International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(14s) 2026 pp. 931-941
https://doi.org/10.70917/ijcisim-2026-4300
Article

Data-Driven Relaying System for Transmission Line Series Compensated with Double Circuit

Manjusha Parve[1], Rashmi Keswani[2]

[1] Department of Electrical Engineering, Priyadarshini College of Engineering, Nagpur, Maharashtra, India.
Email: manjuparve2022@gmail.com
[2] Department of Electrical Engineering, Priyadarshini College of Engineering, Nagpur, Maharashtra, India.
Email: keswani_rashmi@rediffmail.com

Abstract: This paper introduces double circuit transmission lines data-based modelling, control, defect identification and categorization of fixed series capacitor compensated. One of the severe problems of double circuit transmission lines is reciprocal connection between two of circuits of compensated transmission line in series for which most of the conventional schemes will not work. One of the solutions for this type of problems is to design a scheme considering the situations that may arise in the system. Different situations can be represented with different data and from data the algorithm should able to predict the outcome. So in this paper in double circuit line Artificial Neural Networks are employed to identify faults and categorize them with fixed series capacitor compensated lines on which mutual coupling between the lines have no effect. The data-driven relaying plan is tested for a variety of malfunction scenarios, including short-circuit defect, cross-country error, fault kind, and malfunction location, defect resistance, and angle of error inception. For every evaluated defect condition, the suggested data-driven relaying technique is proved to be 100% accurate.
Keywords: Compensated Transmission line, Bayesian Predictors, error detection, error categorization

1. Introduction

Of all the protection problems with series capacitor compensated transmission lines (SCCTL), including inversion of voltage and current, error impedance loops, short-circuit defect, and mutual coupling, the most severe is mutual coupling between the double circuit. Conventional relaying schemes will not be applicable in this scenario because it will detect both circuits faulty leading to mal-operation of circuit breaker to trip as signals of healthy circuits will change near to range of fault condition due to mutual coupling between phases. So the relaying schemes that are designed for single circuit lines also will not work in this case. So it is necessary to design relaying schemes which correctly detect the faults so that reliability, dependability and security of power flow increase.

For protection of compensated line distinct relaying techniques have been reported as given in [1-11]. Data based techniques are more suitable for double circuit SCCTL than equation based techniques as all the situations that system goes through can be represented with data. Researchers have suggested ANN and SVM as data-based methods for power system protection. ANN has been used to categorize transmission line faults because of its capacity to identify patterns. [1]. In [2], series-compensated EHV transmission an ANN-based protection method for controlled is described. This scheme use post-fault data which produces better results with two or three cycle. In [3], a radial basis neural network with series compensated line is protected with a thyristor-controlled device. However, as ANN-based techniques rely on trial and error, there are no set standards for selecting the network architecture. The amount of the training data has an impact on the network's performance, which is another disadvantage of ANN. In [4], SVM are used to categorize deviation in series-compensated lines. [5] Proposes advanced compensated transmission line using SVM to identify portions and categorize defect. SVM-based approaches are also affected by the quantity of learning data; hence, the performance of the method may decrease as the size of the training data increases. In [6], decision trees are used to categorize faults in flexible AC transmission lines. “It is recommended to use an extreme learning machine for compensated transmission lines in series protection” [7].

Many researchers employ wavelet transforms to secure power systems. Wavelet transform protection of series compensated lines has been documented by [8]. A discrete wavelet transform is suggested in [9] for phase selection and fault portion identification in thyristor-controlled series compensated lines. However, these techniques rely on thresholding levels that might not be effective for protecting double circuit series compensated lines. So hybrid methods are suggested by researchers for protection of SCCTL. "Faults in series compensated lines are classified using fuzzy logic and wavelet transform" [10]. "The adaptive neuro-fuzzy inference system (ANFIS) and wavelet transform are recommended for fault classification" [11].However, because of the reciprocal coupling effect in single circuit, the majority of protection strategies are designed for compensated lines, which may not be effective for double circuit SCCTL.

This work proposes a data-based approach to double circuit SCCTL protection that takes into account short-circuit faults and mutual coupling. In double circuit SCCTL effect of mutual coupling can be overcome if the networks will be designed with datasets in that fault situations. Therefore, in this work, fault detection and fault phase identification in double circuits are done using Bayesian predictors. SCCTL to solve the mutual coupling issue. The power system simulation is displayed in Portion 2, the suggested approach is explained in Portion 3, the results are presented in Portion 4, and the conclusion is presented in Portion 5.

2. Modelling Networks and Processing Signals

Figure 1 depicts the 400 kV, 50 Hz double circuit series capacitor used in this work with compensated line. It is made up of a three-phase source connected to both ends by a 200 kilometre cable. The source end has an X/R ratio of 10, a load angle of 150, a load of 100MW and 100MVar, and a short circuit capacity of 1250MVA. Receiving end has load angle of 00, and X/R ratio 10, load of 250MW, short circuit capacity 1250MVA. Series capacitors C1 and C2 are installed near to source end in both circuit1 and circuit 2 respectively. In this work, 40% series compensation was applied. All the modelling and simulation works are done in MATLAB/SIMULINK. After designing the circuit, it is simulated and waveforms are observed to design algorithm for protection of SCCTL. It is observed that in compensated double circuit lines the healthy phase current magnitude increases due to mutual coupling and becomes equal to magnitude at some faulty situation. A fault case is shown in Figure2 during C1G fault at 10km with R=0.001Ω.

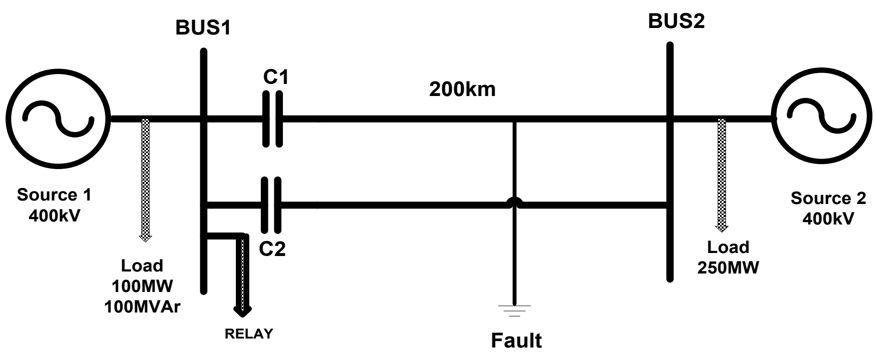

Figure 1.SCCTL Single Line diagram

The electrical signals are displayed in Figure 2 during a fault to illustrate the impact of mutual coupling. The network's current signals are evident in Figure 2 (a), while voltage signals are noticed in Figure 2 (b). The current magnitude of C1 phase should be higher during fault than other phases as it is a C1G fault. Due to mutual coupling C2 phase current magnitude may increase but, in this case, it has large increase in current magnitude almost equivalent to faulty phases although it is not faulty phase. Conventional thresholding-based protection strategies will not work in this situation. So, for protection of double circuit a scheme is designed for series compensated lines which will overcome this type of problem.

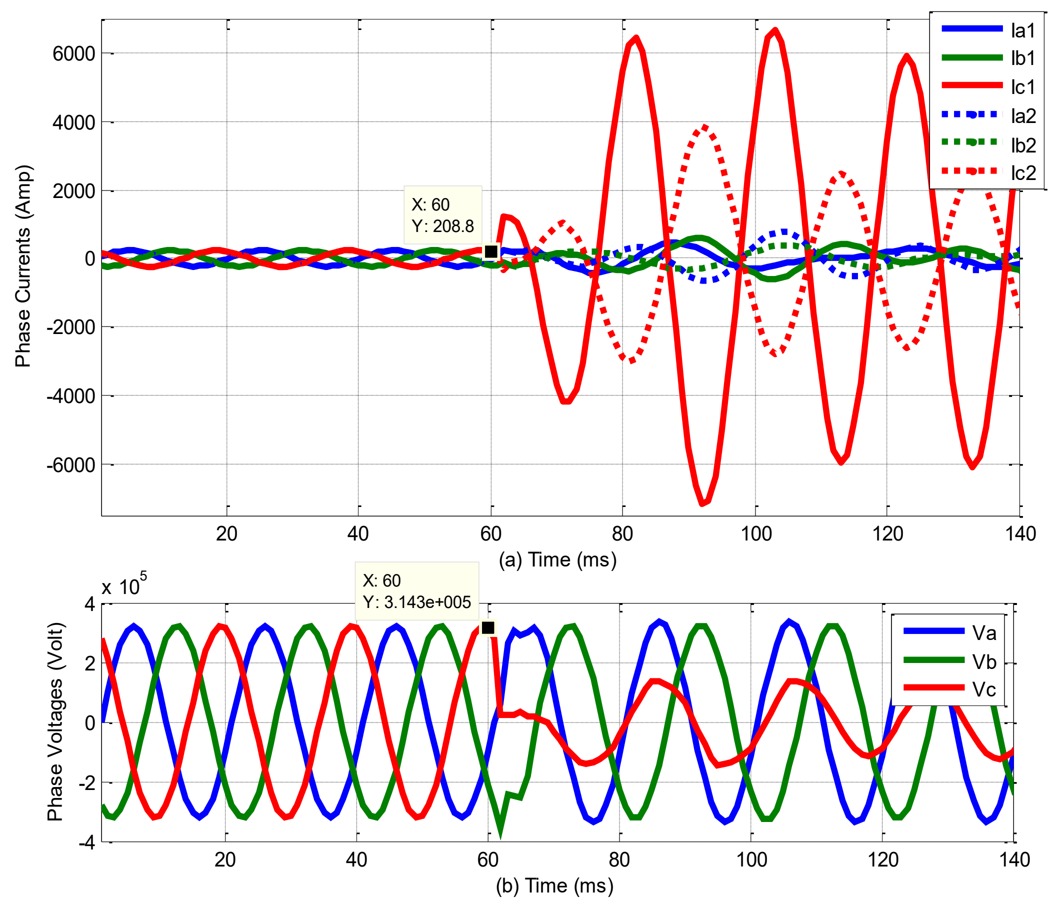

Figure 2. (a) Current and (b) voltage notifications at 10 km with R=0.001Ω during a C1G fault.

After simulating the fault cases varying type of error, spot of the fault, resistance of error and angle of fault inception, the electrical signals are captured at the source with 1 kHz frequency of samples. The pulses are then framework with frequency-domain spectral analysis to get the essential element of signals. The phase C1 current signals although C1G error at 10 km with R=0.001Ω are displayed in Figure 3 (a). The basic component of phase C1 current responses obtained after DFT processing is shown in Figure 3 (b). Pre-disturbance and post disturbance signal points of main spectral components of signals are used to design the data driven relaying scheme. Data driven relaying scheme designed with the help of a tool called Bayesian predictors. Design of the proposed method will be described in detail in next portion.

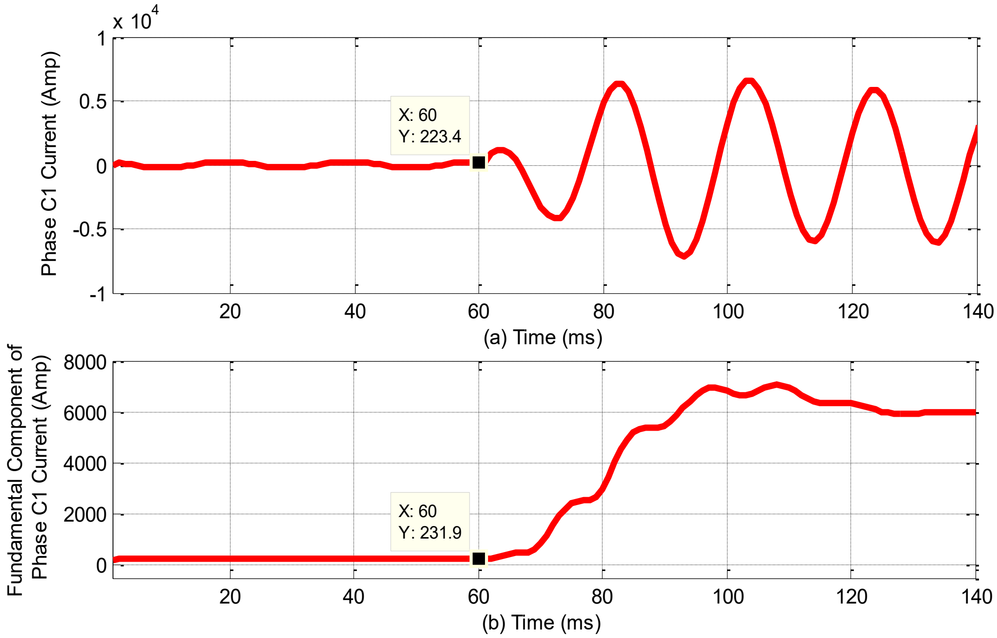

Figure 3. (a) C1 Phase current and (b) Fundamental component of phase C1 currents during C1G fault at 10km with R=0.001Ω.

3. Data Driven Relaying Scheme Using Bayesian Predictors

Proposed data based relaying scheme using Bayesian predictors is represented diagrammatically in Figure4. As proposed scheme is data based, it is required to acquire data of different situations the system goes through. Data required for are generated for fault situations varying disturbance type, fault zone, fault path resistance and fault occurrence angle.

Various parameters that are used for model fitting and model validation are given below:

i. Training Data:

a. Short-circuit faults and LG, LLG, LL, LLL, faults are the disturbance types.

b. Fault Zone– 20 locations (5 – 195 km in step of 10km)

c. Fault Occurrence Angle – 00

d. Fault Resistances – 2 resistances (0Ω and 100Ω)

ii. Testing Data:

a. Short-circuit faults and LG, LLG, LL, LLL, faults are the disturbance types.

b. Faulty Locations – 20 locations (0.1 - 199km)

c. Angle of Fault Inception – 0-3600 in the step of 300

d. Fault Resistances – 0Ω - 100Ω in step of 5Ω

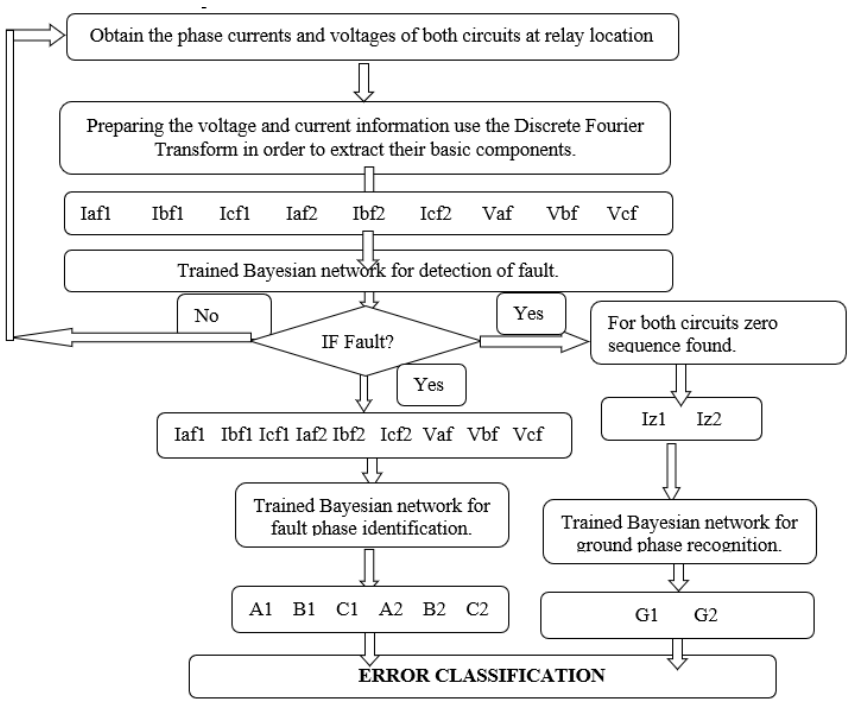

Figure 4. Data-driven strategy schematic.

After generating the data, signals are processed with DFT to get essential spectral components and zero sequence quantity which are used as input to data driven Bayesian network. Data driven schemes can be designed with data mining tools like ANN, decision, trees, nearest neighbour algorithm, Bayesian algorithm etc. [12]. Bayesian algorithm is chosen because it is very simple which uses only posterior probabilities to anticipate the class and it is invariant to large training data unlike ANN and SVM based methods. The Bayesian prediction algorithm is built on probability distributions, and it uses these probabilities and observable facts to make the best decisions [13]. In this study, Naive Bayes classifiers and other Bayesian learning methods calculate explicit probability for hypotheses. The foundation of the Bayesian prediction algorithm is Baye's Theorem. The prior probability can be used to calculate the posterior probability using the Bayes theorem as in (1)

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)} \qquad -(1)$$

Where P (h) = Prior-probability of h.

P (D) = Prior probability that training data D will be observed.

P$(D|h)$ = Probability of observing data D in which hypothesis h holds.

P$(h|D)$ = Posterior probability of h.

Unlike prior probability, which is independent of the training dataset, posterior probability takes into account information from the training data. Probability distribution used in this work is the normal or Gaussian distribution and kernel distribution as shown in (2) and (3),

$$P\left(h_k \middle| D_j\right) = \left\{\frac{1}{\sigma_{kj}\sqrt{2\pi}} exp\left(\frac{-\left(h-\mu_{kj}\right)^2}{2\sigma_{kj}}\right)\right\}, \ -\infty < h < \infty, \quad and \ -\infty < \mu_{kj} < \infty, \sigma_{kj} > 0 \quad -(2)$$

Where μ_{kj} = Mean and σ_{kj}= Standard deviation.

$$\overrightarrow{f_m}(D) = \frac{1}{mn}\sum_{i=1}^{n} K\left(\frac{D-D_i}{m}\right), \qquad -\infty < D < \infty \qquad -(3)$$

Where f = Unknown probability density

n = Number of samples

The non-negative function K(•) = Kernel has a mean of zero and integrates to one.

m = Bandwidth, smoothing coefficient.

Bayesian predictors have two phases training the network with known targets and predicting the output with unknown data. In training phase of Bayesian network different fault and no fault situations are learned by taking different data sets. To represent the normal operating conditions of power system, current and voltage 60 samples of fundamental components of normal operating condition are taken. Fault samples from 10 post each fault case to represent the fault situations, are taken. If a system malfunction occurs, it will be identified, as illustrated in Figure 4. Then fault phases are identified, ground involves or not is identified and faults are classified. The electrical signals are basic components fed into a Bayesian method to create a training network for fault detection. When there is no fault the output will be '0' and for fault condition the output will be '1'. The confusion matrix is computed as indicated in Table 1 and the defect detection network's training performance is assessed in terms of re-substitution mean square error. Test scenarios are created and examined to evaluate the network's performance once they have been trained.

For the circuit breaker to operate correctly, fault phases should be identified if a system problem is found. Using basic current and voltage components as input, a fault phase recognition training network is created using Bayesian predictors. Input data in training data set is same as fault detection. Outputs are designed by assigning numerical value to each fault type. So output for no fault, A1, B1, C1, A1 & B1, B1 & C1, C1 & A1, A1 & B1& C1, A2, B2, C2, A2 & B2, B2 & C2, C2 & A2, A2 & B2 & C2, A1 & B2, A1 & C2, B1 & A2, B1 & C2, C1 & A2, C1 & B2 are 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21 respectively. The zero sequence components of the current from both circuits are used as input to create the ground identification training network. Output for not ground and ground are 1 and 2 respectively. Table 1 displays the fault phase detection and ground identification network's training performance. Training time of both normal and kernel probability distribution are few seconds. But the mis-classification rate is more in normal distribution than kernel distribution. Test cases are created and tested to evaluate the networks' performance once they have been trained. The following part will address the findings of the suggested data-driven approach.

Table 1. Fault detection and classification network performance using Bayesian classifiers

Networks	**Probability Distribution Used**	**Training Time (seconds)**	**Confusion Matrix**	**Accuracy (%)**
			True classification	**Mis-classification**
Fault detection	Normal	0.039	10489	2371
	Kernel	88.023	12831	29
Fault Phase Identification	Normal	0.173	12170	690
	Kernel	156.428	12721	139
Ground Identification	Normal	0.008	12737	123
	Kernel	0.608	12860	0

4. Performance Evaluation of Data Driven Relaying Scheme

Proposed data driven relaying scheme using Bayesian predictors are tested for various fault cases simulated in double circuit SCCTL with variation of defect parameters like error type, defect location, Angle of defect Inception and error resistance. We will go into great depth about how the suggested solution is affected by mutual coupling, short-circuit faults, high fault resistance, multi-location faults, transforming forming faults, etc.

A. *The Impact of Coupling*

To study the effect of mutual coupling on the data based method various fault cases are generated varying fault parameters and tested. All the tested fault cases are correctly detect the faults, identify the phase of the faults and identify ground or not. Input and outputs of one of the fault one cases is shown in Figure 5 during A1B1 fault at 19km with R=0.001Ω at 60ms time. Current and voltage signal's fundamental and zero sequence components are shown in Figure 5 (a), (b), and (c). Although the A2 and B2 phases are not defective, Figure 5 (a) and (b) show that the current magnitude increases significantly, which may occur in a variety of fault scenarios. The fault detection output, which changes from "1" to "2" after a defect occurs at 60 milliseconds, is displayed in Figure 5 (d). Consequently, it takes 62–60 ms = 2 ms to find the flaw, following which trip signals can be sent to circuit breakers. The fault phase identification output in Figure 5 (e) shifts from "1" to "5" after a fault occurs at 60 ms, indicating the presence of A1 and B1 phase faults. The ground identification output in Figure 5 (f) does not alter when a fault occurs at 60 ms, indicating that no ground is involved. So the fault is classified as A1B1 double line phase faults. For each of the three jobs, every tested fault condition yields precise results. The effect of mutual in double circuit SCCTL has no bearing on the suggested data-based approach.

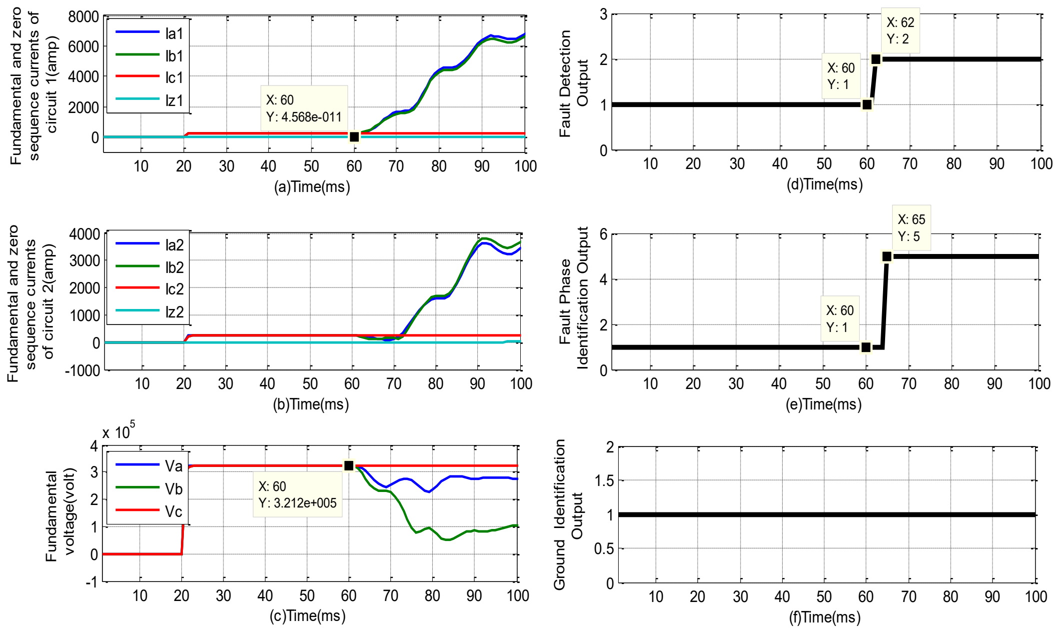

Figure 5. Inputs and outputs during A1B1 fault at 19km with R=0.001Ω at 60ms time

a. Basic elements and the zero sequence component of circuit 1's currents

b. Basic elements and the zero sequence component of circuit 2's currents

c. Fundamental components of voltages

d. Fault detection output

e. output of fault phase identification

f. output of ground identification

B. *Short-circuit Fault's Impact*

Inter-circuit faults are more common in double circuit SCC transmission lines. Faults involving two phases of separate circuits are known as short-circuit faults. The suggested Bayesian predictor-based approach is tested with a variety of short-circuit faults, and the test results show that it can reliably identify the faults. One fault case outputs is shown in Figure 6 during B1C2G fault at 51km with R=0.001Ω at 60ms time. The fault detection output, which changes from "1" to "2" after a defect occurs at 60 milliseconds, is displayed in Figure 6 (a). The fault phase identification output in Figure 6 (b) shifts from "1" to "19" after a fault occurs at 60 ms, indicating the presence of B1 and C2 phase faults. The ground identification output in Figure 6 (c) shifts from "1" to "2" after a fault occurs at 60 ms, indicating that the fault includes the ground. Therefore, the problem is categorized as a short-circuit B1C2G fault. Short-circuit problems have no effect on the suggested data-based approach.

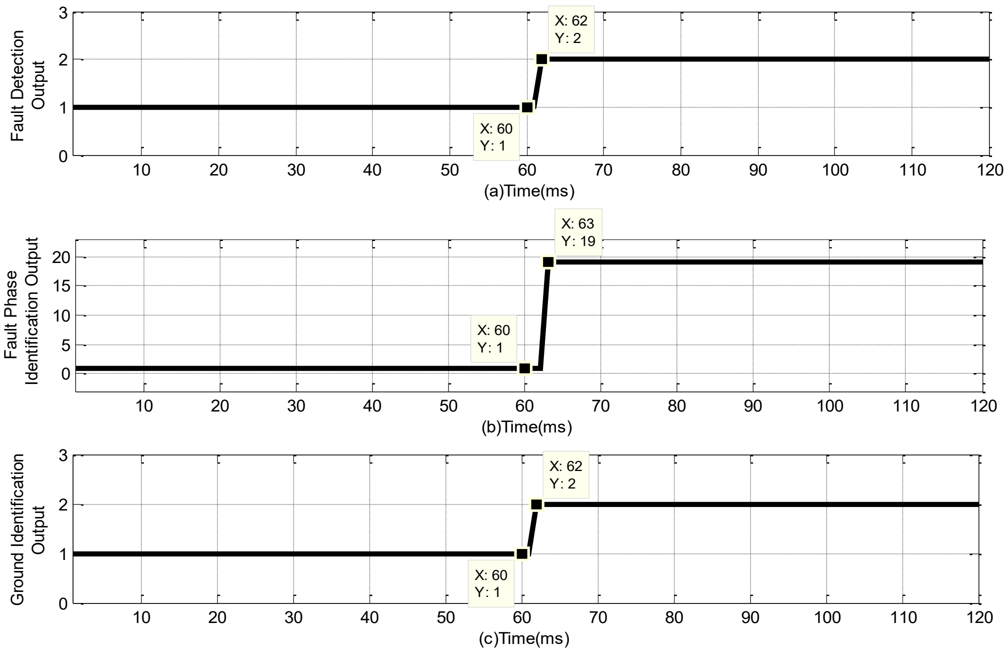

Figure 6 .Outputs during B1C2G fault at 51km with R=0.001Ω at 60ms time

a. Fault detection output

b. Fault phase identification output

c. Ground identification output

C. Fault Resistance's Impact

The effect of fault resistance on transmission line relaying is on any relaying scheme as, depending on the grounding medium, the circuit's resistance increases when a fault involves ground. There are no definite criteria to estimate up to what level the resistance may increase. So in this work fault resistance effect is studied from 0Ω to 150Ω in step of 10. The suggested data-based approach is unaffected by high resistance faults, as demonstrated by the fact that all of the tested fault scenarios correctly identify and categorize the defects. The results for different fault resistance circumstances are shown in the picture below.

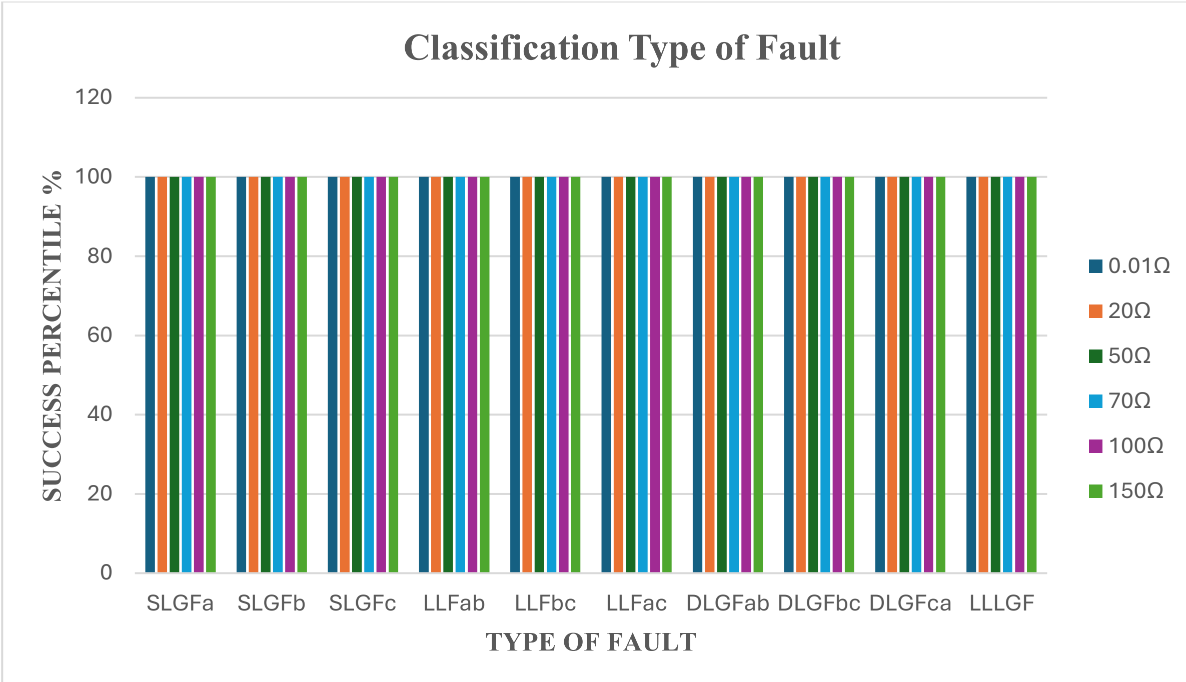

Figure 7. Performance results for varying fault resistance levels

D. Multi-Location Fault's Impact

Multi-location faults are those that occasionally occur in multiple locations within a specific protective zone. A variety of multi-location faults are used to test the suggested Bayesian predictor-based approach. Figure 7 depicts a fault instance with R=0.001Ω at 60 ms time during A1G fault at 33 km and C1G fault at 109 km. The signals for voltage and current produced during the fault are displayed in Figure 7(a) and (b). The fault detection output, which shifts from "1" to "2" in Figure 7(c), indicates that there is a problem with the system. The fault phase identification output in Figure 7 (d) shifts from "1" to "7" after a fault occurs at 60 ms, indicating that there are A1 and C2 phase faults. The ground identification output in Figure 7 (e) shifts from "1" to "2," indicating that a fault involves the ground. So the defect is classified as A1C1G fault although it is A1G fault and C1G fault at two different locations. Proposed data based method accurately detect multi-location faults.

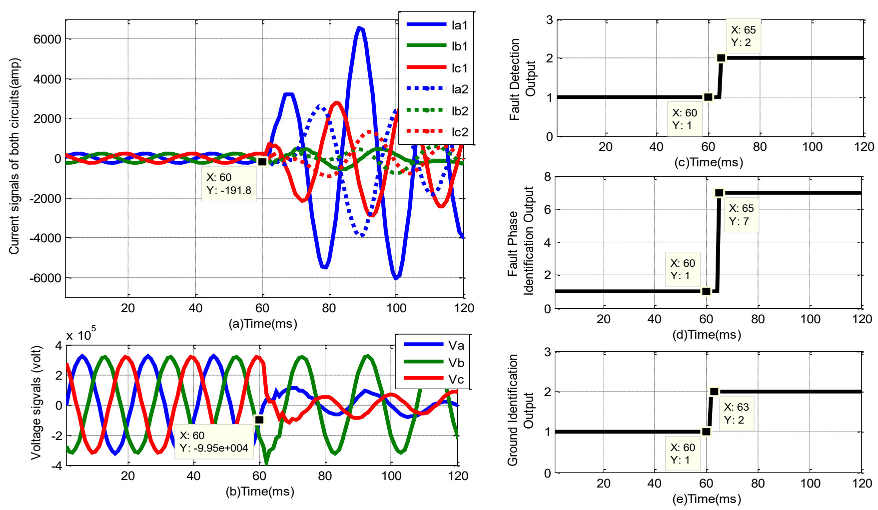

Figure 7. Signals and outputs during A1G fault at 33km and C1G fault at 109 km with R=0.001Ω at 60ms time

a. Current signals of circuit 1 and circuit 2

b. Voltage signals

c. Fault detection output

d. Fault phase identification output

e. Ground identification output

E. *Effect of Angle of Fault Inception*

Study of effect of Angle of Fault Inceptions in any relaying scheme is necessary as fault may occur in any instant of time. Different fault cases are generated in SCCTL varying Angle of Fault Inceptions 00 - 3600 with a step of 300 and tested with Bayesian predictor based scheme. Proposed method is designed in time domain means as the signals are recorded in every instant the algorithm is applied simultaneously to detect faults. So Angle of Fault Inceptions do not have any effect on post data based relaying scheme. For different angles of fault inceptions, every tested fault case yields accurate results.

F. *Effect of Pre-Fault Load Angle*

In any power transmission lines pre-fault load angles may change due to extreme operating conditions. So it is expected from any relaying scheme that it should not be affected by slight variation of initial load angle. Suggested scheme is examined for different fault cases varying pre-fault load angle in double circuit SCCTL up to ±50%. Every fault case that has been examined for various initial-fault load angles is 100% accurate in identifying and classifying defects.

5. Conclusion

It is difficult to protect double circuit series compensated lines because of the mutual coupling effect, which renders conventional protection methods useless. In order to secure double circuit SCCTL, a data-driven protection mechanism is created in this work using the Bayesian predictor method. The Bayesian strategy was selected because, in contrast to ANN and SVM-based techniques, it is very straightforward, relies just on posterior probabilities to anticipate the fault state, and is unaffected by vast amounts of training data. The term "data driven relaying scheme" refers to the relaying schemes established in this study that use data generated from various fault situations for error detection, malfunction phase identification, defect classification, and ground identification. The data-driven relaying technique is tested for a variety of fault scenarios, including pre-fault load angles, short-circuit faults, cross-country faults, fault type, fault location, fault resistance, and angle of the error inception. For every tested error instance, the suggested method's accuracy is 100%.

References

1. Kamran H.: Short Circuit Fault Classification and Location in Transmission Lines Using A Combination of Wavelet Transform and Support Vector Machines, International Journal on Electrical Engineering and Informatics, Vol. 7, No. 2, pp.353-363, June 2015.
2. Dalstein.T., Kulicke, B.: Neural network approach to fault classification for high speed protective relaying.IEEE Trans. on Power Delivery, vol. 10, No.2, pp. 1002–1011,April 1995.
3. Song, Y.H., Johns, A.T., Xuan, Q.Y.: ‘Artificial neural-network-based protection scheme for controllable series-compensated EHV transmission lines. IEE Proc. Gener. Transm. Distrib.Vol.143, No.6, pp. 535-540. November 1996.
4. Song, Y.H., Johns, A.T., and Xuan, Q. Y.: Protection scheme for EHV transmission systems with thyristor controlled series.Vol.25, No.5, pp. 553-565, May 1997.
5. Parikh, U.B., Das, B., Maheshwari, R.: Fault classification technique for compensated transmission line in series using support vector machine. Int. Journal of Elect. Power & Energy Syst., Vol.32, No.6, pp. 629–636, July 2010.
6. Dash, P., Samantaray, S.R., Panda, and G.: Fault classification and portion identification of an advanced series-compensated transmission line using support vector machine. IEEE Trans. on Power Delivery Vol.22, No.1, pp. 67–73, February 2007.
7. Samantaray, S.R.: Decision Tree based Fault Zone Identification and Fault Classification in Flexible AC Transmission Based Transmission Line’, IET-Gen. Trans. Distribution.Vol.3, No.5, pp. 425-436, May 2009.
8. Malathi, V., Marimuthu, N.S., Baskar, S., Ramar, and K.: Application of extreme learning machine for compensated transmission line in series protection. Eng. Applications of Art. Int. Vol. 24, No.5, pp.880-887, August 2011.
9. Megahed, A.I., Moussa, A.M., Bayoumy, A.E.: Usage of Wavelet Transform in the Protection of Series-Compensated Transmission Lines. IEEE Trans. on Power Delivery.Vol.21, No.3, pp. 1213-1221, August 2006.
10. Dash, P.K., Samantray, S.R.: Phase selection and fault portion identification in thyristor controlled series compensated line using discrete wavelet transform Int. J. Electric Power Energy System.Vol.26, No.9, pp. 725-732, January 2004.

11. Pradhan, A.K., Routray, A., Pati, S., Pradhan, D.K.: Wavelet Fuzzy Combined Approach for Fault Classification of a Series-Compensated Transmission Line. IEEE Trans. on Power Delivery. Vol. 19, No.4, pp. 1612-1618, October 2004.
12. Eristi, H.: Fault diagnosis system for compensated transmission line in series based on wavelet transform and adaptive neuro-fuzzy inference system. Measurement, Vol. 46, No.1, pp. 393-401, January 2013.
13. Han, J., Kamber, and M.: Data Mining: Concepts and Techniques 2.nd Ed, Morgan Kaufmann Publishers, Elsevier Inc, 2006.
14. Mitchell, T.: Machine Learning. McGraw Hill, 1997.

	Manjusha K.Parve is an Assistant Professor in the Department of Electrical Engineering at Priyadarshini College of Engineering, Nagpur. She received M.Tech. degree in Electrical Engineering from VNIT.Her research focuses on Power System Protection, Smart Grid, Power system applications, and AI based techniques in Power system protection.
	Dr. Rashmi A. Keswani is an Associate Professor and Head in the Department of Electrical Engineering at Priyadarshini College of Engineering, Nagpur. She received her Ph.D. in Electrical Engineering from VNIT, Nagpur in 2015. Her research focuses on Drives, Power Electronics Application to Drives, Power System Analysis and has been published papers in many leading journals. She is a presently guiding four research scholars.