Electronics and Electrical Engineering

http://www.aimspress.com/journal/ElectrEng

AIMS Electronics and Electrical Engineering, 6(4): 370–384.
DOI: 10.3934/electreng.2022022
Received: 29 July 2022
Revised: 01 September 2022
Accepted: 25 September 2022
Published: 30 September 2022

Research article

Machine learning assessment of IoT managed microgrid protection in existence of SVC using wavelet methodology

K.V. Dhana Lakshmi[1,*], **P.K. Panigrahi**[1] **and Ravi kumar Goli**[2]

[1] Department of Electrical and Electronics Engineering, GIET University, Gunupur, Odisha, India

[2] Department of Electrical and Electronics Engineering, Bapatla Engineering college, Bapatla, AndhraPradesh, India

* **Correspondence:** Email: kv.dhanalakshmi@giet.edu.

Abstract: In the last decade, research has been started due to accelerated growth in power demand has mainly concentrated on the large power production and quality of power. After the digital revolution, non-conventional energy sources, many state-of-art equipment, power electronics loads, reactive power compensating devices, sophisticated measuring devices, etc., entered the power industry. The reactive power compensating devices, connected electrical equipment, renewable energy sources can be anticipated/unanticipated action can cause considerable reactions may be failure issues to power grids. To deal with these challenges, the power sector crucially needs to design and implement new security systems to protect its systems. The Internet-of-Things (IoT) is treated as revolution technology after the invention of the digital machine and the internet. New developments in sensor devices with wireless technologies through embedded processors provide effective monitoring and different types of faults can be detected during electric power transmission. The wavelet (WT) is one of the mathematical tools to asses transient signals of different frequencies and provides crucial information in the form of detailed coefficients. Machine learning (ML) methods are recommended in the power systems community to simplify digital reform. ML and AI techniques can make effective and rapid decisions to improve the stability and safety of the power grid. This recommended approach can contribute critical information about symmetrical or asymmetrical faults through machine learning assessment of IoT supervised microgrid protection in the presence of SVC using the wavelet approach covers diversified types of faults combined with fault-inception-angles (FIA).

Keywords: distributed generator; SVC; microgrid, machine learning; wavelet transform; fault-detection; Internet-of-Things (IoT)

1. Introduction

The conventional power network has a top-down approach that starts at power generation, transportation through transmission lines, and distribution, and ends at consumers. Under these schemes, the expansion of the network follows three possible ways: 1. efficient power generation and transmission; 2. power source allocation and integration with load centers; 3. power quality and continuous power supply.

Regular planning is not suitable for the stable operation of modern systems due to numerous control units and plenty of data to be generated across the system every minute [1]. It is impossible for humans to analyse instantaneous data and are unable to make optimal decisions. Because of the extent of problems with renewable energy sources with power electronic control circuits [2], complicated problems enter the grid. Nowadays, power electronic-based compensating devices are mixed with the grid network to minimise losses and power fluctuations. Numerous protective devices and distribution generators installed in the network [3] may cause immediate change and develop stability issues for the grid. The classical system is unable to control fast changes in the current system. So, it is necessary to enhance system analysis tools for both utilities and micro-grids using the latest technologies. Static Var Compensator (SVC) is a power electronics device that is a parallel combination of a fixed shunt capacitor and a variable reactor that is used in a power network to regulate transmission voltage and improve power quality by injecting reactive energy into the network dynamically [4]. The antecedent research is unable to present correct performance of SVC at the time of fault, hence the expedition of the distance protection is not clearly evaluated at the time of short-circuit faults.

The researchers are thinking of alternative solutions for microgrid management to minimise the disturbance caused by the fault in the existing system. The impact of the fault level depends on DG power output, fault current level, reverse power flow, relay false tripping, and selectivity are the important issues to be considered for the new protection scheme [5]. Micro-grids are regarded as a prominent solution for dealing with significant power outages due to their ability to be peninsular and to sustain the penetration of renewable energy sources. To develop the role of micro-grids in enhancing the resilience strategies used by different types of energy management systems, communication resilience, and the resilience of individual components reported in [6]. A barrier found when deploying experimental smart grids consists of handling the heterogeneity of the required hardware and software components as well as the available commercial equipment. The reported drawbacks are commonly experimental validation, industry-specific equipment specifications, and standardisation of communication protocols. To compensate for these drawbacks, innovative multi-layered architecture can be used to develop heterogeneous automation and monitoring systems [7]. The traditional security mechanism has challenges due to power electronics control circuits, reactive power compensation, and power flow direction. The design of a new security system is a complicated task due to the interconnection of the smart and utility grid with reactive power compensation. Some of the electrical transmission networks have problems due to mechanical damage to the equipment. Most of the popular methods are based only on electrical issues and not on mechanical complications.

The protection scheme must respond to not only electrical but also mechanical and physical problems. Existing electric power transmission and distribution networks have a number of challenges, including response time delays, power losses, data thefts, distributed energy resource (DER) integration, and physical monitoring. Digitizing the actual network with IoT can mitigate these challenges. Although fault indicator technology has provided a reliable means of locating permanent faults, physical patrolling and long time-consuming for failure equipment detection. IoT includes smart environmental sensors, including temperature and humidity sensors, smoke and air sensors, water sensors, and light sensors that can be capable of monitoring electrical networks [8].

The wavelet is a mathematical function fabricated from signal shape. The WT has the ability to analyse transient signals of different frequencies [9]. The most popular applications in the power systems protection area are those that improve the performance of protective relays by analysing transient signals at the time of fault. There are two important concise methods to follow for the selection of mother wavelet (1). Shape and mathematical expression (2). must allow fast calculation of coefficients.

The modern power network builds numerous control units and generates plenty of data across the network every second, which obstructs making positive decisions. In this situation, supervised and unsupervised ML algorithms can make data exploration abilities that enable hidden intelligence encapsulated in plenty of information from power networks to improve protection methods without human intervention [10]. The major reasons for choosing ML for power systems include a large number of algorithms for solving numerous problems from classification, detection, prediction, and location related to power network protection [11]. These algorithms can be capable of formulating solutions by collecting the measurement information without the use of redundant data.

The protection system mainly focused on two major tasks: fault description and forecasting the location of a fault to withstand the assembled accessories as well as serving personnel. Most probably, balanced and unbalanced faults will occur in the power network. After identifying the faults must take care of protection and restore the stability of the system. An algorithm is described for the protection of micro-grids [12] with the assistance of provisional current signals using wavelet listed quantities. The prospective work concentrates on machine learning assessment of IoT managed microgrid protection in the existence of SVC using wavelet methodology with the help of wavelet based multi-resolution-analysis (MRA) is used and the calibration of coefficients of Bior-1.5mother-wavelet at distinct fault inception angle and distance is performed. The test system is designed using MATLAB Simulink software. The system parameters are calibrated using synchronisation of simulation diagrams and MATLAB programming. The research paper consists of four sections. The first section starts with mathematical modelling analysis and describes the system applicable parameters and conventional analysis of SVC [13] and fault analysis under SVC impact [14]. The second section narrates IoT-Machine learning implementation for physical time-to-time performance of system unimaginative conditions and the formulation of procedural frame work for diagnosis of faults in the system. The third section reports the impact of SVC integration is illustrated through graphs and calibrated through tabular representation, and then finally concludes the research theme.

2. System mathematical modeling and analysis

Figure 1 shows the single line diagram of proposed system used for the study. It consists of nine zones. The positive and negative sequence line impedance and zero sequence impedance is $Z_{1,2}$ = 0.173 + j0.432 Ω/Km and Z_0 = 0.346 + j1.800 Ω/km, with the SVC placed in the center of the Zone-3. Short Circuit Level (SCL) at utility grid = 900 MVA;

A static-VAr-compensator (SVC), whose output is varied to exchange capacitive or inductive

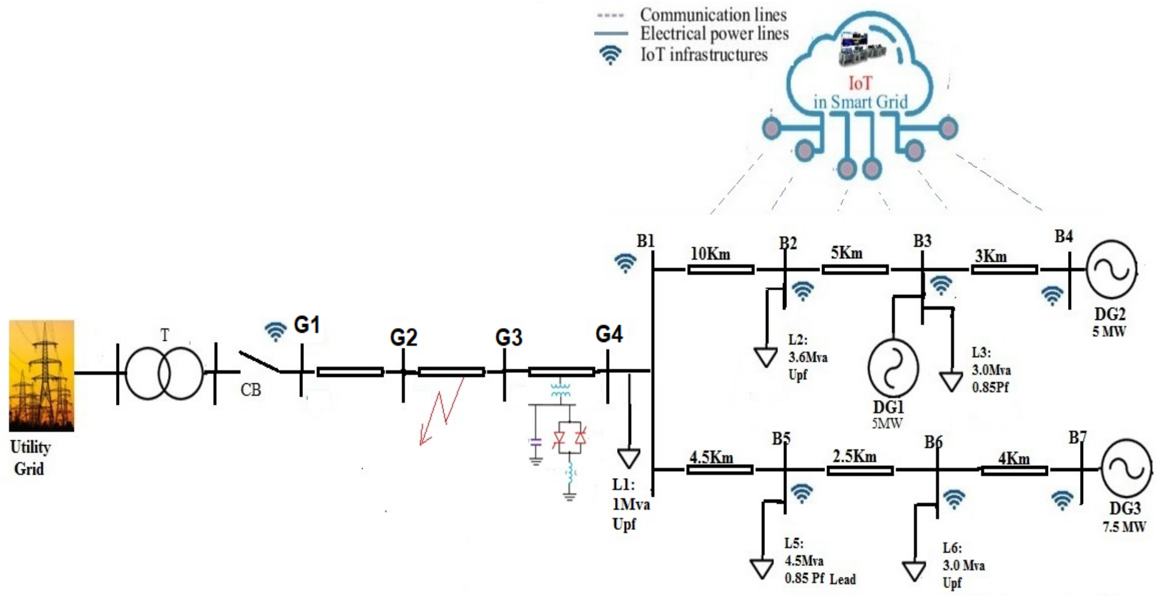
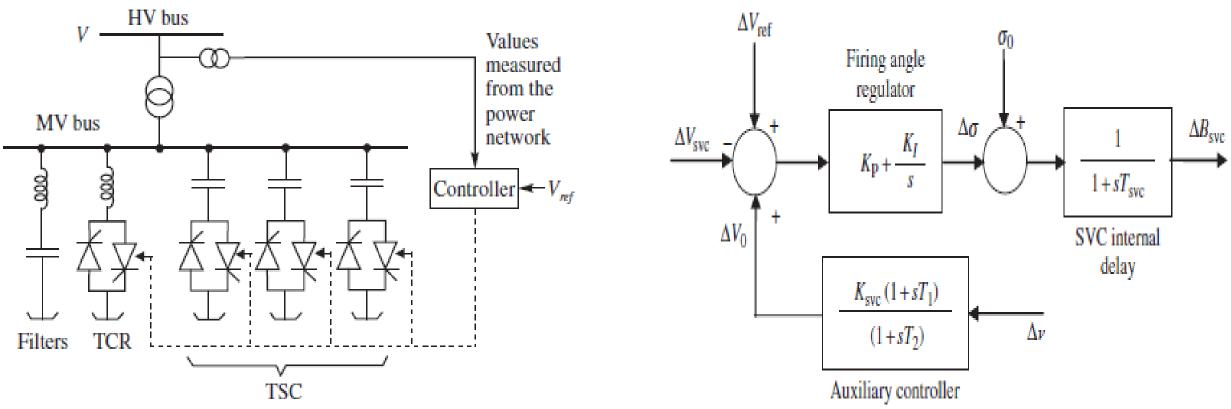


Figure 1. Proposed system model-main parameters.

DG1: 7.5 MVA, 4.16 kV-DG unit at bus 3.
DG2: 5 MVA , 4.16 kV -DG unit at bus 4
DG3: 5 MVA , 4.16 kV DG unit at bus 7
Line-12 = 10 km, Line-23 = 5 km, Line-34 = 3 km
Line-15 = 4.5 km, Line-56 = 2.5 km, Line-67 = 4 km
Z_1,2 = 0.173 + j0.432 Ω/km

L1:1 MVA, PF = 1
L2:=3.6 MVA, PF = 1
L3:3.0 MVA, PF = 0.85 lag
L5:4.5 MVA, PF = 0.85 lead
L6:3.0 MVA, PF = 1
Z_0 = 0.346 + j1.800 Ω/km

current so as to maintain or control specific parameters of the electric power system, typically bus voltages. The SVC contains Three number TSC = 10 Mvar and one TSC = 10 Mvar are connected midle of Zone-3 which are connected to the middle of Line 1 using a 34.5 kV/16 kV (Yg/d), 50 MVA coupling transformer. Each group connected in delta three-phase bank is connected in delta so that, during normal balanced operation, the zero-sequence 3rd harmonics (3rd, 9th, etc.) remain trapped inside the delta, thus reducing harmonic injection into the power system. Switching the TSCs in and out allows a discrete variation of the secondary reactive power from zero to 30 Mvar capacitive (at 16 kV) by steps of 10 Mvar, whereas phase control of the TCR allows a continuous variation from zero to 10 Mvar inductive the connected SVR Rating:33.33 MVAR. The representation of SVC and control diagram [10] are illustrated in Figure 2. There are two major components in SVC described as
1. Thyristor-controlled-reactor (TCR): which can control inductance continuously from L = 0 to L = max i.e Thyristor blocked mode to full conduction mode.
2. Thyristor-switched-Capacitors (TSCs): Which can control between maximum inductive to max capacitive of SVC is achieved by absorb/produce the required reactive power.
The simplified model of SVC is shown in Figure 2. The fundamental TCR configuration contains fixed reactor has an inductance, L and two bidirectional thyristore valves (one is conduction mode and other is blocking mode) are connected in series controlled by firing angle, α. Consider the equivalent circuit of SVC shown in Figure 3(a), the current calculation as follows:



(a) SVC -model **(b)** SVC block diagram with controller

Figure 2. Schematic diagram of SVC and control.

$$v(t) = \sqrt{2}V\cos\omega t \tag{2.1}$$

the instantaneous phase voltage,At the supply voltage reaches maximum value,the current in the circuit is

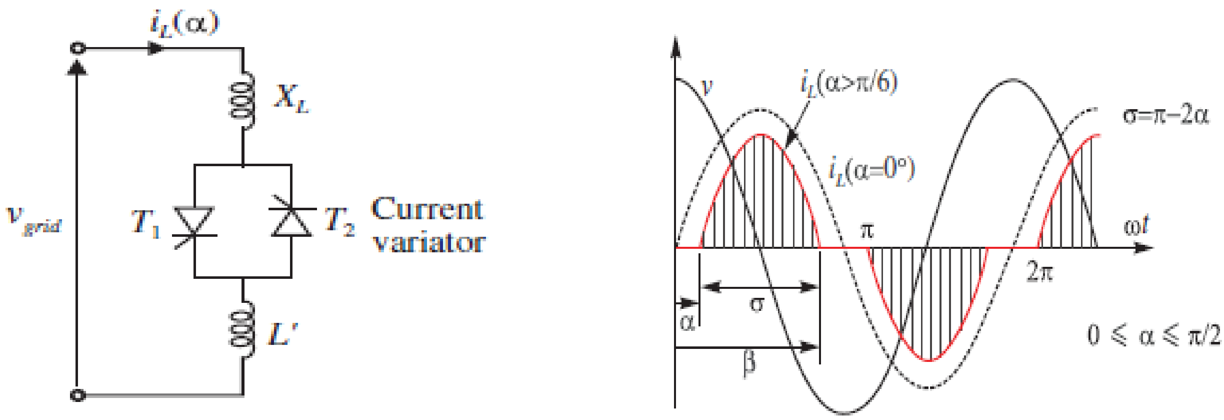
$$L\frac{di}{dt} = \sqrt{2}V\cos\omega t \tag{2.2}$$

integrating on both sides

$$i(t) = \frac{\sqrt{2}V}{\omega L}\sin\omega t + C \tag{2.3}$$

At $\omega(t) = \alpha$ and $I_L(\omega t = \alpha) = 0$

$$C = -\frac{\sqrt{2}V}{\omega L}\sin\alpha \tag{2.4}$$



(a) TCR circuit model **(b)** TCR current and voltage waveform

Figure 3. Operation and analysis of SVC.

The Instantaneous current calculated as,

$$I_L(\omega t) = \frac{\sqrt{2}V}{X_L}(\sin\omega t - \sin\alpha) \tag{2.5}$$

where α is firing angle, σ is conduction angle.

The thyristor conduction period calculated as $\sigma = \phi - 2\alpha$, where V and X_L are applied voltage and inductive reactance at fundamental frequency. The controller of SVC as shown in Figure 2(b). The SVC bus control voltage as input, ΔV_{svc}. The value of susceptance is determined by firing angle, regulated by proportional integral (PI) control which regulated from V_{ref}. The linearised state space representation as follows:

$$\Delta\dot{V}_0 = -\frac{1}{T_2}\Delta V_0 + \frac{k_{svc}}{\omega_s}\left(\frac{1}{T_2}\right)\Delta\omega + \frac{k_{svc}}{\omega_s}\left(\frac{T_1}{T_2}\right)\Delta\omega \tag{2.6}$$

$$\Delta\dot{\alpha} = -k_1\Delta V_0 + k_1\Delta V_{svc} - k_1\Delta V_{Ref} \tag{2.7}$$

$$\Delta\dot{B}_{svc} = -\frac{1}{T_{svc}}\Delta\alpha - \frac{1}{T_{svc}}\Delta B_{svc} \tag{2.8}$$

Where T_1, T_2 and T_{svc} lead, lag and time delay constants, K_{svc} is gain constant.
The linearised SVC Reactive power induce at bus n in the network

$$\Delta Q_n = \frac{dQ_n}{d\theta_n}\Delta\theta_n + \frac{dQ_n}{dV_n}\Delta V_n + \frac{dQ_n}{d\alpha}\Delta\alpha \tag{2.9}$$

where $Q_n = -B_{svc}V_n^2$, the equation modified as

$$Q_n = -B_{svc}V_n^2\begin{bmatrix}0 & -2V_{{}_{n}B_{svc}} & 2V_n^2\left(1-\cos 2\alpha/X_L\right)\end{bmatrix}\begin{bmatrix}\Delta\theta_n \\ \Delta V_n \\ \Delta\alpha\end{bmatrix} \tag{2.10}$$

$$\begin{bmatrix}\Delta P_n \\ \Delta P_n\end{bmatrix} = \begin{bmatrix}0 & 0 & 0 \\ 0 & -2V_{{}_{n}B_{svc}} & 2V_n^2\left(1-\cos 2\alpha/X_L\right)\end{bmatrix}\begin{bmatrix}\Delta\theta_n \\ \Delta V_n \\ \Delta\alpha\end{bmatrix} \tag{2.11}$$

3. Fault analysis under SVC impact

Figure 5 illustrates symmetrical component networks, i.e Zero, positive and negative representation circuits of the sample system of Figure 4 with the SVC in the middle of Zone3. The impact of SVC under various faults calibrated as follows: For positive sequence network equations derived at fault is at node-B

$$V_{1p} = xZ_{1s1}I_{1p1} + (x-0.5)\,Z_{1s1}I_{1sh} + R_f\left(I_{1p1} + I_{1sh} + I_{1q1}\right) + V_{1E} \tag{3.1}$$

$$I_{1q1} = \frac{x}{1-x}I_{1p1} + \frac{x-0.5}{1-x}I_{1sh} \tag{3.2}$$

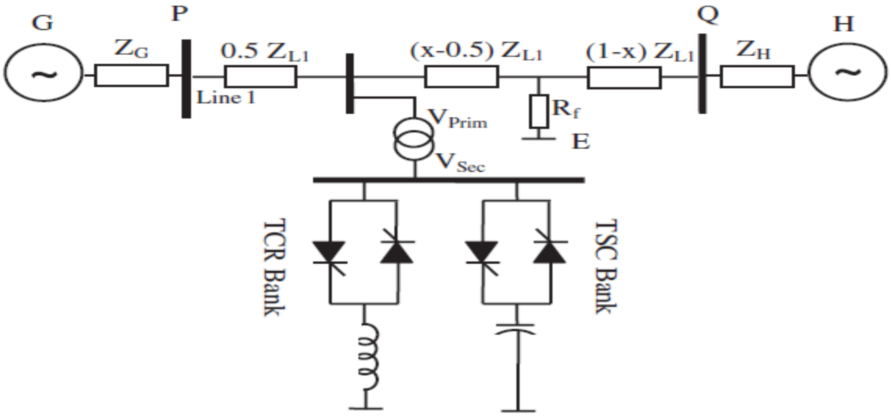
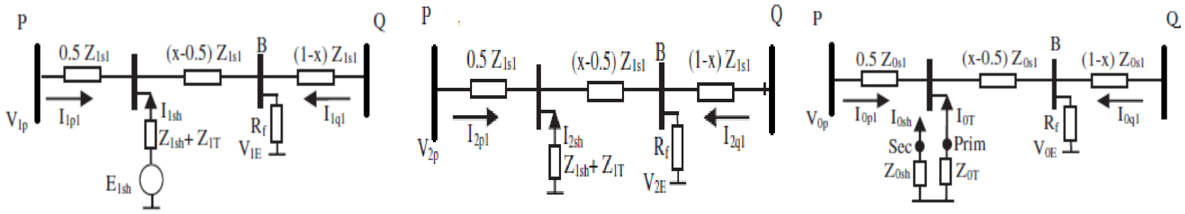


Figure 4. Single line diagram of SVC integrated system model.



(a) Positive sequence **(b)** Negative Sequence **(c)** Zero sequence

Figure 5. SVC impact analysis of faults with symmetrical components.

Substituting equation (13) in to equation (12)

$$V_{1p} = xZ_{1s1}I_{1p1} + (x - 0.5)\,Z_{1s1}I_{1sh} + R_f\left(I_{1p1} + I_{1sh} + \frac{x}{1-x}I_{1p1} + \frac{x-0.5}{1-x}I_{1sh}\right) + V_{1E} \tag{3.3}$$

The negative and Zero sequence currents are

$$V_{2p} = xZ_{1s1}I_{2p1} + (x - 0.5)\,Z_{1s1}I_{2sh} + R_f\left(I_{2p1} + I_{1sh} + \frac{x}{1-x}I_{2p1} + \frac{x-0.5}{1-x}I_{2sh}\right) + V_{2E} \tag{3.4}$$

$$V_{0p} = xZ_{0s1}I_{0p1} + (x - 0.5)\,Z_{0s1}I_{0T} + R_f\left(I_{0p1} + I_{0T} + \frac{x}{1-x}I_{0p1} + \frac{x-0.5}{1-x}I_{2sh}\right) + V_{0E} \tag{3.5}$$

where V_{0p}, V_{0p} and V_{0p} -Sequence component voltages. I_{0p}, I_{0p} and I_{0p} -Sequence component currents. Z_{0p}, Z_{0p} and Z_{0p} -Sequence component impedance.

3.1. Single-line-to-ground(SLG) fault

For SLG fault equations are derived as follows:

$$V_{1E} + V_{2E} + v_{0E} = 0 \tag{3.6}$$

Substituting equations from Eq 14 to Eq 16 resulting

$$V_{LG} = x\left[Z_{1s1}I_{p1} + (Z_{0s1} - Z_{1s1})\,I_{0p1}\right] + \frac{R_f}{(1-x)}\left[I_{p1}\right] + \Delta V_{LG} \tag{3.7}$$

$$V_{1p1} + V_{2p1} + V_{0p1} = V_{LG} \tag{3.8}$$

$$I_{1p1} + I_{2p1} + I_{0p1} = I_{p1} \tag{3.9}$$

$$I_{OT} + I_{1sh} + I_{2sh} = I_{sh} \tag{3.10}$$

$$\Delta V_{LG} = (x-0.5)\,Z_{1s1}I_{sh} + (x-0.5)\,(Z_{0s1} - Z_{1s1})\,I_{OT} + \frac{R_f}{(1-x)}I_{sh} \tag{3.11}$$

The apparent impedance calculated as

$$Z_{LG} = \frac{V_{LG}}{I_{p1} + \left[(Z_{0s1} - Z_{1s1})\,/Z_{1s1}\right]I_{0p1}} = \frac{V_{LG}}{I_{LG}} \tag{3.12}$$

from Eq 23

$$Z_{LG} = xZ_{1s1} + \frac{R_f}{(1-x)\,I_{LG}}\left[I_{p1}\right] + \Delta Z_{LG} \tag{3.13}$$

$Z_{LG} = 0$, since there is no shunt compensation, therefore the impedance is same as uncompensated line,

$$\Delta Z_{LG} = (x-0.5)\,Z_{1s1}\frac{I_{sh}}{I_{LG}} + (x-0.5)\,(z_{0s1} - Z_{1s1})\,\frac{I_{OT}}{I_{LG}} + R_f\frac{0.5}{(1-x)}\frac{I_{sh}}{I_{LG}} \tag{3.14}$$

When the fault distance from the bus is 0.5 p.u. or the SVC compensator is not present in the fault loop, its effect on the impedance Z_{LG} is only through R_f.

3.2. Double-Line(DL) fault

For DL fault in the system

$$V_{1E} = aV_{2E} \tag{3.15}$$

$$\begin{aligned} V_{1p} - aV_{2p} = xZ_{1s1}\left(I_{1p1} - aI_{2p1}\right) + (x-0.5)\,Z_{1s1}\,(I_{1sh} - aI_{2sh}) \\ + \tfrac{R_f}{(1-x)}\left[\left(I_{1p1} - aI_{2p1}\right) + 0.5\,(I_{1sh} - aI_{2sh})\right] \end{aligned} \tag{3.16}$$

The impedance at LL Fault

$$Z_{LL} = \frac{V_{1p} - aV_{2p}}{I_{1p} - aI_{2p}} = \frac{V_{1p} - aV_{2p}}{I_{LL}} \tag{3.17}$$

from equation (27)

$$Z_{LL} = xZ_{1s1} + \frac{R_f}{(1-x)\,I_{LL}}\left[\left(I_{1p1} - aI_{2p1}\right)\right] + \Delta Z_{LL} \tag{3.18}$$

the above equation modified as

$$\Delta Z_{LL} = (x-0.5)\,Z_{1s1}\frac{(I_{1sh} - aI_{2sh})}{I_{LL}} + \frac{0.5R_f}{(1-x)\,I_{LL}}\,(I_{1sh} - aI_{2sh}) \tag{3.19}$$

In above equation R_f is the fault resistance between two phases. According to equation (30) for $R_f = 0$, the shunt compensator impact is due to the negative and positive sequence current differences [14].

4. Machine learning -IoT in power system protection

The power sector is speedily inspiring towards an intelligent and smart environment. There are so many remarkable machine learning methods to be recommended in the power systems community. The conventional protection algorithms are anticipated only for electrical parameters but not for mechanical and/or physical systems. There is a need to investigate new protection schemes which should provide security while rapidly moving towards digitization and intelligence. Using networked microgrids as dispersed systems, the power system's resilience to extreme events can be improved. In order to respond appropriately in emergency situations, resilience is an integrally complicated quality that calls for a thorough grasp of microgrid operation in [15].

Machine Learning (ML), which furnishes a number of extraordinary solution methods, has been recommended in the power systems. When transmitting energy from one location to another location, the scheduled Deep-Learning (DL) based supervision of transmission lines improves the efficiency and maintenance staff safety. The ML established system preservation approach establishes the optimal planning under complex power system configurations. From a technical analysis, ML can have supervised, unsupervised, semi-supervised, and reinforcement learning mechanisms. Supervised learning contributes to acquiring solutions by mapping between input and output relationships based on training data [16]. Typical algorithms include Artificial-Neural-Networks (ANN) for classification of fault analysis in electrical protection methods [17], integrated moving window average technique (used for detection and discrimination of faults), unsupervised learning focuses on getting the solution with the aid of invisible data patterns. Semi-supervised methods are commonly used for fault detection in electrical system protection and load balancing forecasts with available information. The implementation of multi-layer perception (MLP) approach to detect database interruptions of a power system reinforcement learning mechanism, machine learning-based irregularity detection technique successfully identifies the energy database manipulation.

A smart transmission system can be designed under the surveillance of computer data centres, physical data collecting sensors, monitoring using cameras and other sensitive measuring devices, making it possible to design new protection systems with emerging IoT technologies [18]. The classical protection scheme may offer limited protection and control. The proposed system should minimise the prevailing problems related to protection issues with state-of-the-art fault-detection and high-speed isolation from the existing system; physical investigation by dispatching reported information to a central data centre through global information systems; registered warning to be sent to responsible persons; extensible communication framework support for smart environment and other utility services and their web-protocols.

The scheduled network fault investigation is calibrated using wavelet based machine learning analysis performed using four stages, i.e., input data collection, feature extraction, machine learning, and output prediction. In the input data collection stage, in the first stage, the preliminary data is collected from the current waveform, which is generated before and after the fault. In the second stage, the possessed information is converted to detailed coefficients after decomposing the basic waveform bior1.5 mother wavelet, which extracts the required information to diagnosis the fault [19]. It is important to detect and to locate the fault or to evaluate it within a minimum error and time. Normally, faults can be detected using current signal patterns, but it takes a longer time to detect the fault. To minimise the time required for quantum feature extraction, the current signal is formulated by means of wavelet detailed coefficients after decomposing the waveform. The extraction of data from the basic signal pattern to a valid data format is illustrated in Figure 7.

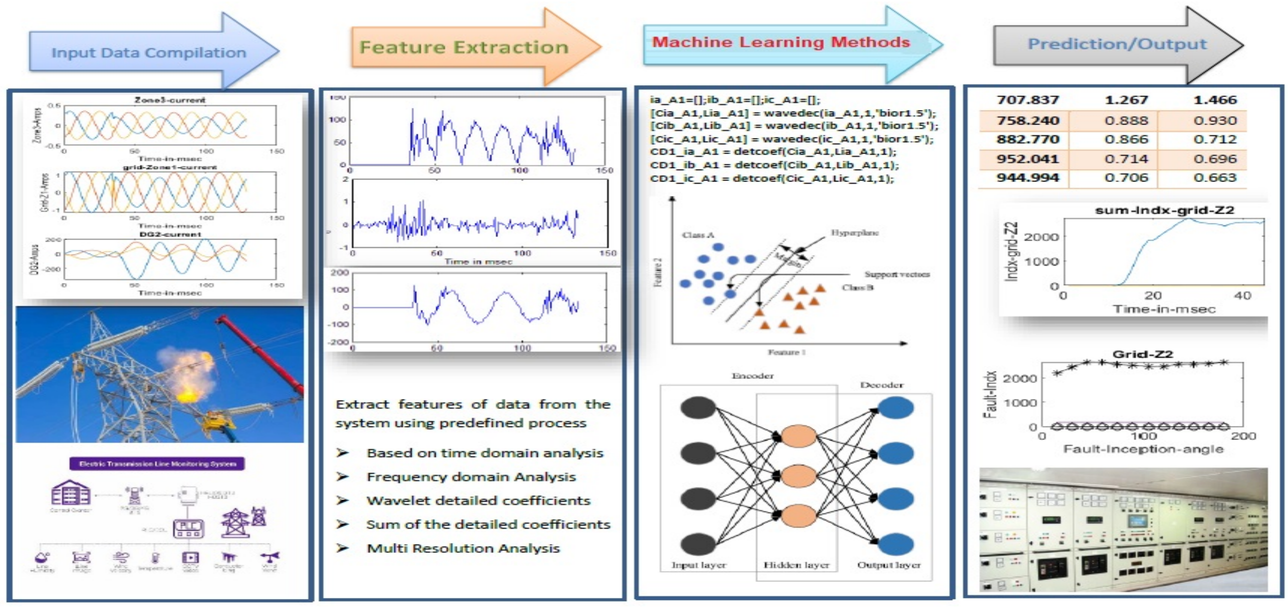


Figure 6. Procedural framework for fault diagnosis using machine learning approach.

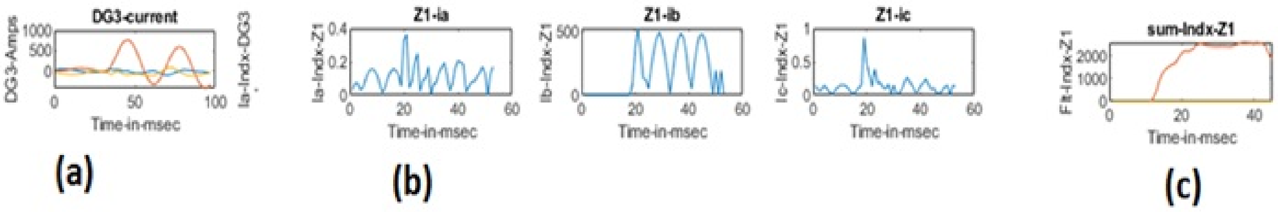


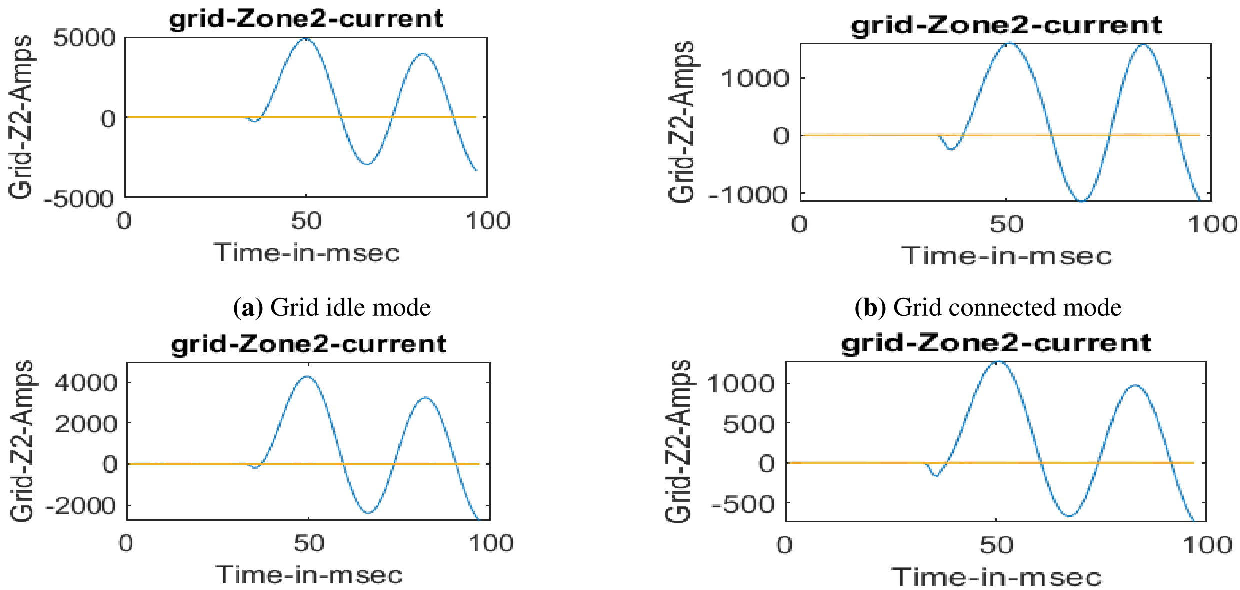
Figure 7. Data extraction from basic signal pattern.

The third stage, machine learning approach, has been initiated with wavelet multi-resolution-analysis (MRA), support vector machines (SVM), the coding and encoding data elements support for the detection and description of faults, and ANN provides non-measuring and non-linear relations between dependent and independent data elements without much statistical data extraction. The final stage concludes that the problem has been solved and predicts the output.

The proposed research works carries three hyper planes are created to classify the fault in every zone of the power network using the wavelet detailed coefficients after decomposing current waveform of individual phases at various fault angles from 0^0 to 180^0, after defining threshold value is known as maximum margin for non-linear SVM, then such data is termed as non-linear data and classify the fault in the network. The SVM is one of the supervised learning methods extensively used in the analysis and calibration of data with remarkable credibility to the training data set (voltage, current, and fault-inception-angle), as input data for fault diagnosis [20]. Machine learning non-linear SVM algorithm has been implemented for 11 types of faults, 8 Zones with 1920 simulations for every type of fault. The implementation of SVM is reported in Figure 9. The suggested research work prevailing new technique in the area of electrical power system protection,investigate the faults within short duration of time compared to traditional impedance based algorithms in presence of SVC using machine learning analysis of IoT supervised microgrid protection in presence of SVC using wavelet approach.

5. Impact investigation of faults in protection scheme

Every ten different types of faults are considered in the fault cases. The test system consists of nine zones, divided into two groups. The first group consists of three zones: Zone 1 keeps the grid idle/connected, Zone 2 calibrates the fault at the grid side, and Zone 3 integrates the shunt compensating device, i.e., SVC is used for reactive power compensation towards the system utility grid side. The remaining zones are separated into two paths, each of which has three zones connected through DGs and loads.



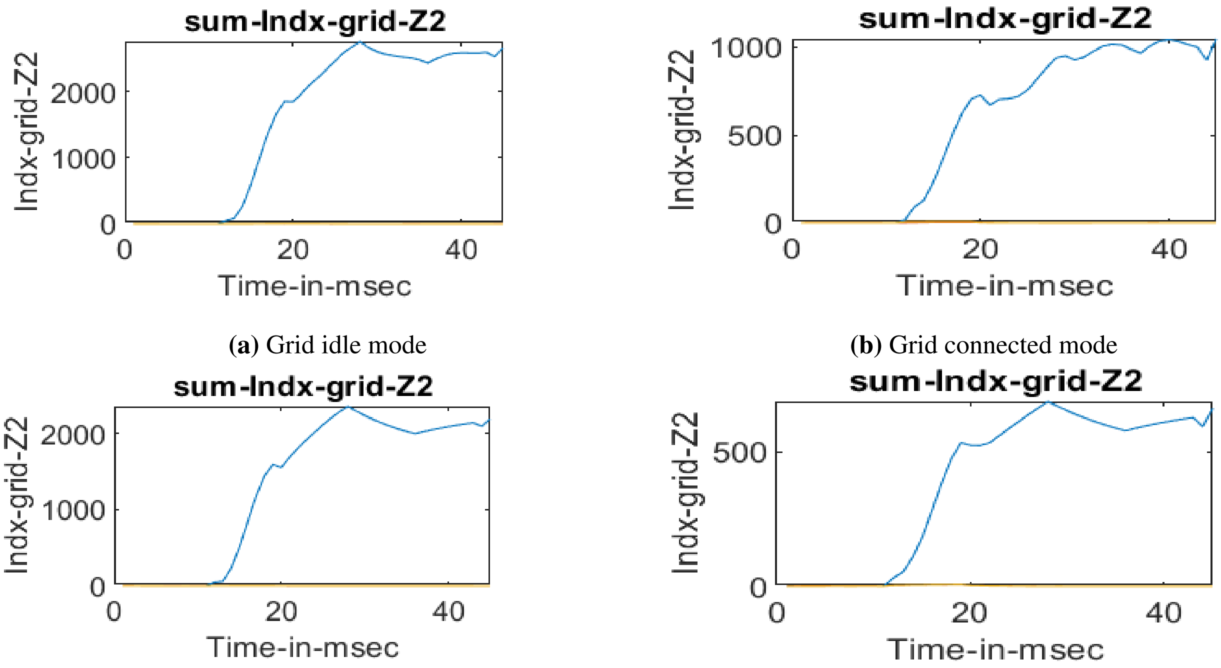
(a) Grid idle mode **(b)** Grid connected mode

(c) SVC integrated and grid idle mode **(d)** grid and SVC integrated mode

Figure 8. Impact analysis of grid with SVC integration through current wave forms.

The nominated work reports finding faults in the system at different zones using current parameters, fault index generated from sum-of-wavelet-detailed-coefficients (SWDC), and studying the impact of reactive power compensation with the aid of SVC embodied in the system.

The faults in the system at utility grid-SVC integrated and idle cases are studied from Figure 8 to Figure 10. Every plot contains four sub-plots arguing for the similarity of the problem and differentiating numerous cases. Figure 7 depicts the interrelationship of system faults at active and inactive grids with SVC incorporated. The system is studied using only current measurement rather than voltage-current pair and compiled so that the impact of SVC is clearly indicated from subplot (a) to (d). The decrement in fault detection time is noticed from Figure 8 to Figure 9. The fault detection time is about less than 15 milliseconds instead of 40 milliseconds, which is quantified from conventional(only current measurement) to the proposed (based on Wavelet-Index) method. Figure 9 mentioned the assessment of fault at a fluctuating fault creation angle and the perceived domination of



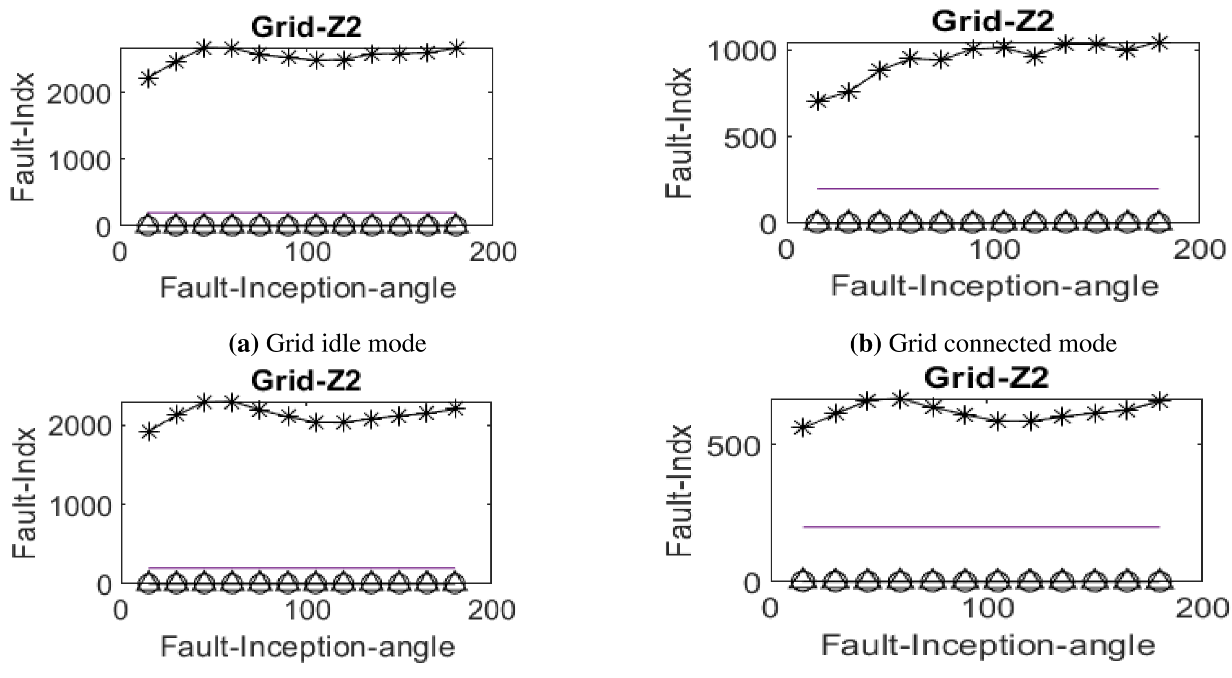
(a) Grid idle mode

(b) Grid connected mode

(c) SVC integrated and grid idle mode

(d) grid and SVC integrated mode

Figure 9. Impact analysis of grid with SVC integration through fault indices.



(a) Grid idle mode

(b) Grid connected mode

(c) SVC integrated and grid idle mode

(d) grid and SVC integrated mode

Figure 10. Impact analysis of grid with SVC integration at distinct Fault-Inception-Angles(FIA).

SVC action in the existing system. The faulty phases are credited with analogy to the healthy phase by a distinguished threshold value, which is the lowest value of faulty line data and healthy line data. The

Table 1. Impact analysis of fault at SVC integrated with DG.

FIA	Fault Index Grid Idle			Fault Index Grid Idle-SVC			Fault Index Grid Connected			Fault Index Grid-SVC Connected		
15	2218.52	2.74	3.95	1919.84	1.12	1.12	707.84	1.27	1.47	560.84	2.32	2.48
30	2464.71	0.96	1.41	2118.57	1.04	1.06	758.24	0.89	0.93	612.30	1.63	1.46
45	2678.22	0.79	0.71	2285.31	0.94	1.00	882.77	0.87	0.71	662.51	0.90	0.73
60	2669.09	0.83	0.85	2291.50	0.89	0.83	952.04	0.71	0.70	668.46	0.69	0.97
75	2567.53	0.83	0.77	2186.26	0.86	0.86	944.99	0.71	0.66	636.47	0.84	0.78
90	2526.59	0.97	0.83	2100.41	0.85	0.85	1006.94	0.97	0.74	609.85	0.79	0.74
105	2484.01	0.98	0.98	2030.36	0.85	0.84	1012.95	1.13	0.77	587.45	0.77	0.77
120	2496.17	1.15	1.14	2027.47	0.85	0.84	967.75	1.33	0.89	586.61	0.77	0.76
135	2579.92	1.45	1.19	2074.21	0.85	0.84	1036.19	1.45	1.05	602.32	0.77	0.76
150	2587.00	1.36	1.21	2112.43	0.85	0.84	1034.10	1.37	1.07	615.50	0.77	0.77
165	2597.35	1.32	1.15	2143.72	0.85	0.83	1000.99	1.23	1.12	626.57	0.78	0.77
180	2666.37	0.98	0.81	2195.24	0.65	0.68	1048.22	1.01	0.90	660.05	0.61	0.61

diagnosis of wavelet based fault analysis of grid active/inactive mode with/without SVC integration was projected with the help of Table 1 information posted through multi-resolution analysis wavelet enumerated values of idle and connected modes of the grid under the AG-fault in zone-2.

The algorithm has been intended for faults using machine learning analysis of IoT supervised microgrid protection in the presence of SVC using the wavelet approach. The fault analysis Table 1 values reported that wavelet multi-resolution analysis was carried out effectively for the detection and discrimination of faults with the impact of reactive power injected shunt compensating device.

6. Conclusions

In the power sector, mainly production and demand should be balanced. The digital revolution has started. Many alternative generation, reactive power compensating devices and control equipment interfered in the existing system. The increase in the number of DGs, reactive power compensating devices, and penetration of non-conventional energy sources may increase the complexity of system security and lead to the development of new protection schemes. The IoT provides effective monitoring and wavelet (WT) provides a mathematical mechanism to analyse transient signals of different frequencies divided into detailed coefficients, providing crucial information about short circuit faults within less than half a cycle. ML and AI techniques can make effective and rapid decisions to improve the stability and safety of the power grid. This proposed method provides machine learning analysis of IoT supervised microgrid protection in the presence of SVC using the wavelet approach under various types of faults at different fault-inception-angles (FIA). The proposed research can extend to finding multiple faults in a wide area monitoring network with a minimum fault detection time quantum.

Conflict of interest

The authors declares no conflict of interest in this manuscript.

References

1. IEEE Std C37.113-2015, *IEEE Guide for Protective Relay Applications to Transmission Lines*, 2015.
2. Ebeed M, Aleem SHEM (2021) Overview of uncertainties in modern power systems: uncertainty models and methods. *Uncertainties in Modern Power Systems*, 1–34. https://doi.org/10.1016/B978-0-12-820491-7.00001-3
3. Aprilia E, Meng K, Zeineldin HH, et al. (2020) Modeling of distributed generators and converters control for power flow analysis of networked islanded hybrid microgrids. *Electr Pow Syst Res* 184: 106343. https://doi.org/10.1016/j.epsr.2020.106343
4. KOCAMAN B, Nurettin AB (2020) The role of static Var compensator at reactive power compensation. *European Journal of Technique (EJT)* 10: 143–152. https://doi.org/10.36222/ejt.659118
5. Moore AT (2008) *Distributed Generation (DG) Protection Overview*. University of Western Ontario.
6. Hussain A, Bui VH, Kim HM (2019) Microgrids as a resilience resource and strategies used by microgrids for enhancing resilience. *Appl Energ* 240: 56–72. https://doi.org/10.1016/j.apenergy.2019.02.055
7. González I, Calderón AJ, Portalo JM (2021) Innovative Multi-Layered Architecture for Heterogeneous Automation and Monitoring Systems: Application Case of a Photovoltaic Smart Microgrid. *Sustainability* 13: 2234. https://doi.org/10.3390/su13042234
8. Jiang A, Yuan H, Li D, et al. (2019) Key technologies of ubiquitous power Internet of Things-aided smart grid. *J Renew Sustain Ener* 11: 062702. https://doi.org/10.1063/1.5121856
9. Shaik M, Rao MN, Gafoor SA (2012) A wavelet based protection scheme for distribution networks with Distributed Generation. *Proceedings - ICETEEEM 2012, International Conference on Emerging Trends in Electrical Engineering and Energy Management*, 33–37. https://doi.org/10.1109/ICETEEEM.2012.6494440
10. Anwar A, Mahmood A, Ray B, et al. (2020) Machine Learning to Ensure Data Integrity in Power System Topological Network Database. *Electronics* 9: 693. https://doi.org/10.3390/electronics9040693
11. Aminifar F, Abedini M, Amraee T, et al. (2021) A review of power system protection and asset management with machine learning techniques. *Energy Systems*, 1–38. https://doi.org/10.1007/s12667-021-00448-6
12. Lasseter RH, Paigi P (2004) Microgrid: a conceptual solution. *Proceedings of the IEEE 35th Annual Power Electronics Specialists Conference (PESC '04)* 6: 4285–4290.
13. Pourbeik P, Sullivan DJ, Bostrom A, et al. (2012) Generic model structure for simulating static VAr systems in power system studies—A WECC Task Force Effort. *IEEE T Power Syst* 27: 1618–1627. https://doi.org/10.1109/TPWRS.2011.2179322
14. Ghorbani A, Khederzadeh M, Mozafari B (2012) Impact of SVC on the protection of transmission lines. *Int J Elec Power* 42: 702–709. https://doi.org/10.1016/j.ijepes.2012.04.029

15. Li Z, Shahidehpour M, Aminifar F, et al. (2017) Networked microgrids for enhancing the power system resilience. *Proc IEEE* 105: 1289–1310. https://doi.org/10.1109/JPROC.2017.2685558

16. Yang H, Liu X, Zhang D, et al. (2021) Machine learning for power system protection and control. *The Electricity Journal* 34: 106881. https://doi.org/10.1016/j.tej.2020.106881

17. Aslan Y (2012) An alternative approach to fault location on power distribution feeders with embedded remote-end power generation using artificial neural networks. *Electr Eng* 94: 125–134. https://doi.org/10.1007/s00202-011-0218-2

18. Bedi G, Venayagamoorthy GK, Singh R, et al. (2018) Review of Internet of Things (IoT) in Electric Power and Energy Systems. *IEEE Internet Things* 5: 847–870. https://doi.org/10.1109/JIOT.2018.2802704

19. Shekar SC, Kumar GR, Lalitha SVNL (2019) A transient current based micro-grid connected power system protection scheme using wavelet approach. *International Journal of Electrical and Computer Engineering* 9: 14. https://doi.org/10.11591/ijece.v9i1.pp14-22

20. Gururajapathy SS, Mokhlis H, Illias HA (2017) Fault location and detection techniques in power distribution systems with distributed generation: a review. *Renew Sust Energy Rev* 74: 949–958. https://doi.org/10.1016/j.rser.2017.03.021