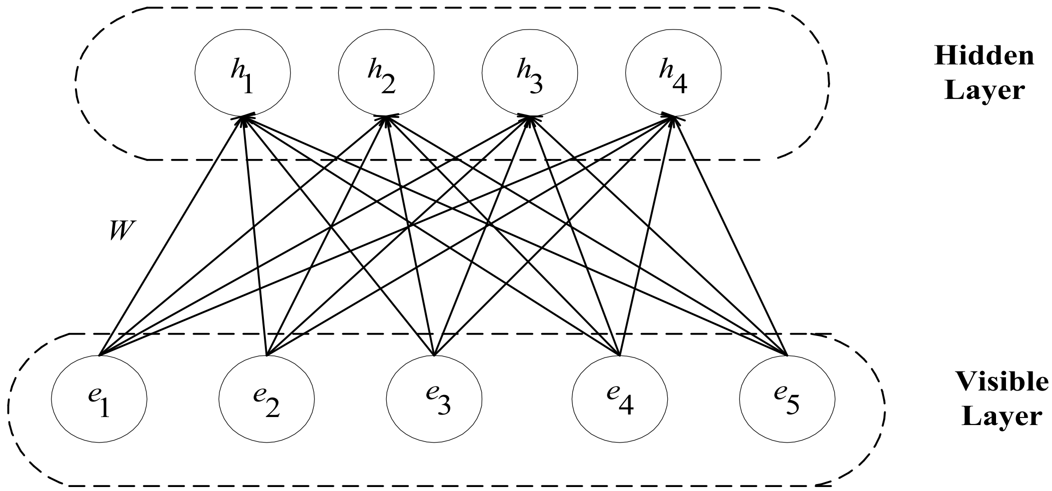


Figure 5.15 Structure of RBM network

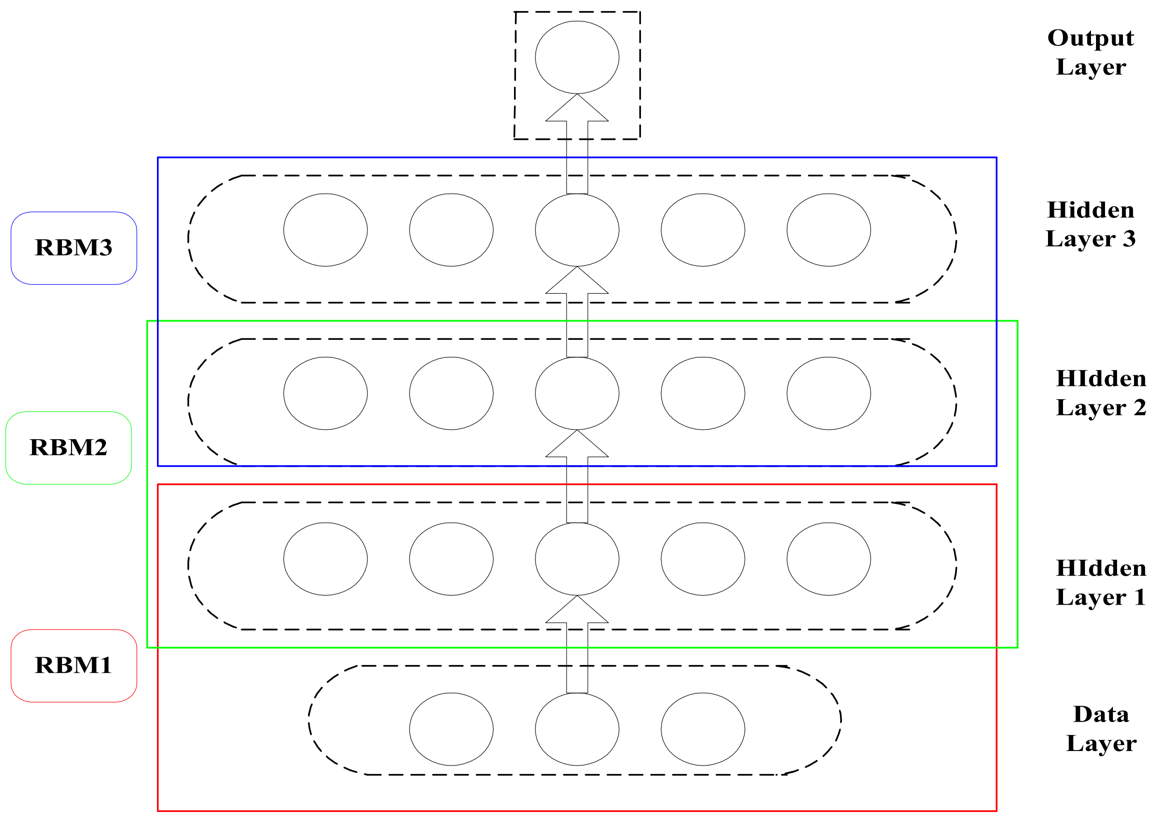


Figure 5.16 DBN structure

5.8.4 Autoencoder: Bengio et al. [113] have introduced the concept of stacked auto-encoder (SAE) based deep architecture for DNN model. An auto-encoder maps all the data points (feature vectors) to itself via various layers of hidden representation. It involves encoding and decoding; the encoder simply transformed the input feature set into some smaller form of representation, whereas the decoder ultimately reconstruct the input procured form the encoders.

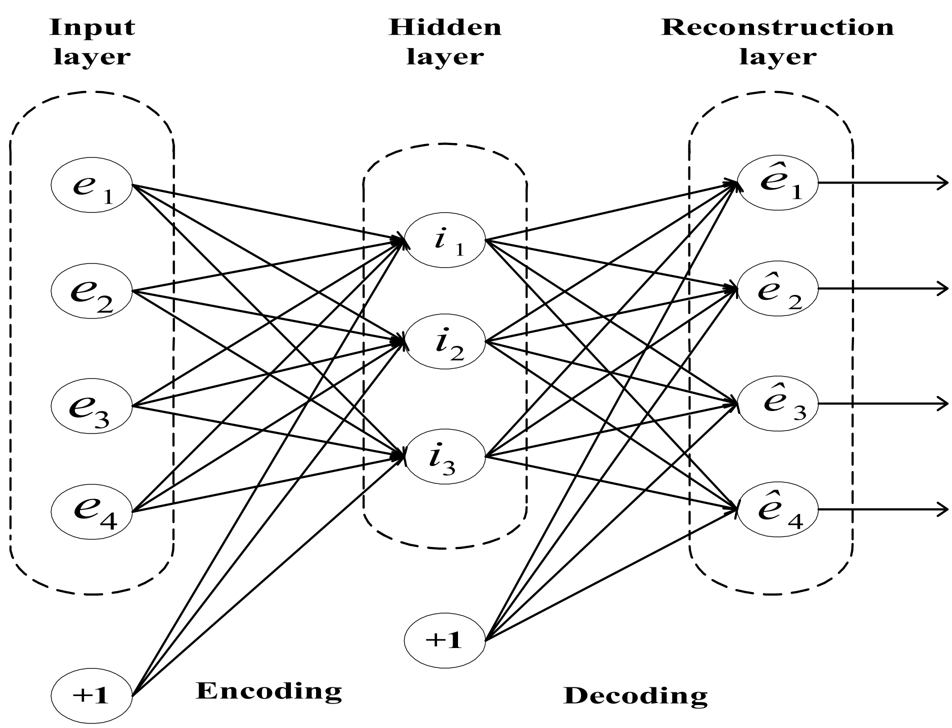


Figure 5.17 Architecture of autoencoder network

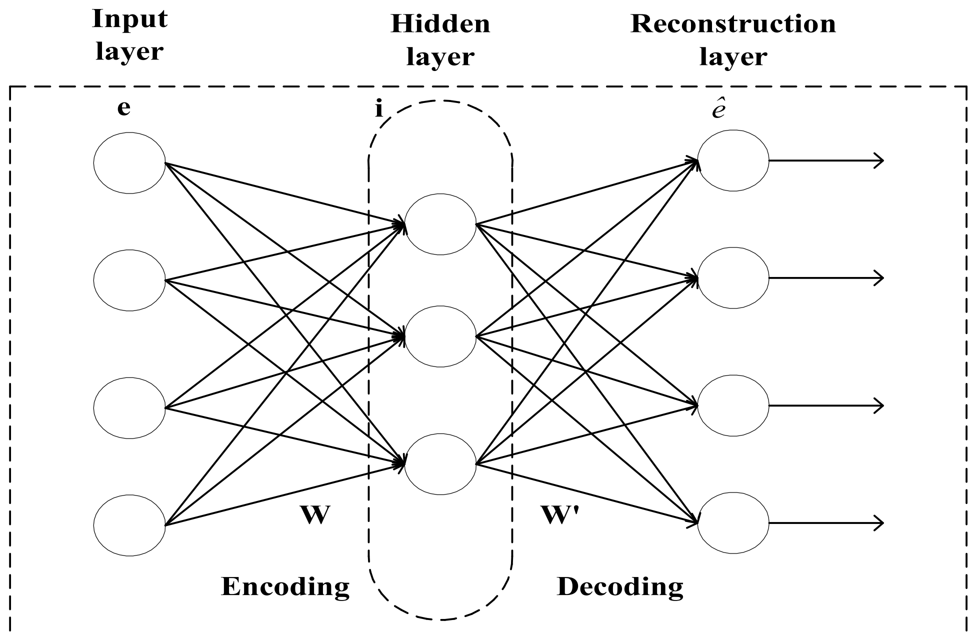


Figure 5.18 One layer structure of an autoencoder

The auto-encoder (AE) network consists of three layers; firstly an input visible layer, than hidden layer and lastly a reconstruction layer with same size as the input layer [114]. Fig. 5.17 shows an autoencoder network and Fig. 5.18 shows one layer structure of an autoencoder. Let $e \in R^n$ is the input vector; $i \in R^n$ is the output of the hidden layer and $\hat{e} \in R^n$ is the output of the reconstruction layer. The corresponding outputs i.e. i and $\hat{e}$ can be estimated using the equations given below-

$$i = f\left(We + b\right) \tag{5.2}$$

$$\hat{e} = f\left(W' i + b'\right) \tag{5.3}$$

Where, $f(.)$ is the activation function (non-linear); W is $d \times n$ weight matrix; b is bias of dimension d of the encoding; W' is $n \times d$ weight matrix and b' is the bias of dimension n of decoding section.

The parameters W, W', b and b' are calculated by using a back propagation algorithm.

$$\underset{W,W',b,b'}{arg\,min}\left[L\left(e,\hat{e}\right)\right] \tag{5.4}$$

Auto-encoders are trained by a specialized training mechanism for minimizing the reconstruction error between the input feature vector e and output vector $\hat{e}$. The loss function $L\left(e,\hat{e}\right)$ adopted in this work is the squared error i.e. $\left\|e-\hat{e}\right\|^2$.

There are different types of autoencoders such as

i) Stacked autoendocer (SAE)
ii) Denoising autoendocer
iii) Sparse autoendocer
iv) Convolutional autoendocer

Stacked autoendocer: SAE is composed of several systematically connected autoencoders having multiple encoders and decoders in it as shown in Figure 5.19. A specialized training mechanism (prior and post training) has been utilized in DNN for expediting the training process. During prior training, each layer of the model is trained individually and the output of every layer is applied as input to the successive layer. Afterward, entire layers are stacked together for building the deep network. In post training period, fine tuning mechanism has been employed for improving the performance of the network. This whole process is called as stacked auto-encoding and the corresponding structure of the deep network is termed as auto-encoder.

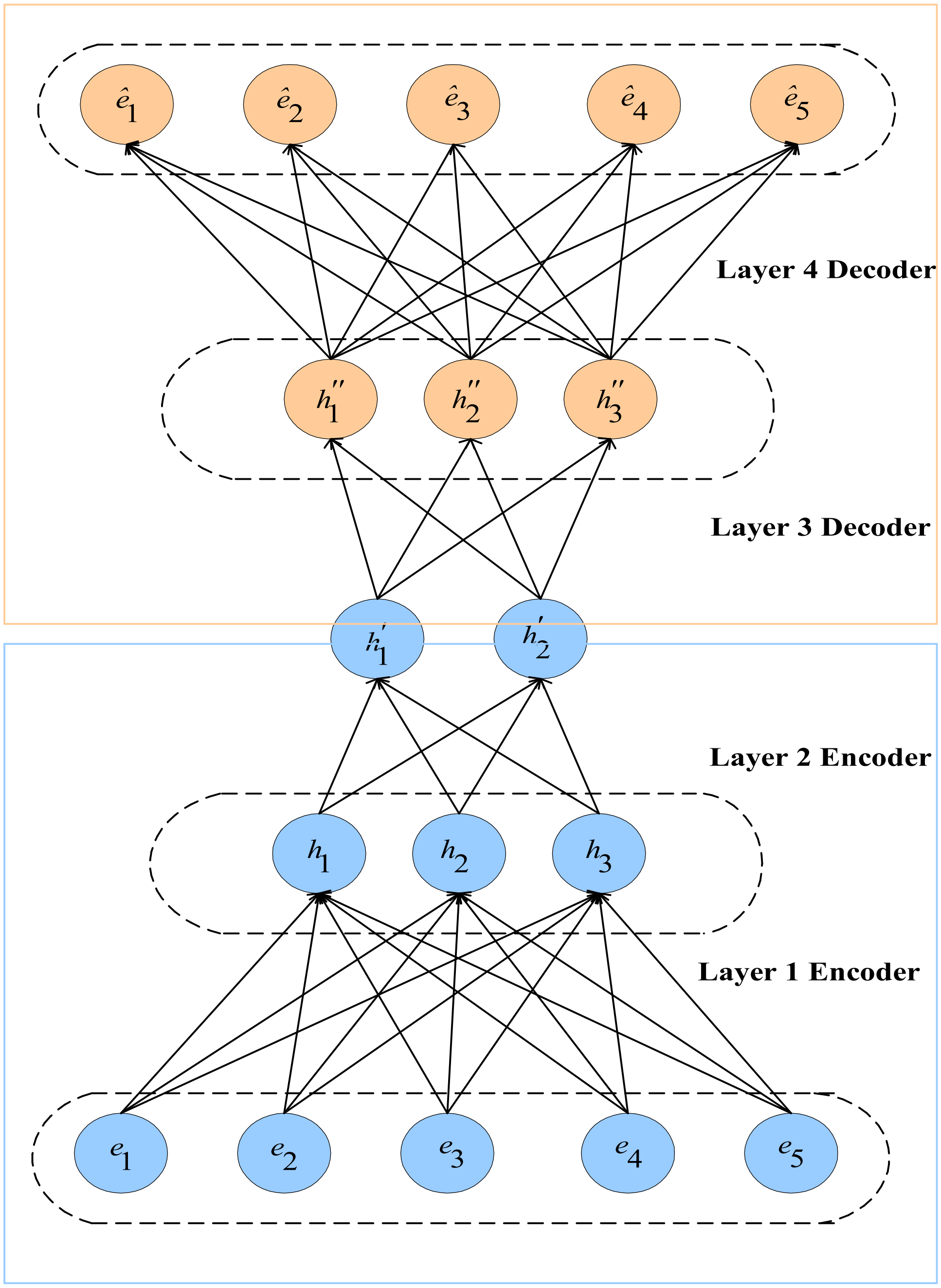


Figure 5.19 Stacked autoencoder structure (with 3-hidden layer)

5.9 Proposed DWT and Deep Learning Based Fault Events Classification Scheme

The work-flow of the proposed DWT and DNN based fault events classification scheme in series compensated transmission network is shown in Figure 5.20. The extracted feature vectors in terms of norm entropy of DWT detail coefficients for each phase i.e. e_a, e_b, and e_c are fed to the autoencoder based deep neural network as training and testing input dataset. The output layer of the designed deep network is consists of softmax classifier units. In the testing phase, the estimated feature sets corresponding to various fault scenarios are applied to the applied to the trained deep network model. The softmax classifier categorizes the different fault events according to their particular class labels based on the learned training patter.

5.9.1 Training and Testing mechanism

In the present work, a deep neural network model has been designed for ascertaining the specific categories of fault events in the compensated transmission network using an autoencoder and softmax layer. During the training, the extracted feature vectors corresponding to training fault cases with varying conditions are applied to the input layer of the autoencoder model. The different fault scenarios are labelled in the similar fashion i.e. AG-class1, BG-class 2, CG-class 3, AB-class 4, AC-class 5, BC-class 6, ABG-class7, BCG-class 8, ACG-class 9, ABC-class 10. Once the training feature vectors i.e. e_a, e_b, and e_c are applied to autoencoder model, it maps all input feature vectors to itself using different layers of hidden representation. The encoder simply transformed the input feature set into some smaller form of representation, whereas the decoder ultimately reconstruct the input procured form the encoders. The 'logsig' transfer function has been used as the encoder transfer function, whereas 'purelin' function is applied as decoder transfer function in the designed deep network model. The scaled conjugate gradient back-propagation training mechanism has been employed for updating the weights and bias value in the network. The cross-entropy loss function has been applied for estimating the performance in terms of predicted output and actual target value. The expression for the applied loss function is given in equation 5.5, where T_c is the target class label; P_c is the predicted class by the network.

$$cross_{entropy} = -\frac{1}{m}\sum_{c=1}^{m}\left(T_c \log\left(P_c\right) + \left(1 - T_c\right)\log\left(1 - P_c\right)\right) \tag{5.5}$$

The hidden layer size of the autoencoder network is fixed as 20. Ultimately, the softmax layer has been utilized at the final output layer of the designed network. It predicts the specific class label of the test instance (1-10) as its output.

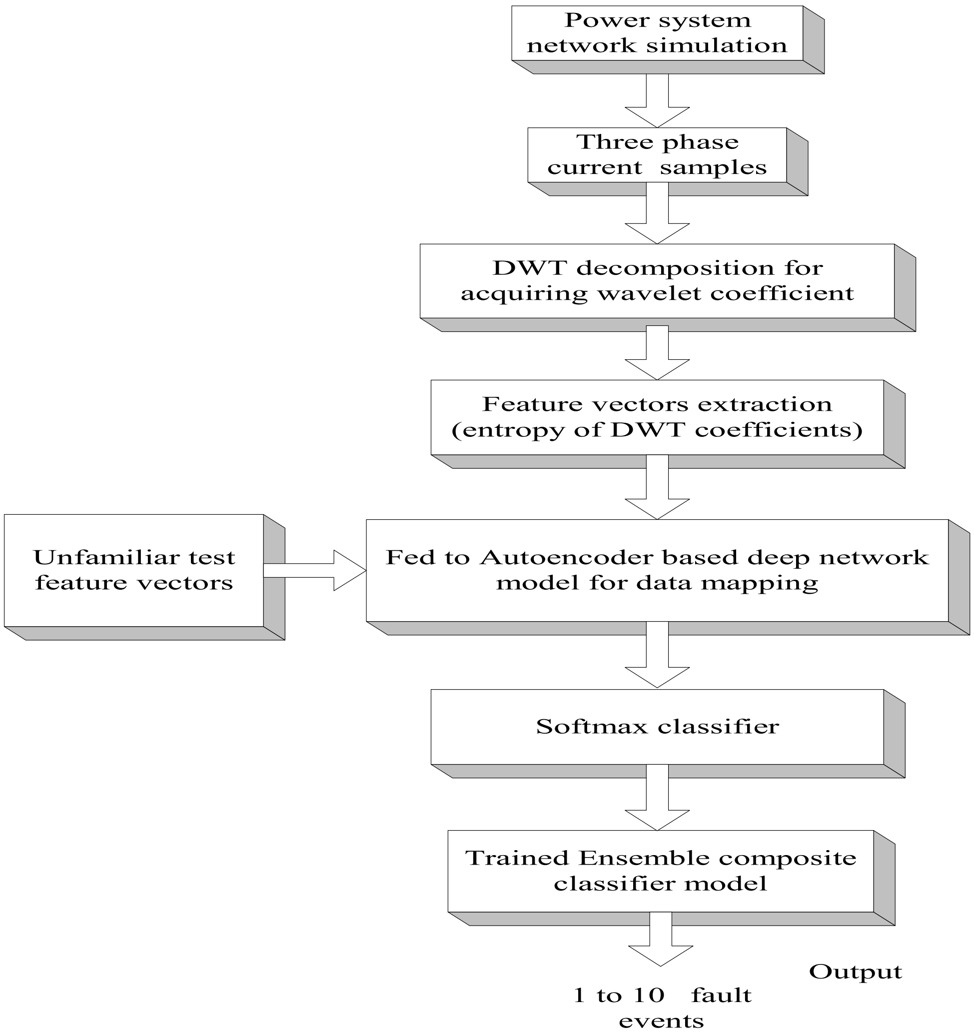


Figure 5.20 Work-flow of the proposed DNN based events classification scheme

5.10 Case Study and Results

In order to exploring the feasibility of the proposed DNN based fault events ascertaining scheme, it has been comprehensively analysed for various fault scenarios in the different simulated test systems. Table 5.14 presents the details of various training and testing cases that are taken into consideration while assessing the proficiency of the deep learning based fault categorization scheme. The feature vectors corresponding to these mentioned circumstances are utilized as the training and testing dataset.

Table 5.14 Training and testing conditions considered on first test system

S. No	Parameters	Training cases	Testing cases
1.	Fault locations	Twenty different locations	Seven new unknown location (30 km, 50km, 110 km, 170 km, 190 km, 230 km and 250 km)
2.	Fault Resistance (ohms)	0.001, 20, 60	0.1, 0.5, 1, 5, 10, 50
3.	Fault inception angle (°)	0, 75, 150	30, 45, 60, 90, 120, 135
4.	Fault events types	All kinds faults events	Unknown all kinds of fault events
5.	Level of line compensation	35 % and 45 %	30 % and 40 %

5.10.1 Test Case I: Two-Bus Series Compensated Transmission Test Network

The practicability of the proposed DNN based events ascertaining scheme is rigorously assessed for various fault events on the first simulated test system as shown in Figure 5.3. It has been also validated for all sorts of shunt fault events, evolving fault events and cross-country fault events with varying circumstances in the simulated test network. The extracted feature vectors corresponding to different considered fault cases are fed to the designed DNN model as training and testing dataset. Finally, in the testing phase the DNN model predicts the class label of the test instance on the basis of learned training pattern set. The events classification accuracy percentage has been computed using the expression given in equation 5.1. Figure 5.21 shows the structure of the utilized autoencoder and softmax layer based DNN model for fault events categorization. There are three presents in the input layer i.e. e_a, e_b, and e_c; whereas on the output layer ten output represents the ten class labels of the fault events. Table 5.15 represents the results of fault events classification provided by the proposed deep neural network based scheme during the testing on the first test system. The overall average fault events categorization accuracy provided by the proposed scheme is 99.31% respectively. Table 5.16 shows the corresponding confusion matrix. These results confirmed that the proposed DWT combined deep neural network based approaches is very efficacious in ascertaining the fault events in compensated transmission networks.

Table 5.15 Faults classification accuracy percentage obtained by DNN based scheme

Fault type	Number of test samples	Number of incorrect classification	Correct classification	Over all Accuracy (%)
Line to Ground	1512	0	1512	100.00
Line to Line	1512	19	1493	98.74
Double Line to Ground	1512	23	1489	98.48
3 phase (LLL)	504	0	504	100.00
Avg. Accuracy				**99.31**

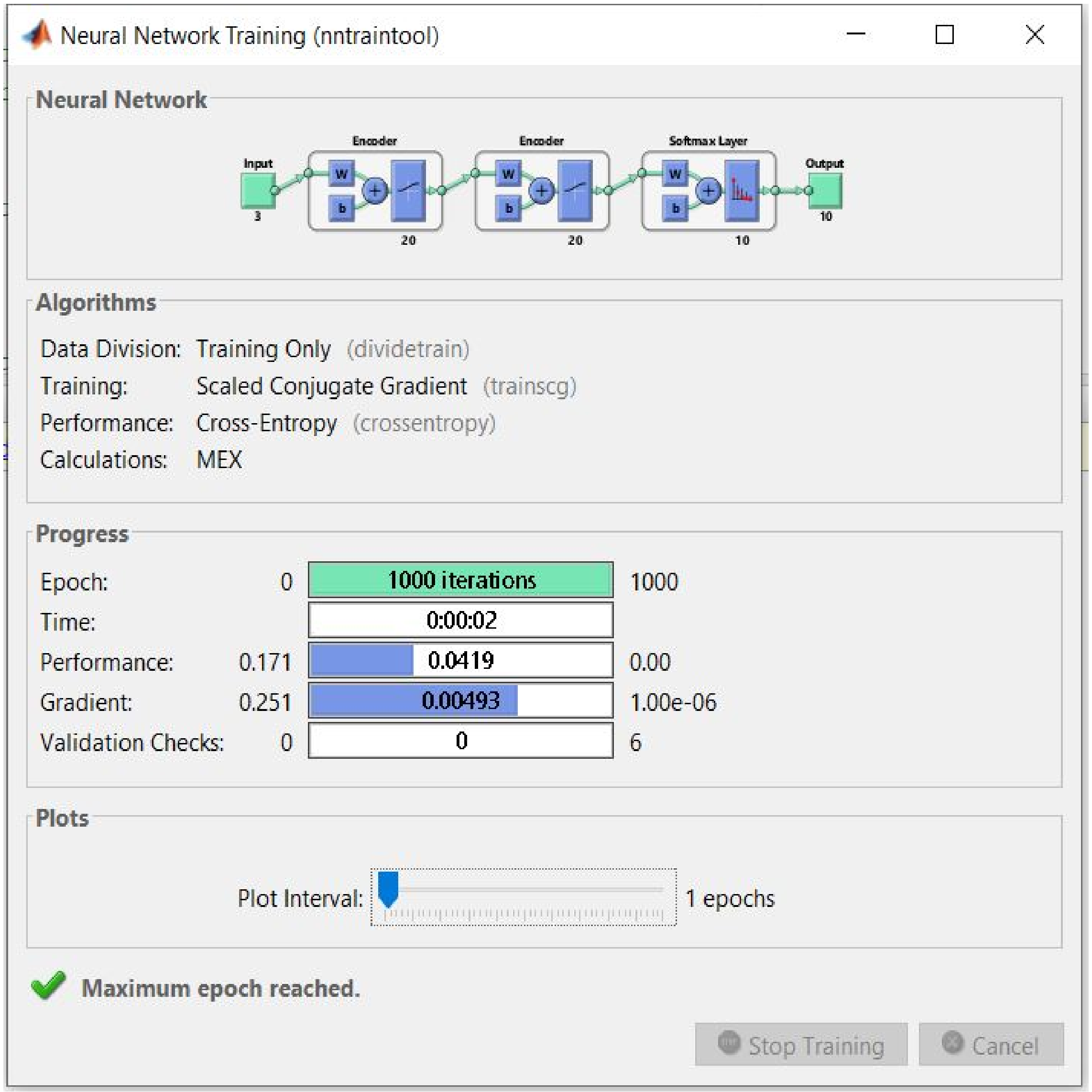


Figure 5.21 Structure of the utilized autoencoder and softmax layer based DNN

Table 5.16 Confusion matrix for the DNN based scheme (First test system)

Actual fault events	Sample size	Predicted fault events											
		AG	BG	CG	AB	AC	BC	ABG	BCG	ACG	ABC	No fault	Accuracy (%)
AG	**504**	**504**	0	0	0	0	0	0	0	0	0	0	**100**
BG	**504**	0	**504**	0	0	0	0	0	0	0	0	0	**100**
CG	**504**	0	0	**504**	0	0	0	0	0	0	0	0	**100**
AB	**504**	0	0	0	**498**	0	0	**6**	0	0	0	0	**98.8**
AC	**504**	0	0	0	0	**495**	0	0	0	**9**	0	0	**98.2**
BC	**504**	0	0	0	0	0	**500**	0	**4**	0	0	0	**99.2**
ABG	**504**	0	0	0	**11**	0	0	**493**	0	0	0	0	**97.8**
BCG	**504**	0	0	0	0	0	**4**	0	**500**	0	0	0	**99.2**
ACG	**504**	0	0	0	0	**8**	0	0	0	**496**	0	0	**98.4**
ABC	**504**	0	0	0	0	0	0	0	0	0	**504**	0	**100**
No fault	**10**	0	0	0	0	0	0	0	0	0	0	**10**	**100**

Table 5.17 shows the time response of the proposed deep neural network based scheme for predicting the category of the fault events in the transmission network. Table 5.18 demonstrates the comparative analysis in terms of events classification accuracy rate of the proposed DNN based scheme with already reported approaches in the literature [58, 39, 32, and 40]. The comparative results depicted in Table 5.18 reaffirmed the aptness of the proposed scheme in ascertaining the fault events in series compensated power transmission network.

Table 5.17 Time of response of DNN based events classification scheme

S. No	Classifier Model Utilized	Time of response
(i)	Deep neural network	5.17e-02 s

Table 5.18 Comparative analysis of average classification accuracy achieved by proposed DNN based scheme with previously reported approaches

Fault type	Ref. [58] (%)	Ref. [39] (%)	Ref. [32] (%)	Ref. [40] (%)	DNN based scheme (%)
Line to ground	97.23	97.447	100.00	99.449	100.00
Line to line	97.29	99.616	97.560	97.687	98.74
Double line to ground	97.84	98.611	98.788	99.314	98.48
3 phase (LLL)	97.68	100.00	100.00	98.565	100.00
Average accuracy	**97.51**	**98.918**	**99.087**	**98.753**	**99.31**

5.10.2 Test Case II: Modified IEEE 9-Bus Series Compensated Test Network

Table 5.19 shows the fault events classification accuracy percentage obtained by the proposed DWT and DNN based scheme during the testing on the second test network (shown in Figure 5.5). It has been noticed that the proposed deep neural network based scheme gives 99.25% over all fault events classification accuracy during the testing. The associated confusion matrix for ensemble learning based scheme is shown in Table 5.20.

Table 5.19 Faults classification accuracy percentage obtained by DNN based scheme

Fault type	Number of test samples	Number of incorrect classification	Correct classification	Over all Accuracy (%)
Line to Ground	600	0	600	100.00
Line to Line	600	7	593	98.83
Double Line to Ground	600	11	589	98.17
3 phase (LLL)	200	0	200	100.00
Avg. Accuracy				**99.25**

Table 5.20 Confusion matrix for DNN based scheme (second test system)

Actual fault events	Sample size	Predicted fault events											
		AG	BG	CG	AB	AC	BC	ABG	BCG	ACG	ABC	No fault	Accuracy (%)
AG	**200**	**200**	0	0	0	0	0	0	0	0	0	0	**100**
BG	**200**	0	**200**	0	0	0	0	0	0	0	0	0	**100**
CG	**200**	0	0	**200**	0	0	0	0	0	0	0	0	**100**
AB	**200**	0	0	0	**196**	0	0	**4**	0	0	0	0	**98.0**
AC	**200**	0	0	0	0	**197**	0	0	0	**3**	0	0	**98.5**
BC	**200**	0	0	0	0	0	**200**	0	0	0	0	0	**100**
ABG	**200**	0	0	0	**5**	0	0	**195**	0	0	0	0	**97.5**
BCG	**200**	0	0	0	0	0	**2**	0	**198**	0	0	0	**99.0**
ACG	**200**	0	0	0	0	**4**	0	0	0	**196**	0	0	**98.0**
ABC	**200**	0	0	0	0	0	0	0	0	0	**200**	0	**100**
No fault	**10**	0	0	0	0	0	0	0	0	0	0	**10**	**100**

5.10.3 Test Case III: Series Compensated Parallel Transmission Network (Third test system)

Table 5.21 provides the fault events classification accuracy percentage obtained by the proposed DWT and deep neural network based scheme for various considered test cases on the third test network shown in Figure 5.16. It has been noticed that proposed DNN based scheme gives 99.28% over all classification accuracy during the testing on third test network.

Table 5.21 Acquired accuracy percentage obtained by DNN technique based scheme

Fault type	Number of test samples	Number of incorrect classification	Correct classification	Over all Accuracy (%)
Line to Ground	450	0	450	100.00
Line to Line	450	5	445	98.89
Double Line to Ground	450	8	442	99.22
3 phase (LLL)	150	0	150	100.00
Avg. Accuracy				**99.28**

5.11 Cross-country Fault Identification using Deep Neural Network based Scheme

The proficiency of the proposed DNN based events classification scheme is also evaluated for cross-country fault situations in the power transmission network. The simulated cases of cross-country faults in the third test system are already discussed in section 5.6. The extracted feature vectors associated with normal double line to ground events and cross-country fault cases are applied to the DNN based classifier modes as input dataset. The normal shunt fault events and CCF are labelled as follows: ABG- class 1, BCG-class 2, ACG-class3, AG-bg-class 4, AG-cg-class 5, BG-ag-class 6, BG-cg-class 7, CG-ag-class 8, and CG-bg-class 9. During the testing, the feature vectors associated with new unknown cases of CCF and normal double line to ground shunt events are applied to the trained ensemble classifier model for discriminating the normal shunt events and CCF events. The classifier model predicts the class label of the test instance as its output. Table 5.22 represents the cross-country fault identification results acquired by the proposed deep neural network based scheme. By observing the Table 5.22, it is deduced that the proposed DNN based scheme is quite effectual is ascertaining the CCF events in series compensated power network.

Table 5.22 Identification of CCF events in the network using DNN model based scheme

S.No.	Cross-country fault type		Cross-country fault or not	Classifier output
	Initial fault (line-1)	CCF event (line-2)		
1.	ABG at 30 km	-	No	1
2.	AG at 30 km	bg at 50 km	Yes	4
3.	ACG at 30 km	-	No	3
4.	AG at 30 km	cg at 50 km	Yes	5
5.	BG at 30 km	ag at 50 km	Yes	6
6.	BCG at 30 km	-	No	2
7.	BG at 30 km	cg at 50 km	Yes	7
8.	CG at 30 km	ag at 50 km	Yes	8
9.	CG at 30 km	bg at 50 km	Yes	9
10.	ABG at 50 km	-	No	1
11.	AG at 50 km	bg at 100 km	Yes	4
12.	ACG at 50 km	-	No	3

13.	AG at 50 km	cg at 100 km	Yes	5
14.	BG at 50 km	ag at 100 km	Yes	6
15.	BCG at 50 km	-	No	2
16.	BG at 50 km	cg at 100 km	Yes	7
17.	CG at 50 km	ag at 100 km	Yes	8
18.	CG at 50 km	bg at 100 km	Yes	9

5.12 Evolving Fault Identification using Deep Neural Network based Scheme

The capability of the proposed deep neural network based events classification scheme is also examined for evolving fault cases in the power transmission network. Two distinct case of evolving faults i.e. AG-bg and AG-cg simulated in the third test system (as described in section 5.7) are considered for the analysis. Table 5.23 provides the evolving fault identification results provided by the proposed deep neural network based scheme.

Table 5.23 Identification of evolving fault events using DNN model based scheme

S.No	Primary fault type	Secondary fault type	Time interval (ms)	Evolving Fault or not	Classifier output
1.	AG	-	-	No	1
2.	ABG	-	-	No	2
3.	AG	bg	5	Yes	3
4.	ACG	-	-	No	4
5.	AG	cg	5	Yes	5
8.	AG	bg	10	Yes	3
9.	AG	cg	10	Yes	5
11.	AG	bg	15	Yes	3
12.	AG	cg	15	Yes	5

5.13 Conclusion

An ensemble learning and deep neural network based scheme is presented in this chapter for ascertaining different fault events in the compensated power transmission network. The basic fundamentals, applied algorithms of ensemble learning and deep learning are thoroughly discussed in detail. Later on, the feasibility and proficiency of the proposed integrated ensemble and deep learning based fault events ascertaining methodology is analyzed for various fault scenarios on simulated test networks. In addition, the efficacy of the proposed schemes is also evaluated during evolving and cross-country faults in the transmission circuits. The results obtained by the proposed ensemble and deep neural network based schemes during all considered test scenarios, has reaffirmed that the proposed schemes are well effectual in ascertaining the fault events in the series compensated power network. It has also been observed that the proposed schemes are competent of providing precise classification of fault events in the compensated circuit irrespective of parameters variations such as types of fault, the location of the events, inception angles, the point of compensation and change in line compensation percentage.