This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3087914, IEEE Access

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

*Digital Object Identifier 10.1109/ACCESS.2017.Doi Number*

# Machine Learning based Intentional Islanding Algorithm for DERs in Disaster Management

**M. Ankush Kumar[1] and Dr. A. Jaya Laxmi[2], Senior Member, IEEE**

[1] Research Scholar, Department of EEE, Jawaharlal Nehru Technological University, Hyderabad, India
[2] Professor, Department of EEE, Jawaharlal Nehru Technological University, Hyderabad, India

Corresponding author: M. Ankush Kumar (e-mail: mudholker.ankush@gmail.com).

**ABSTRACT** Currently, research work is primarily dependent on the collection of large sets of data from systems and making predictions based on the knowledge obtained from the data, which is generally termed as 'data mining'. These data mining algorithms are of great importance in improving the performance of different applications. In this regard, Machine Learning (ML) algorithms have been demonstrated to be excellent tools to cope with difficult problems. In this paper, a classification learner based supervised ML algorithm is proposed for intentional islanding of DERs based on the live data collected from supervisory control and data acquisition (SCADA) system in post disaster situations. Literature presents various islanding detection techniques and also intentional islanding algorithms to address different problems in AC networks. These algorithms majorly work based on the control of current source or voltage source inverters. On the other hand, a low voltage DC distribution system allowing the removal of inverter is proposed, which is supposed to be more advantageous by reducing losses and is also economical when working with DERs. In this paper, ML based intentional islanding algorithm for DERs based low voltage DC distribution system is proposed by considering the effects of natural disasters. The learner models trained are fine tree, linear SVM, quadratic SVM and Gaussian SVM. The training of fine tree model is achieved with higher accuracy of 99.8%. The main objective of this work is to achieve a faster and accurate decision making. The performance of the ML based intentional islanding algorithm is compared with the earlier proposed artificial intelligence (AI) based intentional islanding algorithms. The AI algorithms proposed earlier are fuzzy inference systems (FIS), artificial neural networks (ANN) and adaptive network based fuzzy inference system (ANFIS). The comparison shows that, the decision making with ML based intentional islanding algorithm faster and accurate than all other algorithms.

**INDEX TERMS** Machine Learning, DERs, SCADA, Intentional Islanding, Disaster Management, LVDC Distribution Systems.

## I. INTRODUCTION

Machine Learning (ML), a vast interdisciplinary field with numerous applications is classified into two main categories: supervised and unsupervised. Unsupervised ML is used to draw conclusions from datasets consisting of input data without labeled responses. Supervised ML techniques are further classified into two categories, classification and regression. Classification is a data mining approach that is used to forecast class labels for data instances. There are different classification learners such as decision trees (DT), K-nearest neighbor (KNN) classifiers and support vector machines (SVMs). Every algorithm has its own advantages and disadvantages. When compared, DTs are easy to understand and the decision is obtained using the complete training data set, KNNs have advantages such as transparency and robustness towards noisy training datasets and SVMs are most suitable for large, high dimensional and nonlinear datasets [1].

These classifiers find different applications in electrical systems, significantly where predictions or decisions are obtained from the available large datasets. Most importantly in RES's such as wind and solar, need predictions based on large datasets, as they are variable in nature. These classifiers are being used in various applications like wind speed prediction, pattern prediction of power generation from RES, fault diagnosis and power quality (PQ) indices such as distortions in voltage and current waveforms (sag, swell, notch, interruption, etc.), sudden variations in parameters and frequency deviations. The live data from the RES's or DER's and the distribution system loads are provided by the automated systems such as SCADA. These systems provide moment-to-moment live data across the system, which is bulk in size. The classification learner gives an opportunity, to gain the required knowledge from these big data and utilize this knowledge for making decisions and future predictions [2-3].

Furthermore, classification learners are also finding their applications in the detection of unintentional islands for DERs. An article showed that, SVM is the most effective tool of ML in identifying unintentional islands when compared to conventional relays such as rate of change of frequency (ROCOF) and frequency relays (FRs) in terms of reliability and detection time. Another article showed that, the DTs have been proven to be the fastest and most accurate in identifying unintentional islands of DERs [4-5]. Some articles (Ashish Shrestha, Kashem Muttaqi and Mollah Rezual Alam et. al.,) projected the potential of the classification learners to solve the complicated problems related to interconnections in DERs that comprise micro grids and smart grids.

On the other hand, intentional islanding algorithms are found to be as best solutions for DERs to improve the system reliability. In these articles, the primary concern is to provide solutions for an AC distribution system. The controls mainly work based on the control of the inverter from current source mode to voltage source mode [6]. Advanced algorithms based on clustering and spectral clustering have also been published for AC distribution systems [7-9]. Few papers provide load shedding and battery energy storage systems solutions for intentional islanding in AC systems [10-11]. Additionally, few papers present optimal algorithms based on genetic algorithms and particle swam optimization (PSO) algorithms [12-13]. A recent article shows a fault location, isolation and service restoration (FLISR) application along with integration of an open-source standards-based platform for ADMS application development in AC distribution systems [14].

Utilizing power from DERs for AC loads in islanded mode requires more number of conversion stages. Most of the DERs generate power in DC and then this DC power is given to batteries and inverted to AC and utilized for loads. In present days, most of the loads are inherently DC. This leads to an added conversion stage from AC to DC. As the conversion stages increase, losses in system increases and the overall cost of the system also increases. Here, to effectively utilize the power from DERs by reducing the number of conversion stages, an intentional islanding algorithm is proposed for a low voltage DC (LVDC) distribution system. The LVDC distribution system is designed based on the standards proposed in the literature [15-19].

While islanding the loads with DERs in post disaster situations, even a small disturbance in the system can cause substantial damage to the equipment. Hence, faster decision making is of major concern in post disaster situations. The main objective of this work is to achieve an accurate and faster decision making using ML algorithms. In this paper, a ML based intentional islanding algorithm for DER's is designed by using different classification learners (supervised machine learning) such as DT's and SVM's like Linear SVM's (LSVM's), Gaussian SVM's (GSVM's) and Quadratic SVM's (QSVM's). The algorithms while creating islands, address the post disaster constraints such as effects of natural disasters on electrical networks, the balancing of power between DERs and loads and priorities of loads. Further, the performance of the proposed ML algorithm is compared with the earlier proposed conventional, AI based intentional islanding algorithms like FIS, ANN and ANFIS in terms of decision making time and linearity in decision making. The results show that, the proposed ML based algorithm gives faster and accurate decision making.

**Motivation and Contributions:**

- An intentional islanding algorithm for LVDC distribution system is proposed to reduce the number of conversion stages and to reduce the overall cost of system by removing inverters.
- ML based algorithms such as DT's, LSVM's, QSVM's and GSVM's are proposed for intentional islanding of loads to achieve faster decision making.
- The performance of the proposed ML based algorithms is tested for various case studies to address the differing impacts of natural disasters and also to avoid the overloading of DERs.
- A comparison for the proposed ML based algorithms and earlier proposed Conventional and AI based algorithms is explained detail.
- Results show that, the ML based algorithm gives faster and accurate decision making in comparison with AI based algorithms.

**Flow of paper:**

**I** Introduces the literature and the proposed work.
**II** Designs a base LVDC distribution system.
**III** Presents an analysis of the impacts of natural disasters on the electrical system when compared to the typical faults in the system.
**IV** Describes the proposed intentional islanding algorithm for the LVDC distribution system.
**V** Gives a brief explanation of the training of classification learners in MATLAB and the selection of a classifier with high accuracy.
**VI** Results are elaborated for the ML based intentional islanding algorithm with all contingencies. A comparative analysis of the obtained results of ML with earlier proposed AI is also presented in detail.
**VII** Concludes the comparisons of ML with Conventional and AI based algorithms.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3087914, IEEE Access



## II. BASE LVDC DISTRIBUTION SYSTEM

A base distribution system to integrate RES's is designed based on the IEEE standards and recommendations given in IEEE Std. 1547.6-2011[20]. The distribution system is designed for LVDC so that, the conversion stages are reduced when the power is utilized from DERs. The base LVDC distribution system is shown in Figure 1.

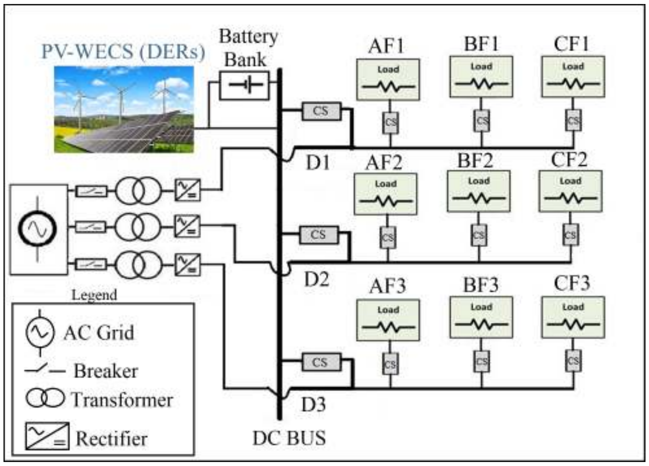


Figure 1. LVDC distribution system with DERs and SCADA

Figure 1 depicts the base distribution system designed by considering three radial feeders of a rural area. On each feeder, three DC loads of 1 kW each are connected, considering a residential load. The three loads are titled A, B and C for feeders $F_1$, $F_2$ and $F_3$. The ratings of the LVDC distribution system and its loads are: voltage - 48 V DC and current - 20 A DC. All the loads are considered resistive since, the inductive and capacitive loads are observed as resistive by the DC supply. The loads of $F_1$ i.e., $AF_1$, $BF_1$ and $CF_1$ are considered first priority loads. The loads of $F_2$ i.e., $AF_2$, $BF_2$ and $CF_2$ are considered second priority loads. The loads of $F_3$ i.e., $AF_3$, $BF_3$ and $CF_3$ are considered the least or third priority loads. The DER considered in this system is an integration of two RES's, the standalone PV (SPV) system and the wind energy conversion system (WECS). Integration is achieved in DC as shown in literature [21]. The distribution system with three radial feeders is connected across the main grid and the DERs in parallel. Power from the main grid to loads is obtained through rectifiers (AC to DC converters), whereas, the power from DERs is obtained directly without any converters. This approach helps reduce the number of conversion stages when the power is obtained from DERs. The main grid is connected to feeders through conventional breakers. The conventional breakers operate based on the information provided by the relays and trip accordingly. The DER's are connected to feeders through the controllable switches (CS's). These CS's are operated based on the binary data, i.e. a binary '1' closes the CS and a binary '0' opens the CS. Automation software such as SCADA is installed in this distribution system to obtain the live data across each load and feeder. The base distribution system with DERs, CS's and SCADA as per the block diagram shown in figure 1 is installed in real-time. This is shown in figure 2. The DERs installed in real time are shown in figure 3.


Figure 2. Real-time prototype distribution system

Figure 3. PV and Wind hybrid DERs installed in real-time

The conventional based intentional islanding algorithm is implemented in real time and prototype distribution system is developed. The results of conventional algorithm in real time system validate the proposed intentional islanding algorithm [22-23].

Further, the live data such as voltage, current and power across each individual load and feeder is obtained from automation system for every moment. This large set of data is analyzed and classified with the help of the proposed 'classification learner based intentional islanding algorithm' in MATLAB/Simulink. Based on the classification, a decision is obtained in binary to open or close the CS, helping to create intentional islands of loads during grid unavailability.

## III. NATURAL DISASTERS AND CONTINGENCY ANALYSIS

Natural disasters are unannounced event's that disturb many important services such as medical services, transportation and communication, where these services depend on electricity internally. Natural disasters such as floods, landslides and earthquakes have a huge impact on the electrical distribution systems. These impacts are different for different disasters [24] and they are summarized as:

- Power generation units may be out of service
- Transmission and distribution networks are damaged and incomplete
- Multiple faults result from catastrophic damage

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3087914, IEEE Access



- Uncertainty and stochasticity are found with the process of natural disasters
- Spatiotemporal correlation for the faults due to natural disasters
- Interdependence with other infrastructures causes problems
- Difficult with repair and restoration is widespread, e.g., debris after the disaster

In post disaster situations, while creating islands for loads, these impacts of natural disasters must be considered. These impacts may lead to damage to DERs or the interconnecting components of the distribution network and may also lead to the tripping of DER. Hence, in post disaster situations, the DERs cannot be connected to loads without taking precautionary measures. An intentional islanding algorithm is proposed to address these impacts of natural disasters while creating islands of healthy loads.

To address these impacts of natural disasters, a contingency analysis with the help of faults is conducted in this work. The contingencies that resemble the impacts of natural disasters are shown as follows:

- Supply from main grid
- Supply from DERs during:
  a. Multiple faults in system
  b. Small duration fault
  c. Multiple faults on a single line

The contingencies listed above show the working of the distribution system in different situations such as pre- and post-disaster situations [25]. The supply from the main grid represents the operation of the distribution system under normal operating conditions or pre-disaster situations. In the post-disaster situation, as 'the power generation units may not be available', the power is obtained from alternate sources, i.e., DERs. This situation is addressed by the supply from DERs. The impact of disasters show that there will be multiple faults in the system due to catastrophic damage, represented by the contingency of multiple faults in systems. These multiple faults are created in the system at irregular intervals to resemble the actual situation of disasters. Furthermore, the impact of natural disasters consist of uncertainity and stochasticity, represented with a contingency of a small duration fault, where a fault of very small duration, i.e., of $10^{-4}$s is applied in the system and the algorithm is tested for its performance. This approach helps in creating islands while isolating every smallest possible uncertainty in the system. Additionally, the impact of natural disasters show a spatiotemporal correlation between faults, represented by creating multiple faults on a single line at regular intervals. With the help of these contingencies, an attempt can be made to resemble the actual situation of post-disaster conditions in a disaster prone distribution network. The proposed algorithm is tested for its performance during these contingencies.

## IV. PROPOSED ALGORITHM

An algorithm is proposed to address the impact of natural disasters while creating intentional islands in post-disaster situation. However, the power generated by the DER is not constant since it varies with sun, possibly leading to variation in electrical parameters across the system and in-turn, leading to false tripping of DERs. Hence, the proposed algorithm is designed to address the load management between DERs and loads for the successful creation of intentional islanding. The flowchart of the proposed algorithm is shown in Figure 4.

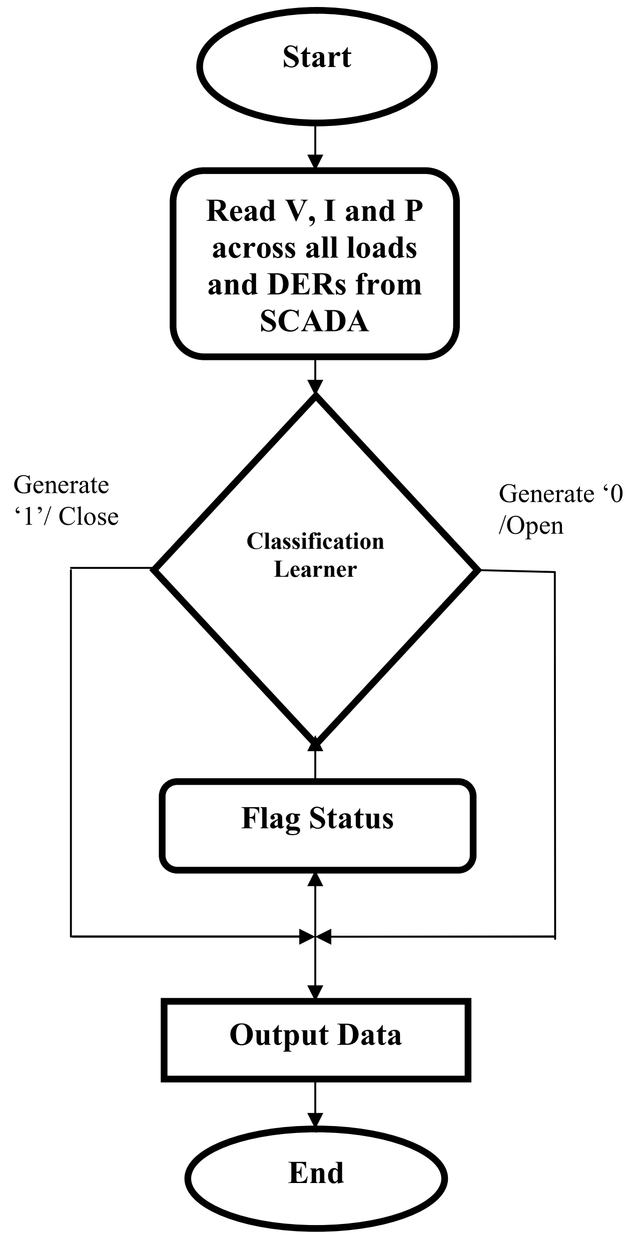


Figure 4. Flowchart of proposed algorithm

The flowchart shows that, the algorithm collects the live data such as voltage, current and power across all loads, feeders and DERs from SCADA. These data are

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3087914, IEEE Access



given as input to the classification learner. This learner classifies the data into two categories as follows: good parameters and violating parameters. Good parameters are the values of voltage, current and power that do not exceed the tolerance limits and violating parameters exceed the tolerance limits. The trained learner classifies the observed value into two categories and makes a decision to generate either '1' or '0'.

In the same way, the control signals for all CSs of respective loads and feeders are generated by using the trained classifier. With this set of generated control signals, the healthy loads are connected to DERs and the disaster impacted loads (which violate the parameters due to faults) are isolated from the DERs, resulting in islanding of healthy loads. If, at any load or feeder, the algorithm makes a decision to open the switch with '0', this information sets a flag on the respective feeder and forwards the same as input to the classifier so that, if the classifier finds the flag, then the respective load or feeder is left disconnected by generating '0' irrespective of the load parameters.

As discussed earlier, the algorithm also takes care of the power management between loads and DERs by solving the equation $P_g$ (generated power from DER) – $P_L$ (sum of load powers) = X. If 'X' is positive, then a balance is achieved between the generation and the power. If 'X' is found to be negative, then the loads exceed the generated power. The classifier generates '0' when it finds 'X' as a negative value helping to achieve a power balance between load and DER while creating islands.

## V. SIMULATIONS

The proposed algorithm for creating intentional islanding is implemented in MATLAB/Simulink. The simulations are carried out by designing the base distribution system according to the training of different classifiers. The best trained learner model is implemented in the base distribution system and the results obtained are compared with the results of the AI-based intentional islanding algorithm from the literature.

### A. SIMULATION OF BASE DISTRIBUTION SYSTEM

The base distribution system shown in Figure 1 is simulated in MATLAB. As discussed earlier, three radial feeders with three loads on each feeder are simulated. Each load is designed for 1 kW resistive. An AC source is simulated as the main grid, which generates three phase AC power at 440 V (L-L) and is connected to loads through the breaker, transformer and rectifiers. Conventional breakers and relays are used for protection during this operation. The transformer steps down the 230 V (L-N) to 48 V (L-N). This 48 V (L-N) is converted to 48 V DC. Each phase is converted to one DC line and the distribution system is fed from the main grid. Furthermore, the distribution system is connected to DERs in parallel to the grid through CS. The distribution system is also included in an automation system with remote terminal units (RTU) across each load, feeder and DER. A CS is associated with each RTU. The data retrieved from each RTU are forwarded to the classification learner. Based on these huge sets of data, the classification learner makes respective decisions and forms islands by closing or opening the CS. These CS's provide both protection and control over distribution system loads when powered by DERs.

### B. SIMULATION OF DERS

In this work, the DERs considered are the SPV system and wind energy conversion system (WECS), so that the SPV system generates power during sun hours and the WECS generates power in night hours. The SPV system is simulated in MATLAB/Simulink based on the equivalent circuit of the PV cell [14]. The WECS is designed in MATLAB/Simulink with a wind turbine connected to permanent magnet synchronous generator (PMSG) through a drive train, pitch angle controller and power converter such that it generates DC power. Its advantages are high efficiency, low maintenance, reduced losses, reduced cost and good controllability [14].

### C. TRAINING OF CLASSIFICATION LEARNERS

The flowchart of the proposed algorithm and the system description show that, the classification learner plays a major role in the creation of intentional islands. The classification learner acts as the heart of the algorithm. The successful and accurate training of the learner leads to the best results. Hence, to obtain the best results, different classifiers are trained and observed for the accuracy of training. The classifiers trained in this work are: Fine tree, Linear SVM, Gaussian SVM and Quadratic SVM.

As discussed earlier, the classification learner is a field of supervised ML. The learner needs training with input variables and an output variable. In this work, the classification learner is trained with 4 input variables: voltage, current, power and flag status, where the flag status is either '0' or '1' for different values of other parameters. The learner is also trained with an output variable with two class labels of '0' and '1'. Each input and the output variable are formed with 1400 samples to train the classifier with different situations. The training data of all inputs and output variables are shown in Figure 5.

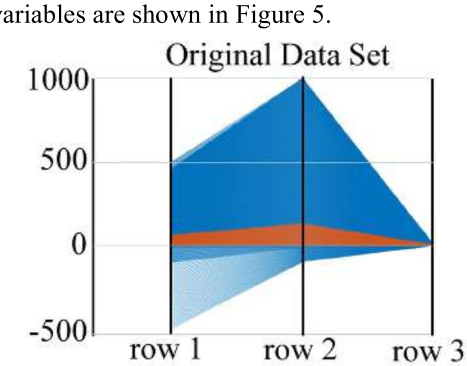


Figure 5. Training data set for classification learner

Figure 5 shows that, the classification learner is trained with 4 input variables as 4 columns. These inputs are segregated into two classes: blue and brown as output. The blue class represents the violated parameter class or class ‘0’ and the brown class represent the good parameter class or class ‘1’. The classifiers listed above are trained with these training data.

The fine tree classifier is a field of DTs in ML and is trained with the above data. The confusion matrix obtained after training is shown in Figure 6, where, a confusion matrix is a summary of the prediction results on a classification problem. The number of correct and incorrect predictions is summarized with count values and broken down by each class, which is also known as an error matrix.

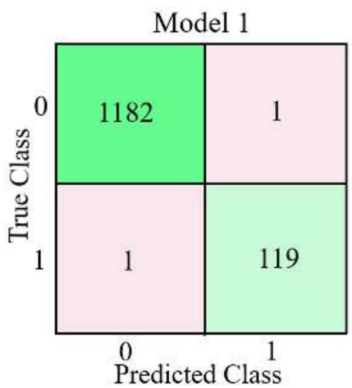


Figure 6. Confusion matrix of Fine Tree classifier

Figure 6 shows that, 1182 samples are trained for blue class or class ‘0’ and 119 samples are trained for brown class or class ‘1’. Only 2 samples have conflicts, leading to 99.8% training accuracy for the fine tree classifier. In the next step, the linear SVM is trained with the same training data and the confusion matrix obtained for this method after training is shown in Figure 7.

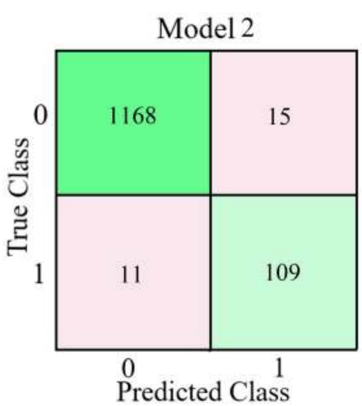


Figure 7. Confusion matrix of Linear SVM

Figure 7 shows that 1168 samples are trained for the blue class and only 109 samples are trained for the class brown. Twenty six samples have conflicts leading to the 98% of training accuracy for LSVM. Furthermore, the Quadratic SVM is trained for the same data, and the confusion matrix obtained for this technique is shown is Figure 8.

The confusion matrix of the QSVM in Figure 8 shows that only 3 samples are in violation from the actual training data, which gives an accuracy of 99.8%. The training accuracies obtained for QSVM and fine tree are the same but there are more conflicting samples in QSVM than in the fine tree model.

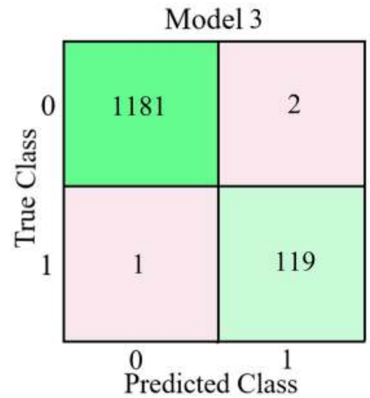


Figure 8. Confusion matrix of Quadratic SVM

Furthermore, the Gaussian SVM is trained for same training data and the confusion matrix obtained is shown in Figure 9.

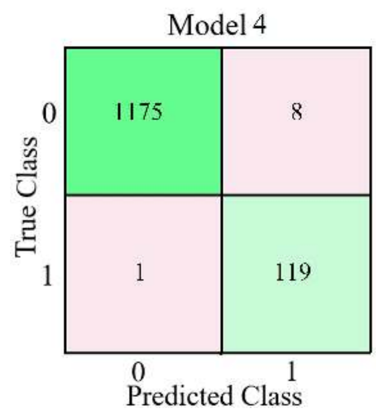


Figure 9. Confusion matrix of Gaussian SVM

Figure 9 shows that the classifier is trained so that the 1175 samples are observed as class blue or class ‘0’, and 119 samples are observed as class brown or class ‘1’. Nine samples deviate from the actual training data, leading to training accuracy of only 99.3 %.

The training accuracies of all the classifier models are as follows:

- Fine tree : 99.8%
- LSVM : 98%
- QSVM : 99.8%
- GSVM : 99.3%

It is observed that, the fine tree gives the best accuracy for the given training data when compared to all other classifier models. The major comparison is only between fine tree and the QSVM, as they are trained with the same accuracy of 99.8%. The samples with conflicts are more abundant in QSVM than in fine tree. Hence, the fine tree classification learner model is considered the best trained classifier when compared to SVM classifiers, leading to the selection of fine tree for decision making while creating intentional islanding.

## VI. RESULTS AND DISCUSSION

From the above discussion, the proposed algorithm is implemented using the fine tree classification learner model on an ML tool. The performance of the proposed ML based intentional islanding algorithm was tested for different case studies as given in section 3. These case studies help in understanding the response of the algorithm when the distribution system is affected by disaster. The results obtained for these case studies are discussed below:

### A. SUPPLY FROM MAIN GRID

This case study presents the working of the distribution system under normal operating conditions. In this situation, the proposed classification learner is trained to turn ON the CS of all loads and turn OFF the DER switches so that, the power is obtained from main grid and protection is given by conventional relays and circuit breakers. The results show that, the learner generates '1' for the CSs of all loads ($AF_1$, $BF_1$, $CF_1$, $AF_2$, $BF_2$, $CF_2$, $AF_3$, $BF_3$ and $CF_3$) and generates '0' for the DER switches ($F_1$, $F_2$ and $F_3$) in the distribution system. The loads receive power from the main grid through rectifiers and the waveforms of voltage, current and power across all loads are shown in Figure 10.

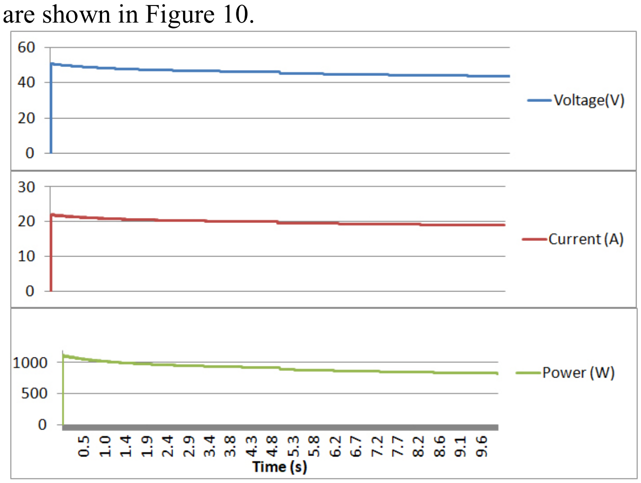


Figure 10. Electrical parameters: Voltage, Current and Power across the loads of distribution system.

Figure 10 shows the waveforms of voltage, current and delivered power to the distribution system loads. The voltage applied to loads is 48 V DC and the current delivered to loads is 20 A to satisfy the power requirement of 1 kW by each DC load. The results show that the distribution system is powered from the main grid under normal operating conditions, keeping DERs isolated.

### B. SUPPLY FROM DERS

This case study presents the operation of distribution system loads when connected to DERs under abnormal conditions. It is considered that, the main grid is disconnected from the distribution system loads by the conventional breakers. In this situation, the DERs are connected to the distribution system loads while observing the load priorities and isolating the disaster affected parts of the distribution system. It is observed from the discussion in section 3 that, the impact of natural disasters are different in different situations. Hence, to address these impacts of natural disasters, the following case studies are implemented for the proposed algorithm when supply is obtained from DERs:

- Single fault on single line
- Multiple faults on single line
- Multiple faults on multiple lines
- Short duration fault

### C. SINGLE FAULT ON SINGLE LINE

An attempt is made in this case to show the response of the proposed algorithm when the minimum effect of a natural disaster is observed in the distribution system. With this consideration, only one fault is applied on feeder $F_2$ in the beginning of execution. The proposed algorithm successfully identifies the applied fault and isolates $F_2$ from the DER by generating '0' for its respective CS. Furthermore, the algorithm sets a flag on this feeder so that the feeder is isolated from the DER for complete execution. As, the feeder $F_2$ is disconnected from DERs, there is no power delivered to the loads of feeder $F_2$. The healthy loads of feeders $F_1$ and $F_3$ are powered from DERs in islanded mode for complete execution. The waveforms of voltage, current and power across the loads of $F_1$ and $F_3$ are as shown in Figure 10. The voltage applied to loads is 48 V, current consumed by loads is 22 A and power delivered is 1000 W. It is observed from results that, there is no disturbance in the parameters across the healthy loads of $F_1$ and $F_3$ for complete execution and an island of $F_1$ and $F_3$ with DERs is successfully created.

### D. MULTIPLE FAULTS ON SINGLE LINE

This case study represents a situation when a line is affected by the disaster so that the poles are tumbling and touching the ground one after the other, showing the spatiotemporal correlation of faults. The contingency is applied so that two faults are applied on feeder $F_2$ with time and space differences. One fault is applied at the beginning of execution near $CF_2$ and the second fault is applied at 3 s near $BF_2$. The proposed algorithm responds to the first fault applied in the beginning of execution near $CF_2$ and isolates $F_2$ by generating '0' for its respective CS. Furthermore, as the algorithm sets a flag on this feeder, it is left isolated from DERs for complete execution. The second fault applied at 3 s near $BF_2$ does not show any impact on the system. As the feeder $F_2$ is disconnected from DERs, there is no power delivered to the loads of $F_2$. The healthy loads of feeders $F_1$ and $F_3$ are powered by DERs in islanded mode. The parameters: voltage, current and power across the loads of $F_1$ and $F_3$ are as per the ratings. Voltage applied is 48 V, current consumed is 22 A and power delivered is 1000 W. These are shown in Figure 10. The results show that the proposed algorithm successfully addresses the spatiotemporal correlation of faults during natural disasters and creates an island of healthy feeders $F_1$ and $F_3$ and DERs for complete execution without any disturbances.

### E. MULTIPLE FAULTS ON MULTIPLE LINES

This case study represents the catastrophic damage that occurred in the distribution system due to natural disasters. To address this catastrophic damage, the contingency is applied so that 3 faults on 2 feeders are applied in the system. Two faults on $F_2$ and one fault on $F_3$ are applied in the distribution system. Two faults applied on $F_2$ are similar to earlier case study, one at beginning of execution and another at 3s. As the feeder $F_2$ is disconnected from DERs by algorithm for complete execution, there is no power delivered to the loads of $F_2$. Further, one fault at 5 s is applied on $F_3$. As the fault on feeder $F_3$ is identified by algorithm at 5 s, it is disconnected from DERs by generating '0' for its respective switch after 5 s. The results show that, the feeder $F_3$ is powered from DERs with rated power upto 5 s. Thereafter, as the feeder is disconnected from DER, the power delivered to it is 0 W. This is shown in figure 11.

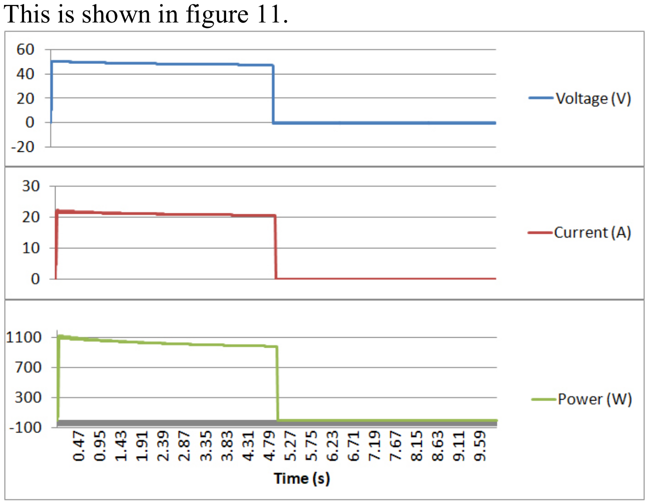


Figure 11. Electrical parameters across the loads of F3.

The results also show that the loads of healthy feeder $F_1$ are powered from DER in islanded mode for complete execution. The parameters across the loads of F1 are as per the ratings. Voltage applied is 48 V, current consumed is 22 A and power delivered is 1000 W. These waveforms are shown in figure 10.

This operation shows that, the catastrophic damage is successfully addressed by the algorithm and the healthy loads are only powered in islanded mode by DERs.

### F. SMALL DURATION FAULT

In this case study, the performance of the algorithm is tested for the smallest possible uncertainity in the system. To represent this uncertainity, a very small fault of $10^{-4}$ s duration is applied on feeder $F_3$ at 3 s. The algorithm connects the feeder $F_3$ to DERs only upto 3 s. Thereafter, as the uncertainity is identified, the feeder $F_3$ is disconnected from DERs by generating '0' for its respective switch. The results show that, the power delivered to the loads of $F_3$ upto 3 s is as per ratings. Thereafter, as the feeder is disconnected, the power delivered is 0 W. This is shown in Figure 12.

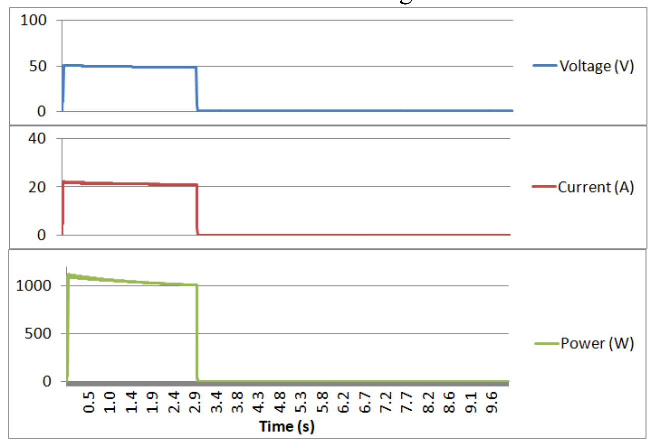


Figure 12. V, I and Power across the loads of feeder F3.

Further, the healthy loads of feeders $F_1$ and $F_2$ are powered through DER for complete execution. The waveforms of voltage, current and power across the loads of $F_1$ and $F_2$ are shown in Figure 10. Voltage applied is 48 V, current consumed by these loads is 22 A and power delivered is 1000 W. This shows that, the proposed algorithm successfully addresses the smallest possible uncertainity in the system and provides power to the healthy loads in the islanded mode of operation.

The above case studies show that the proposed algorithm works successfully for all contingencies as by the performance of the proposed algorithm in creating intentional islanding while addressing the impact of natural disasters.

### G. COMPARATIVE RESULTS

Furthermore, the results obtained from the ML based algorithm were compared with the results of the Conventional and AI based intentional islanding algorithms. The comparative results are shown in Figure 13.

Figure 13 describes the switching pulses generated for the load switches of $AF_2$, $BF_2$ and $CF_2$ of $F_2$. In the case of single fault, a fault is applied on feeder $F_2$ at the beginning of execution. The conventional MATLAB programming based intentional islanding algorithm identifies the fault and generates '0' for the respective load switches at 0.01 ms. For the same situation, FIS makes decisions at different times; for $AF_2$ it generates '0' at 0.01 ms, and for $BF_2$ and $CF_2$ it generates '0' at 0.05 ms.

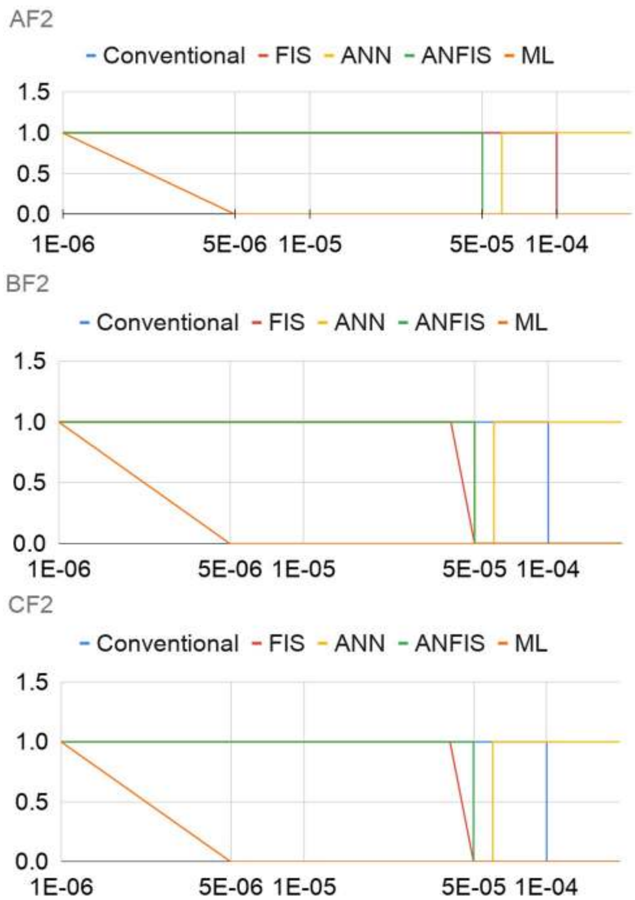


Figure 13. Comparative results of Machine learning with AI based algorithms

Furthermore, ANN identifies faults and generates '0' at 0.05 ms for all switches, but it again generates '1' after the fault is isolated. ANFIS gives satisfactory results by generating '0' for all switches at 0.05 ms and continuing to isolate these loads by generating '0' for the rest of the execution. The ML based algorithm proposed in this work is found to be the best, as it generates '0' for all switches at 5 µs. The results are tabulated in Table I. The detailed flow of comparisons is shown in figure 14.

TABLE I
COMPARISON OF PROPOSED ALGORITHM WITH CONVENTIONAL AND AI BASED ALGORITHMS

| *S.No.* | *Type of Algorithm* | *Time taken to identify the contingencies* |
|---|---|---|
| 01 | Conventional MATLAB Programming | 0.01 ms for all loads |
| 02 | FIS based algorithm | 0.01 ms for $AF_2$ and 0.05 ms for $BF_2$ and $CF_2$ |
| 03 | ANN based algorithm | 0.05 ms for all loads |
| 04 | ANFIS based algorithm | 0.05 ms for all loads |
| 05 | ML based algorithm | 5 µs for all loads |

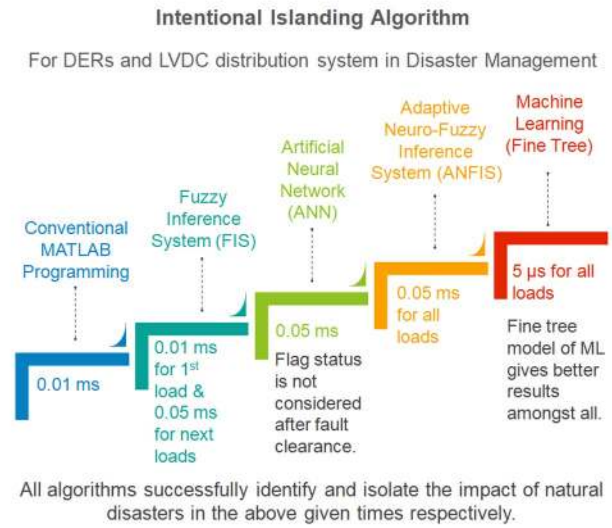


Figure 14. Comparative analysis of all algorithms

Table I and figure 14 shows that, the proposed ML algorithm classifies the load or feeder situation within no time and makes faster and accurate decisions than the AI- and conventional-based intentional islanding algorithms.

## VII. MERITS AND DEMERITS OF PROPOSED METHODOLOGY

In comparison to the literature, the proposed methodology of LVDC distribution system over the traditional AC distribution system has merits. LVDC distribution system reduces the number of conversion stages and the overall cost of system by removing the inverter. Further, the referred articles show different methodologies for intentional islanding of DERs to increase the system reliability. In comparison, the proposed methodology targets the post disaster situations while creating intentional islanding of DERs. Also, the proposed methodology uses Machine Learning based algorithms to achieve faster and accurate decision making while creating islands. The demerit of the proposed methodology is, it requires huge changes in the present system to incorporate the proposed algorithm.

## IX. CONCLUSION

In this paper, a ML-based intentional islanding algorithm for DERs is proposed for post-disaster situations. The performance of the proposed algorithm was tested for different contingencies (case studies), and the results obtained were compared with the earlier proposed AI-based intentional islanding algorithms. A classification learner model was designed for making decisions for the status of line or load based on binary data, i.e., class '0' for disaster-affected feeders or loads and class '1' for healthy feeders or loads. The live parameters across all loads and feeders were obtained with the help of the SCADA system, and these data are given as input to the classification learner model. Different learner models such as LSVM, QSVM, GSVM and fine tree are trained for these data and the fine tree model is trained with an accuracy of 99.8% when compared to the other learner models (LSVM, QSVM and GSVM). The fine tree based algorithm was implemented and tested for different contingencies.

The results obtained for different case studies were compared with the results of Conventional and AI-based intentional islanding algorithms such as FIS, ANN and ANFIS. These results show that, the proposed algorithm makes decisions in no time, i.e., within 5 µs, which is less than the time required by AI-based algorithms. Also, the real-time implementation of conventional islanding algorithm validates the working of proposed algorithm.

## ACKNOWLEDGEMENT

Authors are thankful to Centre of Excellence under TEQIP-II, JNTU Hyderabad for giving an opportunity to be a part of the prestigious project titled 'Disaster Management' and supporting us to implement the project in real time.

## REFERENCES

[1]. Aized Amin Soofi and Arshad Awan, "Classification Techniques in Machine Learning: Applications and Issues", Journal of Basic & Applied Sciences, 2017, Vol. 13. pp. 459-465.

[2]. Osisanwo F.Y, Akinsola J.E.T, Awodele O, Hinmikaiye J. O, Olakanmi O, Akinjobi J, "Supervised Machine Learning Algorithms: Classification and Comparison", International Journal of Computer Trends and Technology (IJCTT), Vol. 48 No. 3, June 2017. pp. 128-138.

[3]. María Pérez-Ortiz, Silvia Jiménez-Fernández, Pedro A. Gutiérrez, Enrique Alexandre, César Hervás-Martínez and Sancho Salcedo-Sanz, "A Review of Classification Problems and Algorithms in Renewable Energy Applications", Energies 2016, Vol. 9, No. 607.

[4]. Ashish Shrestha, Roshan Kattel, Manish Dachhepatic, Bijen Mali, Rajiv Thapa, Ajay Singh, Diwakar Bista, Brijesh Adhikary, Antonis Papadakis and Ramesh Kumar Maskey, "Comparative Study of Different Approaches for Islanding Detection of Distributed Generation Systems", Applied System Innovation 2019, Vol. 2, No. 25.

[5]. Mollah Rezaul Alam, Kashem M. Muttaqi and Abdesselam Bouzerdoum, "Evaluating the effectiveness of a machine learning approach based on response time and reliability for islanding detection of distributed generation", IET Renewable Power Generation 2017, Vol. 11 Iss. 11, pp. 1392-1400.

[6]. M. A. Salam and S. Sethulakshmi, "Control for grid connected and intentional islanded operation of distributed generation," 2017 Innovations in Power and Advanced Computing Technologies (i-PACT), Vellore, 2017, pp. 1-6, doi: 10.1109/IPACT.2017.8245110.

[7]. M. Dabbaghjamanesh et al., "A Novel Two-Stage Multi-Layer Constrained Spectral Clustering Strategy for Intentional Islanding of Power Grids," in IEEE Transactions on Power Delivery, vol. 35, no. 2, pp. 560-570, April 2020, DOI: 10.1109/TPWRD.2019.2915342.

[8]. Znidi, Faycal, et al. "Multi-layer spectral clustering approach to intentional islanding in bulk power systems." Journal of Modern Power Systems and Clean Energy 7.5 (2019): 1044-1055.

[9]. Esmaeilian, Ahad, and Mladen Kezunovic. "Prevention of power grid blackouts using intentional islanding scheme." IEEE transactions on industry applications 53.1 (2016): 622-629.

[10]. A. M. Elkholy, H. A. A. El-Ghany and A. M. Azmy, "An Advanced Load Shedding Algorithm to Enhance Intentional-Islanding Dynamics," 2018 Twentieth International Middle East Power Systems Conference (MEPCON), Cairo, Egypt, 2018, pp. 797-802, doi: 10.1109/MEPCON.2018.8635139.

[11]. P. Demetriou, A. Kyriacou, E. Kyriakides and C. Panayiotou, "Intentional Controlled Islanding of Power Systems Equipped With Battery Energy Storage Systems," 2019 IEEE Milan PowerTech, Milan, Italy, 2019, pp. 1-6, doi: 10.1109/PTC.2019.8810501.

[12]. R. Bratifich, E. A. R. Theodoro, B. C. Bispo and D. H. Spatti, "Intentional islanding using genetic algorithms and algebraic-graph techniques," 2018 Simposio Brasileiro de Sistemas Eletricos (SBSE), Niteroi, 2018, pp. 1-6, doi: 10.1109/SBSE.2018.8395597.

[13]. N. Z. Saharuddin, I. Z. Abidin and H. bin Mokhlis, "Intentional Islanding Solution Based on Modified Discrete Particle Swarm Optimization Technique," 2018 IEEE 7th International Conference on Power and Energy (PECon), Kuala Lumpur, Malaysia, 2018, pp. 399-404, doi: 10.1109/PECON.2018.8684097.

[14]. S. Poudel, P. Sharma, A. Dubey and K. P. Schneider, "Advanced FLISR With Intentional Islanding Operations in an ADMS Environment Using GridAPPS-D," in IEEE Access, vol. 8, pp. 113766-113778, 2020, doi: 10.1109/ACCESS.2020.3003325.

[15]. Ashok Jhunjhunwala, Aditya Lolla and Prabhjot Kaur, "Solar DC Micro-Grid for Indian Homes", IEEE Electrification Magazine June 2016. pp . 10-19.

[16]. Prabhjot Kaur, Sudeep Jain and Ashok Jhunjhunwala, "Solar-DC Deployment Experience in Off-Grid and Near Off-Grid Homes: Economics, Technology and Policy Analysis", IEEE First International Conference on DC Microgrids (ICDCM) 2015. pp. 26-31.

[17]. Venkat Rajaraman, Ashok Jhunjhunwala, Prabhjot Kaur and Uma Rajesh, "Economic Analysis of deployment of DC power and Appliances along with Solar in urban multi-storied buildings", IEEE First International Conference on DC Microgrids (ICDCM) 2015, pp. 32-37.

[18]. Ashok Jhunjhunwala, Krishna Vasudevan, Lakshmi Narasamma and Bhaskar Ramamurthi, "Technological and Deployment Challenges and User-Response to Uninterrupted DC (UDC) deployment in Indian homes", IEEE First International Conference on DC Microgrids (ICDCM) 2015, pp. 38-42.

[19]. Joon Han, Yun-Sik Oh, Gi-Hyeon Gwon, Chul-Ho Noh, Tack Hyun Jung, Soon-Jeong Lee and Chul-hwan Kim "Modeling and Analysis of Low-voltage DC Distribution System", Resources 2015, pp. 713-735.

[20]. "IEEE Recommended Practice for Interconnecting Distributed Resources with Electric Power Systems Distribution Secondary Networks", IEEE Std. 1547.6™2011, Sponsored by the IEEE Standards Coordinating Committee 21 on fuel Cells, Photovoltaics, Dispersed Generation, and Energy Storage.

[21]. M. Ankush Kumar and Dr. A. Jaya Laxmi, "Application of Intentional Islanding Algorithm for Distributed Energy Resources in Disaster Management" IEEE International Conference on Power System Technologies (POWERCON2016) at University of Wollonghong, Australia during 28th September to 1st October 2016.

[22]. M. Ankush Kumar and Dr. A. Jaya Laxmi, "Real-Time Implementation of Intentional Islanding Algorithm for Distributed Energy Resources", International Journal of Electrical Engineering and Technology by Springer. https://doi.org/10.1007/s42835-021-00744-2.

[23]. Method and System for Providing Power Resilience During and Aftermath of Disasters Using Intentional Islanding, by M. Ankush Kumar and Dr. A. Jaya Laxmi (2021, April 30). https://ipindiaservices.gov.in/PublicSearch?aspxerrorpath=/PatentSearch/PatentSearch/ViewApplicationStatus.

[24]. Yezhou Wang, Chen chen, and Ross baldick "Research on Resilience of Power Systems Under Natural Disasters – A Review," March 2016, IEEE Transactions on Power Systems, Vol. 31, No. 2. pp. 1604-1613.

[25]. M. Ankush Kumar and Dr. A. Jaya Laxmi, "Power Restoration Based on Intentional Islanding Algorithm for Distributed Energy Resources in Disaster Management", International Journal of Modelling and Simulation (T&F), Vol. 38, Issue 3, 2018. pp. 189-206.