

RELIABILITY EVALUATION, CRITICALITY ANALYSIS OF SVC AND FAST PROTECTION ALGORITHM FOR SVC COMPENSATED TRANSMISSION LINE

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Abstract

This article reports a relay algorithm based protection of static var compensator (SVC) based compensated transmission line utilizing artificial neural networks (ANN). The sequentially involved four artificial neural networks (ANNs) are used. The first ANN detects fault and the second ANN classifies it as either a ground or a phase fault. The faulted phases are then detected using ground fault ANN or phase fault ANN, depending on the situation. A transmission line (100 km, 230 kV, 50Hz) is simulated with SVC at the midpoint using a sampling frequency of 1 kHz in PSCAD/EMTDC. The sequence current ratios are used in fast protection algorithm with 100% accuracy in 4 milliseconds and identify them as phase or ground faults in 8 milliseconds. Finally, the identification of the faulted phase/phases requires just 13 milliseconds. Further, the number of thyristor-switched capacitors (TSC) in SVC depends on several factors such as thyristor valve, reactive power output, and electrical network type. However, the effect of the number of TSCs on the SVC reliability and criticality is not found in the existing literature. The reliability of SVC is increased is reported in this work by varying the number of TSC branches. The observations found increase of 15.47% in the SVC reliability by increasing TSC branches from one to three. In this way, the number of TSC branches in SVC can be optimized to increase the system's reliability with minimum cost.

Keywords: Artificial Neural Network (ANN), criticality, pattern recognition, reliability, Static Var Compensator (SVC)

Introduction

Static Var Compensator (SVC) has been used since the 1970s for improving power systems dynamic performance (Ali and Ul Asar, 2013). The effect of SVC in the power system has been studied extensively (Ramana Reddy *et al.*, 2014; Ranganathan and Kalavathi, 2014; Adni Binti Mat Le *et al.*, 2017; Jumaat *et al.*, 2017). However, in an electric power system made up of several dynamic interacting

components, there is always the risk of a disturbance or a fault. Faults not only cause damage to the equipment but also result in poor power quality. Power system faults need to be detected and classified correctly to ensure the system's smooth operation and enhance the power quality. The transmission protection system is designed in such a way as to identify the fault and isolate only

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the faulty section. During a fault, both voltage and current waveforms experience transients. Hence, the measured signals can be used for relaying conditions (Kezunovic, 2003).

Analytical and detailed simulations are used to analyse the effects of VSC-based FACTS controllers on distance relays for controlling the power flow of compensated lines. (Khederzadeh and Ghorbani, 2012).

Ghorbani *et al.* (2012) investigated the effect of the Static Var Compensator (SVC) on the apparent impedance measured by the transmission line distance relay. The authors have made an important observation that the way of connection of the SVC coupling transformer has a remarkable effect on the apparent impedance seen by the distance relay. Suppose the SVC coupling transformer winding connection is changed from Yg/Δ to Δ/Yg or Y/Δ . In that case, the zero-sequence current in the coupling transformer's primary connection is zero, and the effect of SVC on the apparent impedance for an A-G fault with low R_f values is eliminated.

The impacts of 48-pulse STATCOM/SVC, which are the most prevalent shunt-compensated devices in the FACTS family, on transmission line distance protection are investigated theoretically and through specialized simulations (Khederzadeh and Ghorbani, 2011).

Considerable research has been carried out using various artificial intelligence-based techniques for fault detection and classification in uncompensated and series compensated transmission networks.

In 1997, ANN was used as a pattern classifier for a transmission line of 100 km with a source at both ends (Coury and Jorge, 1997). The source impedance, fault inception angles, fault distance, fault resistance, source capacities, and power transfer angle were varied in phase to ground fault simulation. To prevent overreaching, the protected zone was set at 80% of the line within which the network was trained to classify fault patterns. The fault was detected with an accuracy of 78.82% only without attempting the fault classification as only one type of fault was simulated. In 2014 another fault detection and classification algorithm based on k-NN (k-Nearest Neighbor) technique was reported by (Yadav and Swetapadma, 2014). Inputs to the classifier are the fundamental frequency components and zero sequence components of line currents. The accuracy claimed is 99%, and the relay operation is claimed to take place within half a cycle (10 ms) for most of the fault and within one cycle (20 ms) for the remaining faults. Another study using ANN to identify and classify faults in uncompensated transmission lines was published by

(Fayaz *et al.*, 2016). The study by (Ghorbani and Mehrjerdi, 2020) describes an accurate fault location technique for SVC compensated double-circuit transmission lines. The proposed technique depends on the transmission system's negative-sequence circuit and relies entirely on the current data obtained from one end of the line. Regardless of high fault resistance, mutual coupling effect, or SVC current injection information, it can effectively locate all types of unbalanced faults.

The system was simulated in PSCAD/EMTDC at a sampling frequency of 2 kHz. An accuracy of 100% was obtained with a maximum relay operating time of 12.5 ms.

Over the last ten years, some literature on artificial intelligence (AI) techniques has been published. In 2009, authors detected and located the faults in Thyristor-Controlled Series Compensated (TCSC) transmission lines using ANN (Hosny and Safiuddin, 2009). Multi-layer Perceptron Neural Networks (MLPNN) were used in the suggested scheme. Three-phase currents and voltages at the relay site were the inputs to the MLPNN-based relay. This algorithm's output was said to be satisfactory.

While no maximum time of operation has been specified in the paper, the average time is 3 ms. In 2011, an algorithm for detecting and classifying faults and determining the location in a transmission line with respect to the FACTS device was proposed by (El-Zonkoly and Desouki, 2011). To make a trip decision during a fault, the compensated transmission line's current and voltage signals are interpreted using differential wavelet transform and wavelet entropy. The authors claim that the accuracy is reasonable, but they don't have any quantitative results on the accuracy or relay operating time. The fault is detected, classified, and located using a combination of ANN and wavelet transforms in another paper published by (Kumar *et al.*, 2012). The simulation results from distance relays for transmission line protection with FACTS devices like SVC have been published. Again quantitative results for relay accuracy and operating time are not given. Reliability studies of different systems, including relays, have been carried out in the literature and applicable to the transmission lines and SVC (Fayaz and Pahuja, 2020; Gupta and Pahuja, 2020).

In the research work reported in this paper, with 100 % accuracy, the ANN technique has been used to build a relay algorithm to detect and classify all types of faults, as well as identify the faulted phase/phases on an SVC-compensated transmission line. The results obtained from extensive training and testing, along with simulated data, are presented here. To train and test the ANN, the data is obtained

from the SVC-compensated transmission line which is simulated in PSCAD/EMTDC at a signal sampling frequency of 1 kHz. A back-propagation algorithm is used to train and test the ANNs. Only sequence current ratios have been used as inputs to the ANN for ground and phase fault identification and classification. To identify the faulted phase, phase voltages, RMS line voltages, and sequence component ratio of line currents are used as inputs. Source end signals are used. For an extensive inspection of all four ANNs, a four-fold cross-verification approach is used. The entire information set is split into equivalent and separate data sets d1, d2, d3, and d4, respectively, collected at different fault inception angles of 0°, 60°, 90°, and 120°. Different combinations of these data sets are used in each of the (four) stages of the verification technique. The paper provides detailed validation results based on the four-fold cross-verification methodology.

Based on the literature survey, the objectives of the present work are stated as

1. To protect the static var compensator (SVC) compensated transmission line using an artificial neural network (ANN) based relay algorithm.
2. To detect fault and classify it as either a ground or a phase fault.
3. To detect the faulted phase using ground fault ANN or phase fault ANN, depending on the situation.
4. To optimize the reliability of SVC by varying the number of TSC branches.
5. To critically rank the components of static var compensator (SVC) using importance measures.

Structure and Topologies of SVC

Structure

Static VAr Compensators (SVC) based on thyristors are made up of passive elements including inductances and capacitances that thyristors may regulate quickly. As with the synchronous condenser, the goal of fine control over the entire VAr range is achieved while still benefiting from faster response times. Further, in comparison to a synchronous condenser, SVC has a lower cost, requires less maintenance, and is more compact. Capacitive branches, which are either fixed (FC) and attached to the LV bus, or switched by thyristor valves (TSC), are installed to meet the system's capacitive power requirements. Fixed Capacitor (FC) branches are generally tuned in by series reactors for harmonic filtering. Thyristor Controlled Reactors (TCR) smoothly monitor the inductive power that is mounted in single-phase or three-phase combinations.

A specific SVC transformer attaches the branches to the HV grid, changing the system voltage to a degree appropriate for thyristor operation. The primary system of SVC comprises of three subsystems:

1. Main Circuit.
2. Power Supply
3. Protection and Control

This paper concentrates on the reliability and criticality of the main circuit. Similarly, the criticality of other subsystems can be carried out.

The schematic diagram of the SVC main circuit of SVC is depicted in Figure 1.

The components of the main SVC circuit are given below:

- Thyristor Controlled Reactor
- Thyristor Switched Capacitor
- Harmonic Filters
- Medium Voltage Switchgear
- Step-down Transformer

Thyristor Controlled Reactor (TCR)

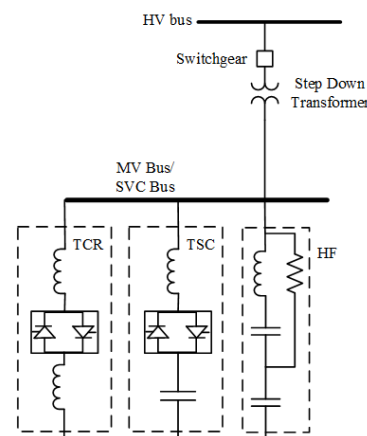


Figure 1. Main circuit of SVC (TSC-TCR)

A fixed reactor is connected to a thyristor valve (bidirectional) in a TCR. The thyristors are regulated by gate pulses applied to the valve. The thyristor valve is the controlling element. The thyristors are placed in a symmetrical manner allowing the maximum possible firing angle of 180°. By varying the amplitude of the current through the reactor, the reactive power can be controlled.

Thyristor Switched Capacitor (TSC)

The TSC is made up of a set of capacitors that are switched by the thyristor to provide discrete steps of reactive power. TSC consists of a capacitor in series with two anti-parallel thyristors and a damping reactor. The number of TSC's depends

upon many factors such as the current rating of thyristor valves and reactive power output.

Harmonic Filters

Harmonic Filters are composed of resistors, reactors, and capacitors. AC Filters are capacitive at the fundamental frequency and deliver reactive power in the range of 10-30% of the TCR MVar rating. A harmonic filter absorbs the harmonics generated by the TCR.

Medium Voltage Switchgear

Due to the high voltage levels, medium voltage switchgear is connected to SVC and are insulated. It plays a vital role during the clearance of faults to isolate the faulty part from the rest of the system.

Step-down Transformer

SVC is connected to the HV bus via step-down transformer, also known as the coupling transformer. It regulates the system voltage to a suitable level based on the thyristor's working capability.

Topologies

The SVC is made up of multiple fixed or switched branches, at least one of which contains thyristors, and the branch combinations can be differed widely based on the requirements. The commonly used SVC schemes are as given below.

1. Thyristor controlled reactor - Fixed capacitor (TCR-FC)
2. Thyristor-switched capacitor - Thyristor controlled reactor (TSC-TCR)

The key benefit of using topology for TSC branches is that losses are reduced by reducing the filter size. To optimize the total reactive power support beyond the dynamic range, mechanically switched banks can be used on both the HV and LV sides of the SVC transformer.

Criticality of Static Var Compensators

The use of SVCs in power systems dates back to the 1970s. SVCs are a combination of thyristor-controlled shunt capacitors and reactors that compensate for reactive power in the power grid. The most common SVC configuration is a fixed capacitor (FC) and TCR combination. To maintain voltage and synchronous stability and prevent voltage failure after a major interruption, the SVC operates in capacitive or inductive mode to inject or absorb reactive power at the point of contact. SVC also minimizes power loss, balances the voltage profile, maintains the voltage stability, and increases the transmission line's power transfer capability.

During the contingencies that occur in the power system, the reactive power component changes considerably as compared to the active power flow. Hence the SVC will have a dominant effect on the power system stability. Therefore, it becomes necessary to evaluate the risk and reliability of SVC.

Significant research regarding the control and operation of SVC has been carried out (Masood *et al.*, 2010; Wang *et al.*, 2016). Nevertheless, not much research is present in the literature for the risk and reliability of SVC. In the power system's reliability evaluation, little attention is given to the reactive power equipment's failure. The improvement in the distribution system's reliability by the use of shunt capacitors is explained by (Sallam *et al.*, 1994). The authors have calculated the reliability indices of the system with and without shunt capacitors. A comparison of both the cases is made, and it is found that reliability indices improve while using shunt capacitors.

Authors (Huang and Li, 2003) discuss the reliability of a hybrid power system with SVC at the transmission line. The reliability model of SVC is built using State Space Approach. Two examples are given to demonstrate how the composite power system's reliability has increased. However, the reliability of SVC has not been investigated.

Each component of the power system is vulnerable to faults. However, some components are more likely to fail than others. The chances of failure are defined in terms of failure rates. However, it becomes necessary to find the criticality of the components that depend on other factors and failure rates. And apart from assessing the SVC's reliability, it's also important to look at its component importance. In risk assessments, especially probability risk assessments, component importance measures are frequently used. Component importance measures are used in various configurations of electrical network design in the power system. In these systems, component importance measures are referred to as risk importance measures, and they are used to determine the components that need to be improved in order to minimize the risk. Component importance procedures are used at various stages of a system's lifecycle. Component importance measures are used in the design phase to determine weak points and areas that need to be improved to enhance the system's reliability. A component's reliability can be improved by replacing it with a better quality component, redundant components, or improving the component's maintenance. The component importance procedures are used to prioritize the critical components' inspection and repair services during execution period. Component importance measures prioritize system components

according to their criticality, allowing for optimum reliability and maintenance. To put it another way, importance measures measure the contribution of individual devices to overall system performance (e.g., reliability, availability, and risk). Component importance procedures in a system often use a numerical rank depending on particular attributes including the component's exposure to system failure and rank the components based on criticality. Birnbaum conducted the first analysis in this field in 1969, and it is now one of the most commonly used effective analysis importance measures.

The other frequently used importance measures are criticality importance (CI), reliability reduction worth (RRW), and reliability achievement worth (RAW), Fussell-Vesely importance measure. The priority, need to maintain the components are decided based on their ranks. The importance of component maintenance has been selected depending on their ranks (Birnbaum, 1969). The cost for maintaining the components and developing the system will all be minimized by prioritizing system components using importance measures (Gao *et al.*, 2010). Different component importance procedures, such as Fussell-Vesely (FV) value, Birnbaum importance, risk reduction, differential importance, and structure importance, have been proposed in the literature (Birnbaum, 1969; Fussell, 1975; Van der Borst and Schoonakker, 2001; Epstein and Rauzy, 2005; Kuo and Zhu, 2012a, 2012b, 2012c, 2014). (Cai *et al.*, 2016) introduced a Birnbaum-importance-based genetic algorithm for finding the near-global optimal solution for the linear consecutive k-out-of-n scheme. The authors (Katsavounis *et al.*, 2014) addressed an importance analysis of each component of a wind turbine system's electrical, control, and hydraulic subsystems. FV, RAW and RRW were the three types of importance procedures examined.

These measures of importance are fundamentally different. They evaluate slightly distinct features of system behavior, and therefore each can be used to determine different information. There is no conclusion about which measure is the "effective."

Joint Importance Measure

The reliability importance of an individual component is focused in the preceding section. The Joint Reliability Importance (JRI) measures are importance measures for a pair or set of components that consider influence of group of components on system performance (Amrutkar and Kamalja, 2017). Hong and Lie introduced JRI in 1993 (Hong and Lie, 1993). The measure of interaction between states of two or more components can be described as joint reliability importance for two or more

components (Chacko and Manoharan, 2008). The co-relation between two or more different elements in terms of device reliability is expressed by the value of Joint Reliability Importance.

System Simulation

The single line schematic of the simulated system is presented in Figure 2. EMTDC/PSCAD, electromagnetic transient software, is used to simulate the system, consisting of a transmission line with SVC installed at the midpoint to compensate for voltage drops under steady-state and transient situations. A 230 kV source is installed on one side of the transmission line in this configuration. The transmission line is coupled to SVC by a breaker. The line is compensated with SVC when the breaker is closed, but otherwise, it is uncompensated. To achieve the desired compensation, SVC is operated by a control circuit.

All 11 situations, including all types of faults and no-fault events, are simulated using a three-phase fault module. For both the uncompensated line and the line compensated with SVC, all 11 situations are simulated. Five ohms are chosen as the fault resistance. On both compensated and uncompensated transmission lines, the fault inception angle and the faults' location are adjusted to achieve separate data sets.

Fast Fourier Transform (FFT) helps in removing fundamental components from line currents and is then preceded by a sequence

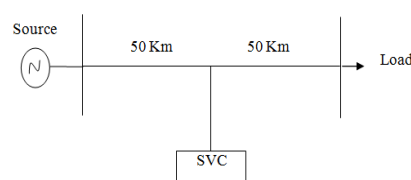


Figure 2. SLD of the system

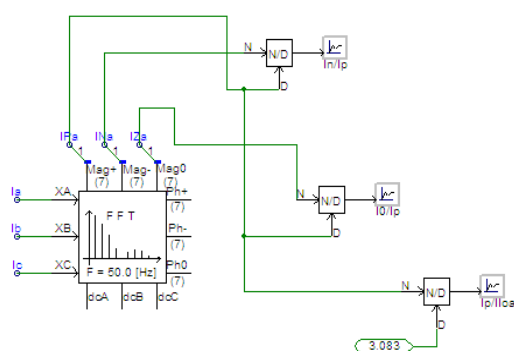


Figure 3. Extraction of sequence currents

extractor to extract sequence currents and their ratios, as seen in Figure 3.

Protection Algorithm

The proposed relay approach for the Relay Algorithm is shown in Figure 4. The ANN is divided into four configurations – ANN-D, ANN-GP, ANN-G, and ANN-P. ANN-D detects the fault, and the faults are classified as ground faults or phase faults by ANN-GP. If there is no fault, the relay will not send any trip signal, and in case of any fault, ANN-GP will be selected. If there is a case of phase faults, ANN-P will be chosen, and ANN-G will be selected for ground faults.

ANN Configurations ANN Configurations

Based on the number of iterations, epochs, and simulation time, the number of neurons in the hidden layer is varied before the optimum number is found. The optimized number of neurons is 10 for ANN-D and ANN-GP and 20 for ANN-G and ANN-P.

1) ANN D

Sequence component ratio of currents (I_n/I_p , I_o/I_p , I_p/I_{load}) are used as inputs for ANN-D configuration (3-10-2) with two outputs and one hidden layer of 10 neurons. The two outcomes of ANN-D configuration include:

1=No Fault, 2= Fault

2) ANN-G

The inputs for the ANN-G configuration (6-20-6) with six outputs and one hidden layer of 20 neurons were RMS values of phase voltages (V_a , V_b , V_c) and ratios of sequence currents (I_n/I_p , I_o/I_p , I_p/I_{load}). The ANN-G configuration has six outputs:

1 = AG Fault,
2 = BG Fault,
3 = CG Fault,
4 = ABG Fault,
5 = BCG Fault,
6 = CAG Fault

3) ANN-P

The inputs for the ANN-P configuration (6-20-4) with four outputs and one hidden layer of 20 neurons were RMS values of line voltages (V_{ab} , V_{bc} , V_{ca}) and ratios of sequence currents (I_n/I_p , I_o/I_p , I_p/I_{load}). The 4 outputs of ANN-P configuration include:

1=AB Fault,
2=BC Fault,
3=CA Fault,
4=ABC Fault

Data Generated by Simulation

Voltages and currents are used as input to the protective relay. For ANN, the same inputs must be used. Other parameters, such as zero sequence currents (I_0), positive sequence currents (I_1), and negative sequence currents (I_2), are used to distinguish between fault types.

With two positions of fault (midpoint and remote end) and four values of fault inception angle, data is generated for both compensated and uncompensated lines. Only data for L-G faults with a 0° fault inception angle and fault location at the remote end are shown. The RMS value of line voltages, phase voltages, and sequence component ratios of line currents are among the data generated. The entire data set is split into four equivalent and separate data sets, d1, d2, d3, and d4, respectively, collected at different fault inception angles of 0° , 60° , 90° , and 120° and fault resistances 0, 5, 20, and 30 ohms. Different combinations of these data sets are used in each of the (four) stages of the verification technique.

Graphs of RMS line voltages, phase voltages, and sequence current ratios for uncompensated lines are shown in Figure 5, and graphs of RMS line

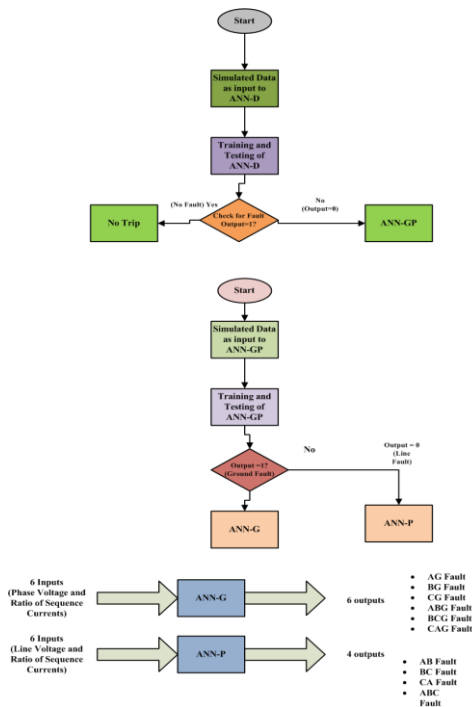


Figure 4. Proposed relay approach

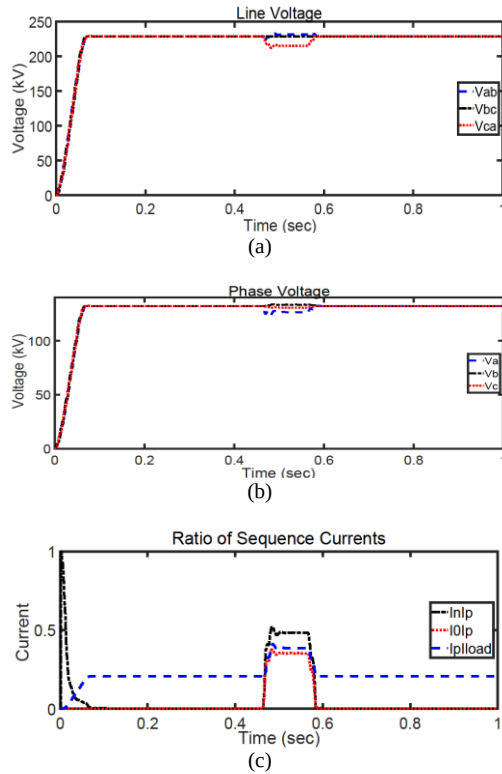


Figure 5. (a) RMS line voltages, (b) RMS phase voltages, and (c) Ratios of sequence currents for an uncompensated line with L-G fault at the remote end

voltages, phase voltages, and ratios of sequence currents for SVC compensated lines are shown in Figure 6.

Fault Tree of SVC

Of all SVC configurations, TSC-TCR is by far the most robust. TSC-TCR compensators are composed of several TSC banks and a single TCR connected in parallel. The number of TSC's depends upon many factors such as the current rating of thyristor valves and reactive power output. The effect of the number of TSC's on the reliability of SVC is shown in this paper. Various factors decide the choice of a particular SVC topology, including capital cost, losses, speed of response, and operation frequency. Reliability can also be a deciding factor for the selection of a specific SVC topology. An example for the same is illustrated in the paper where the fault tree of two cases of TCR-TSC is constructed as shown in Figures 7 and 8. The two cases differ in the number of TSC branches. In this way, the number of TSC branches can be optimized in terms of reliability.

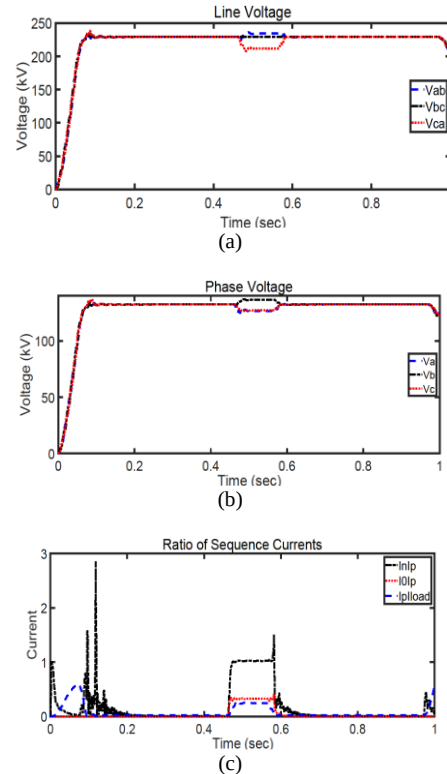


Figure 6. (a) RMS line voltages, (b) RMS phase voltages, and (c) Ratios of sequence currents for compensated line with L-G fault at the remote end

The data for failure rates is taken from (Alvarez-Alvarado and Jayaweera, 2017) and is reported below (Table 1).

Table 1. Failure rate data of svc components

S. No.	Components	Failure Rate (per year)
1	Switchgear	0.0017
2	TCR	0.0599
3	TSC	0.0361
4	Harmonic Filter	0.0438
5	Step down Transformer	0.0050

Case I:

In this case, SVC (TSC-TCR) 's main circuit consists of switchgear, harmonic filter, step down transformer, and one branch each of TCR and TSC. The fault tree analysis is done using interface software for reliability forecasting (GRIF-Workshop). Figure 7 depicts the fault tree diagram for Case I. The importance measures are calculated for this case.

Case II:

In this case, SVC (TSC-TCR)'s main circuit consists of switchgear, harmonic filter, step down

transformer and one branch of TCR, and three branches of TSC. The fault tree analysis is carried out as in Case I. Figure 8 shows the fault tree diagram for Case II. The importance measures are evaluated in comparison to Case I, and plots for the importance measures are shown in the results column.

Results

Validation of Relay Algorithm

The ability of neural networks to recognize and classify patterns has been used to create an algorithm for transmission line protection. As output functions, log sigmoid functions were used. All four ANN configurations are trained and tested using a four-fold cross-verification technique, and the entire data set is divided into four equal and independent data sets, d1, d2, d3, and d4, respectively, at fault inception angles. The networks are first trained with d1, d2, and d3 and then tested with d4, with the results being collected. The networks were then trained with d1, d2, and d4 and tested with d3 in the second step. Similarly, d1, d3, and d4 were used for training, and d2 was used for testing in the third step. In the last step, d2, d3, and d4 were used to train the networks, while d1 was used to test them.

All of the steps produce similar results and the results from the first step of each configuration are presented in this paper.

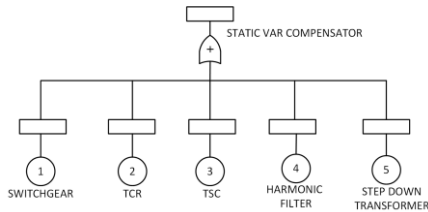


Figure 7. Fault Tree of SVC for with single TSC branch

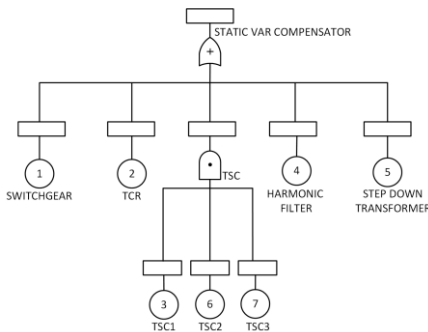


Figure 8. Fault Tree of SVC for with three TSC branches

With a 4 ms delay for fault detection and an 8 ms delay for fault classification between ground and phase faults, 100% accuracy was achieved. A delay of 13 ms gives 100% accuracy in phase identification by ANN-G and a delay of 12 ms by ANN-P. Similar results have been obtained in all four steps of the verification process.

Reliability and Criticality

For both cases, the reliability and importance measures are evaluated and are plotted against time. Figure 9 shows the reliability comparison for both cases, which clearly shows an increase in the reliability when the number of TSC branches increases from one to three.

$$R(5)_{\text{CASE I}} = 0.5687$$

$$R(5)_{\text{CASE II}} = 0.4807$$

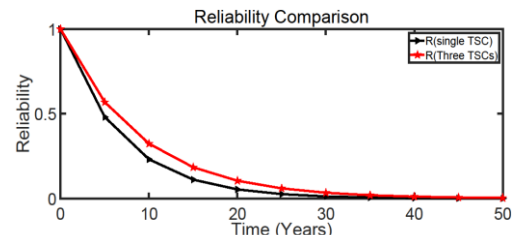


Figure 9. Reliability comparison of Case I and Case II

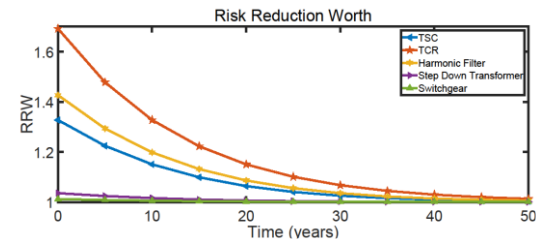
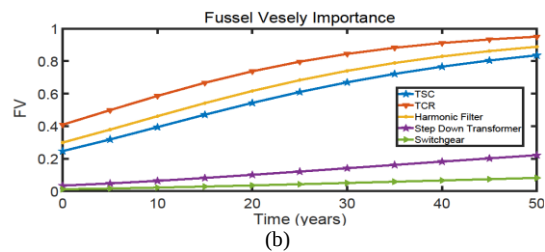
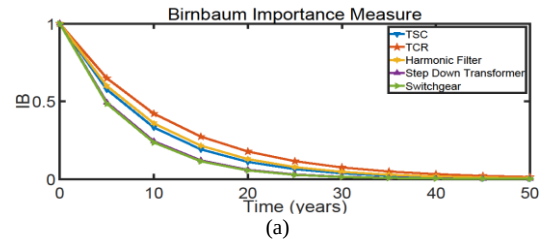


Figure 10. Birnbaum Importance Measure, b) Fussell Vesely Importance Measure, c) Risk Reduction Worth Importance Measure

where $R(5)_{CASE I}$ = Reliability of SVC at $t = 5$ for Case I and $R(5)_{CASE II}$ = Reliability of SVC at $t = 5$ for Case II

Thus the increase in the number of TSC branches from one to three increases the reliability by 15.47%.

The ranking of SVC (TSC-TCR) components in terms of risk and criticality are evaluated using importance measures for both cases. The importance measures used include Birnbaum importance, fussell vesely importance, risk reduction worth and joint reliability importance is used to compute the importance of a pair of components, which demonstrates how the pair of components work in terms of system reliability. The criticality ranking of the individual components and pair of components for Case I is reported in Figures 10 and 11, respectively. The TCR is the most critical component from the graphs, and Step-down Transformer is the least critical. It will help to identify the weak components. Hence, we can get a clear idea about which component needs to be improved or replaced to improve the overall reliability of SVC. From Figure 11, it is evident that J (2,4) is the most critical combination of a pair of components where the components are TCR and Harmonic Filter (refer to for the notations). Figure 12 shows the criticality ranking of SVC components for Case II, where we have used three TSC branches. It is evident from Figure 11 that by adding two more TSC branches, the criticality ranking of TSC changes from 3 to 4, i.e., it becomes less critical. In this way, the criticality of the components can be improved by changing the SVC's topology.

Conclusions

In presence of SVC, the use of neural networks for fault detection, classification, and identification of faulted phase/phases is investigated. In PSCAD/EMTDC, all faults (symmetrical and unsymmetrical) are simulated in the presence and absence of SVC on an SVC compensated transmission line. Various factors, such as the position of the fault and the angle of the fault inception, are varied. The data from the simulation is used to train and validate the artificial neural network. The algorithm detects and classifies the faults using ANN in four configurations, namely detection-ANN (ANN-D), classification-ANN (ANN-GP), ground ANN (ANN-G), and phase ANN (ANN-P). In ANN-D, faults are detected and subsequently classified into line faults and ground faults in ANN-GP. Following the detection and classification of a fault, phase identification is performed using one of two configurations: ANN-G or ANN-P, based on the type of fault observed.

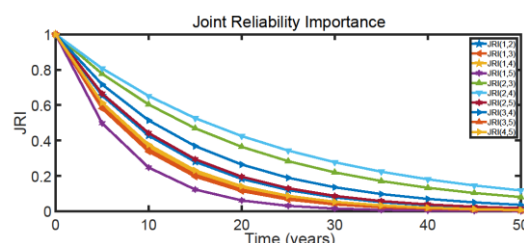


Figure 11. Joint reliability importance

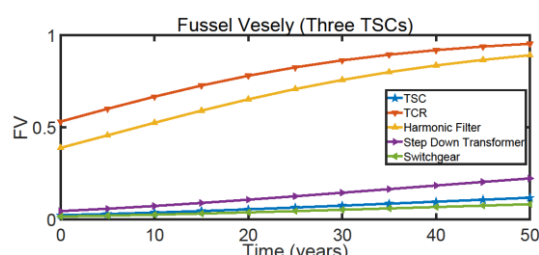


Figure 12. Fussell Vesely Importance Measure for Case I

A four-fold cross-verification methodology is used to fully validate the networks.

The reliability of the TSC-TCR configuration of SVC has been evaluated, and further, the number of TSCs has been varied and optimized in terms of reliability. Using importance measures, the components of SVC are ranked in terms of criticality. Hence, the reliability of SVC can be further improved by focusing on the most critical component by repairing or replacement of the component.

With a 4 ms delay for fault detection and an 8 ms delay for fault classification between ground and phase faults, 100 percent accuracy is achieved. ANN-G achieves 100% phase identification accuracy with a delay of 13 ms, while ANN-P achieves 100% accuracy with a delay of 12 ms. When a large volume of data set is available for training, fault detection and classification using ANN is easy, reliable, and accurate. Finally, the work presented here is novel in the following ways:

I. For fault detection and classification, sequence component ratios of line currents have been used as inputs to ANN, which have shown to be superior to line currents used by other researchers.

II. To speed up fault detection a simpler configuration of the ANN with 3 inputs only has been used. The other three ANNs with three or six inputs perform the fault classification and phase identification afterwards. This had led to a fault detection time of 4 ms whereas the time required for

fault classification between ground and phase faults is 8 ms and the time required for phase identification is 12/13 ms. It needs to be emphasized that reduction in fault detection time is much more important than the fault classification time as the tripping is initiated as soon as the fault is initiated. The papers mentioned in the introduction either don't discuss the relay's operating time or claim it to be 10 ms, 20 ms, or 12.5 ms, which is considerably longer than the time reported in this article.

III. The choice of inputs to fault classification and phase identification algorithms has led to 100% accuracy of fault classification. Either no accuracy has been indicated in the references or it is less than 100%. The proposed algorithm has been validated for 100% accuracy in both uncompensated and compensated line cases. The algorithms reported in the references are meant either for the uncompensated line only or validated for compensated lines only.

IV. Static Var Compensator regulates the system voltage, harmonics, power factor and maintains the system stability. During the faults in the power system, SVC has a dominant effect on the system stability. Hence it becomes necessary to evaluate and optimize the reliability of SVC.

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