IOP Conference Series: Earth and Environmental Science

PURPOSE-LED PUBLISHING™

PAPER • OPEN ACCESS

An image classification based approach for islanding detection in a sustainable distributed generation system using convolutional neural network

To cite this article: F.T. Adenugba *et al* 2022 *IOP Conf. Ser.: Earth Environ. Sci.* **993** 012021

View the article online for updates and enhancements.

You may also like

- Deep learning for classification of islanding and grid disturbance based on multi-resolution singular spectrum entropy
Tie Li, Xiaoyang He, Junci Tang et al.
- Research on island detection method based on integrated impedance sequence component
Wang Kaichang, Gao Shuping and Fu Zhouxing
- Research on a new method of islanding detection based on lifting wavelet and neural network
Dong Xie, Dajin Zang and Peng Gao

This content was downloaded from IP address 165.73.223.224 on 29/11/2024 at 14:47

IOP Conf. Series: Earth and Environmental Science **993** (2022) 012021 doi:10.1088/1755-1315/993/1/012021

An image classification based approach for islanding detection in a sustainable distributed generation system using convolutional neural network

F.T. Adenugba[1*], H.E. Orovwode[1], O.F. Ademola[1]

[1]Department of Electrical and Information Engineering, Covenant University, Ota, Ogun State, Nigeria

Corresponding Email: favour.adenugba@stu.cu.edu.ng (ORCID: 0000-0003-0614-7188); hope.orovwode@covenantuniversity.edu.ng

Abstract. In today's power system, distributed generation (DG) penetration level has increased to match the ever-increasing demand for energy. DG integration introduces peculiar challenges to the entire power system. Due to the increased DG penetration, these challenges have become technically and economically very important. Effective and fast islanding detection is necessary to prevent power quality degradation, equipment loss, and human life loss. In this study, an islanding detection model based on convolutional neural network (CNN) is proposed. The method utilizes the ability of CNN to perform accurate image classification. It identifies islanding by classifying scalogram images obtained by applying wavelet transform to the concatenated voltage waveforms for each event. The islanding detection model is trained with well-processed images to improve classification accuracy. Noise is incorporated into the data to investigate the susceptibility of the method to noise. The results obtained prove that the proposed islanding detection model can handle the problem of islanding detection.

Keywords: Scalogram, distributed generation (DG), unintentional islanding, convolutional neural network (CNN), islanding detection.

1. Introduction

The lack of a stable supply of electricity is still a significant source of concern around the globe [1]. 1.5 billion people are without any form of electrification. This absence of stable electricity is a significant challenge that has been known to hamper sustainable development and economic growth [2].

The centralized type structure of power systems has been used over the years to generate, transmit, and distribute electricity to end-users. This centralized structure has led to operational disadvantages such as losses experienced on transmission lines and the high cost of transmission. This, coupled with the ever-increasing demand for electricity and the need for increased renewable energy utilization, has given rise to a different perception ofelectrical power systems structure[3].

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.
Published under licence by IOP Publishing Ltd

Distributed generation (DG) refers to decentralized power generation in which generation is carried out close to the local load at the distribution level [4]. This structure mitigates most of the issues that pertain to centralized generation [5,6]. With numerous advantages like environmental benefit, increase in power system reliability, deferral of transmission investment, increased capacity, and reduction in losses, DG integration with the grid has been on the rise [7].Despite these, technical challengeshave to be accounted for when integrating DG into the grid. An important one of such challenges is islanding detection.

Islanding refers to when a part of the power system is still actively connected to one or more DG(s) while severed from the grid [8]. During islanding the part of the distribution network is isolated from the grid while still connected to one or more DG.This can be premeditated (intentional) or unintentional. The former is a deliberate action that mostly occurs during maintenance.On the other hand,the unregulated nature of unintentional islanding can lead to operational issues and instability. These issues occur because, during unintentional islanding,essential system parameters at the point of common coupling (PCC) such as frequency and voltage go beyond permissible limits [9,10]. These operational issues include customer equipment damage, utility damage, power quality degradation, and loss of lives. Thereforeislanding should be detected quickly when it occurs. According to the IEEE standard 1547, when islanding occurs, it must be quickly detected, and the DG should trip within 2 seconds when stability cannot be restricted automatically. This has given rise to different islanding detection models to detect islanding when it occurs, enabling protection and control devices to take appropriate actions.

Islanding detection methods range from active [11] to passive [12] to intelligence-based methods [13–15]. Active methods are fast-acting and possess a lot of significant advantages but then degrade power quality. Passive methods do not degrade power quality but are not as accurate and efficient as active methods. Active and passive methods, like all other islanding detection methods monitor and measure system parameters like voltage, current and frequency at the point of common coupling. In recent studies, researchers have introduced the use of machine learning techniques in islanding detection. These learning techniques have shown promise.They are fast, accurate, and do not degrade power quality.

This paper presents an Image Classification-based approach for Islanding Detection in an Inverter-based Grid-Connected DG system using a convolutional neural network (CNN). The rest of this article is organized thus; Section 2 presents a theoretical basis and literature review pertaining to islanding detection. Section 3, 4, and 5 present the power system under study, data generation, and the proposed islanding detection method, respectively, making up the adopted methodology. In section 6, the results obtained are presented and discussed. Section 7 concludes the paper, highlighting the conclusion drawn from the study, limitations of the study, and possible future research that can be done to improve the present work.

2. Theoretical Background/ Review

When the grid and one or more DG(s) supply power in synchronism to end-users, the DG is in non-islanded (grid-connected) mode, while when the DG is disengaged from the grid and still actively supplying consumers, the DG is in islanded mode [16].Islanding (unintentional islanding) is a significant problem that power engineers are faced with. Islanding can severely impact power quality and can lead to an unsafe working environment [17]. Islanding also hurts protection device coordination. Islanding detection is a critical part of modern power system engineering.

Researchers have put in a lot of work in creating and proposing islanding detection methods (IDMs). In islanding detection, the non-detection zone (NDZ) refers to the imbalance in reactive and active power for which islanding is not identified by the IDM[18]. This happens when there is insufficient power mismatch to disruptively vary critical parameters at the PCC when islanding occurs.

Passive IDMs are the oldest form of IDMs. They measure the variations in key system parameters at the PCC to determine if islanding has occurred [7]. These types of IDMs possess large NDZ and have a slow detection speed.Active IDMs were introduced to solve the issue of large NDZ in passive IDMs. The operation of these IDMs iscentered on the addition of an external disturbance. This perturbation is amplified when islanding occurs; therefore, even small mismatches are detected. Due to the injection of external perturbation, this type of IDMs lead to power quality degradation. One advantage, however, is that they are fast-acting. These IDMs do not function well in multiple DG environment and non-inverter based DG power systems [19,20].Communication-based IDMs detect islanding by carrying out direct communication with the DG using links between the utility and the DG. These IDMs do not degrade power quality, have no NDZ, and work well with multiple DGs but are very expensive, possess a high computational burden, and are susceptible to cyber-attacks. Signal processing (SP) based IDMs utilize SP techniques like wavelet transform [21], Fourier transform, s-transform [22], amongst others,to monitor key parameters at the PCC to acquirevital features that would aid in detecting islanding [23].

Researchers have proposed the use of intelligence-based models due to the advantages that they possess when compared to other IDMs. Intelligence-based IDMs make use of artificial intelligence(AI) techniques to carry out islanding detection. In these IDMS, feature extraction is done by SP techniques, and AI techniques are used to classify features. These IDMs possess almost no NDZ, are fast-acting, and perform better with increased complexity, although some suffer from a high computational burden. Types of Intelligence-based IDMs include artificial neural network model based models [14,24–26], support vector machine-based models [27–30],probabilistic neural network-based models [31], fuzzy-logic based models [32,33] and deep learning-based models [13,15].

When it comes to islanding detection, deep learning is still a relatively new technique. In most problems type with appropriate data, deep learning outperforms regular neural networks [13]. CNN is a class of deep learning that works with images and is being utilized to analyzeintricate image-based problems. In [15], the authors made use of CNN to carry out islanding detection and achieved a detection accuracy of 98.78%. The authors used a very small dataset, and did not consider a wide range of events. In this paper, islanding detection is carried out using CNN with a farmore extensive data set, with changes in model structure, and considering a wide variety of eventsthat were not explored in [15]. All this is done to improve accuracy and lead to a more robust islanding detection model.

3. Power System Under Study

The grid-connected DG power system used in this study is based on the IEEE 13 standard bus system. A three-phase inverter is utilized as the lone DG in this power system. This inverter system is used to serve an RLC load, which represents the local load. This load is variable to simulate the power system at different load demands and obtain several levels of mismatch when islanding is simulated. Figure 1 shows the power system's single line diagram.An inverter-based DG is utilized in this study due to the fact that they are easily coupled to renewable energy sources practically, which is desirable due to the numerous advantages of renewable energy sources. This is also in line with the sustainable development goals 7 and 13 set in 2015 by the United Nations. An inverter is used to transform direct current to alternating current. The power system is modeled using the Simulink environment on MATLAB software, and the developed model is shown in Figure 2.

The inverter-based DG has a capacity of 155kW. The inverter, grid, and local-load are tied together at what is known as the (PCC), where the DG and local-load are coupled to the grid via a circuit breaker,whichcan be tripped to simulate islanding. LC filter is used to carry out ripple reduction at the output of the inverter to mitigate possible harmonics in the output voltage.The PCC is where key parameters that tell the current status of the power system can be measured. In an islanding detection study [30], the authors concluded that the best parameters to consider are the voltage and current at the PCC when carrying out islanding detection.In this study,the voltage at the PCC is utilized as the detection parameter. CNN is used to analyze the voltage data, and determineislanding occurred or not.

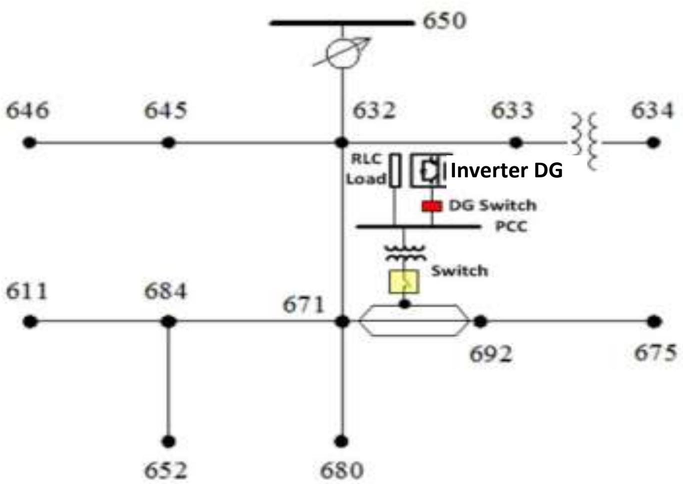

Figure 1. Line diagram for power system model

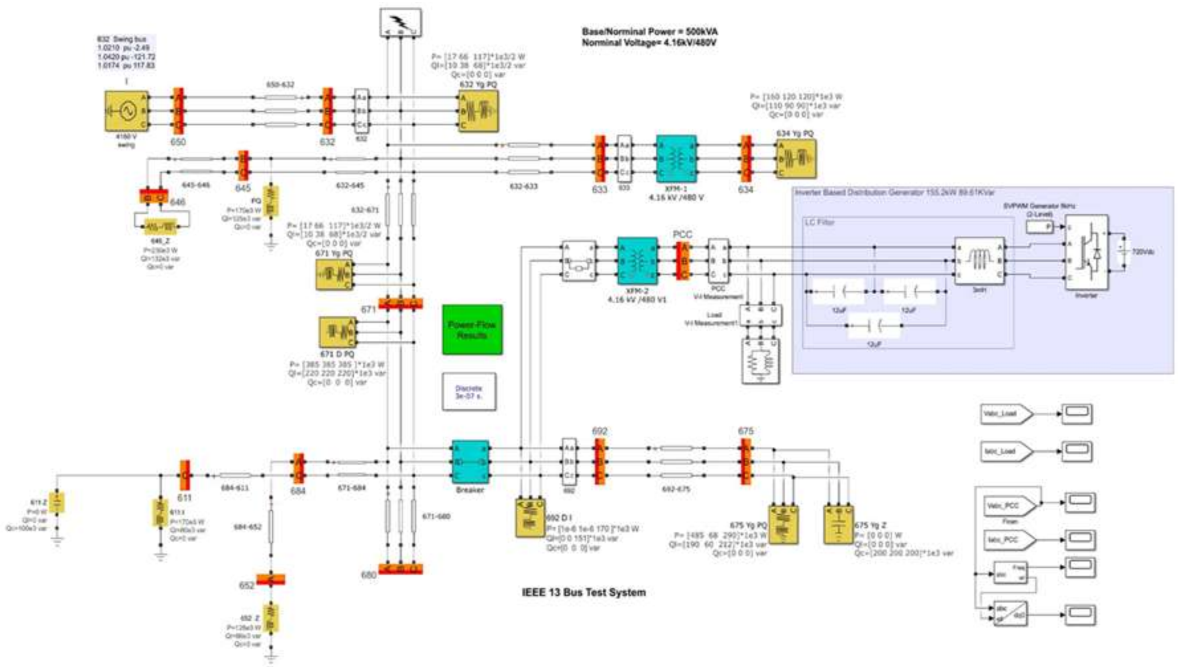

Figure 2. Power system model in Simulink

4. Data Generation

When utilizing any supervised learning algorithm to solve a problem, there is a need for appropriately labeled data to train and test the model. For islanding detection, there is a need for the developed detection model to differentiate islanding from grid-connected disturbances so as to avoid nuisance tripping. The model should be robust enough to account for faults and switching events and classify them as grid-connected events when they occur. Therefore, in this study, islanding event is classified as islanding. Motor switching, load switching, and faults, are classified as non-islanding. To train and test the developed model, the following events, as shown in Table 1, are simulated on the power system on MATLAB/Simulink, and the three-phase voltage data at the PCC is obtained. For each simulation, switching occurs at 0.05s and the entire simulation lasts for 0.1s. In the category section islanding is represented by I and II represents non-islanding.

Table 1. Summary of simulated power system events

<table>
<tr><th>Event</th><th>Category</th><th>No of simulation</th><th>Description</th></tr>
<tr><td>Islanding</td><td>I</td><td>750</td><td>Δp = ±50%
Δq = ±10%</td></tr>
<tr><td>Motor Switching</td><td rowspan="5">II</td><td>150</td><td>Different Motor Configurations</td></tr>
<tr><td>Load Switching</td><td>150</td><td>Several Resistive & Capacitive Load Configurations</td></tr>
<tr><td>Three-Phase Faults</td><td>150</td><td rowspan="3">0.1 - 10Ω</td></tr>
<tr><td>Single Phase Faults</td><td>150</td></tr>
<tr><td>Line-Line Fault</td><td>150</td></tr>
</table>

For islanding, the following possible scenarios were considered:a shortfall of real and reactive power, a surplus of both real and reactive power, a surplus of real and shortfall of reactive power, and vice versa. Noise is added to each simulation event, and the data is stored separatelyto test the developed model and investigate its susceptibility to noise.

Given the fact that the CNN-based islanding detection model to be developed is image-based, there is a need to convert the time series data for every event simulated to an image. To convert the time series voltage data obtained from the PCC to images,continuous wavelet transform (CWT)was used to carry out scalogram computation on each event data. This depicts the absolute value of theCWT of the initial series of data in a pictorial form[34].

In this study,the PCC voltage for each event is recorded. Then CWT is applied using the morse wavelet to convert the voltage data to scalogram image representation. The image dataset is then preprocessed and labeled appropriately to be used as training and testing data for the CNN-based model to be developed.The laptop utilized in this research work is a Dell XPS 15 2018 edition with 8gb ram, 256gb SSD and NVIDIA GTX 1050 card.

5. The proposed islanding detection model and CNN design.

5.1 The Islanding Detection Model

The voltage at the PCC contains vital features that portray the operating mode of the DG[35]. This is used in this study to detect islanding. In other to develop the islanding detection model, time-series data for 750 islanding and 750 non-islanding events are acquired from the power system. The Non-Islanding events considered are faults, motor switching, and load switching. For every event, voltage data is acquired and transformed into a scalogram image representation. The image dataset is then pre-processed and labeled appropriately to serve as input to train and validate the CNN model. Noise-laden dataset is also created to test the vulnerability of the developed model to noise. This is done by adding white noise to the existing data to create two sets of 300 islanding events and 300 non-islanding events at 25dB and 30dB SNR.

60% of the original image dataset is used to train, and 40% is used to validate the CNN model. This process of training and validating is repeated until we arrive at the architecture and set of hyper-parameters that gives the best validation accuracy.

Figure 3 shows the flowchart for the proposed islanding detection model.

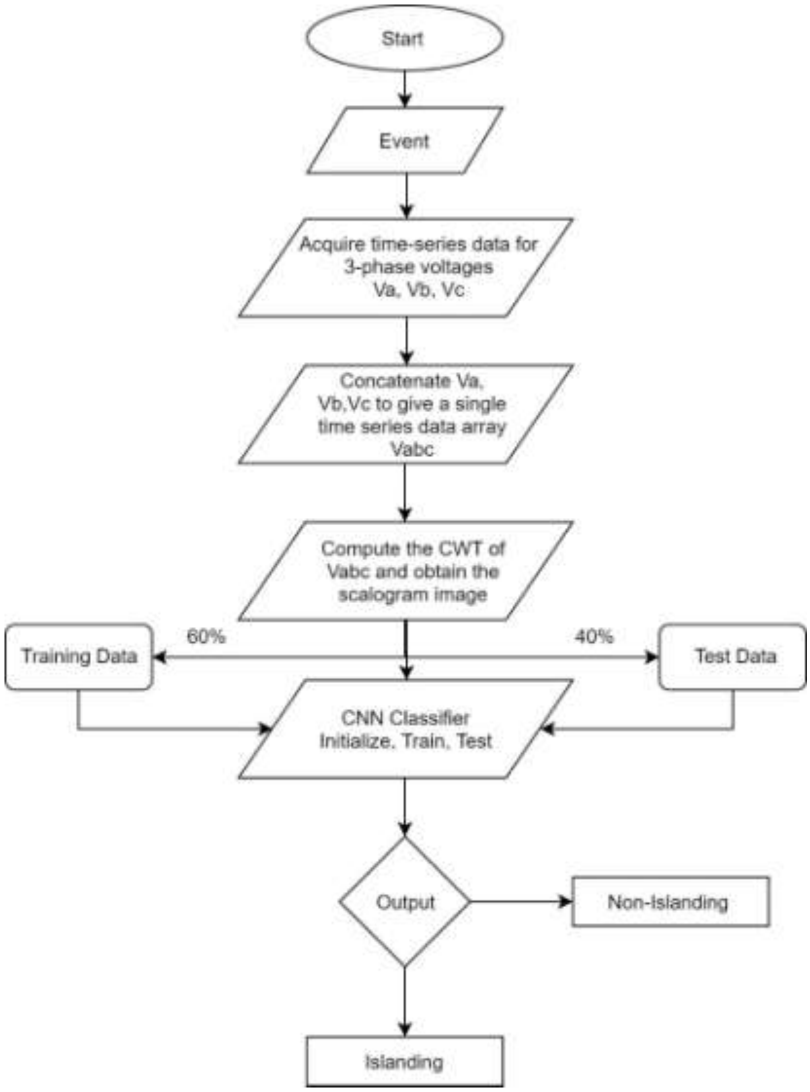

Figure 3. Proposed islanding detection model's flowchart

Figure 4 shows the proposed IDM's operational block diagram.

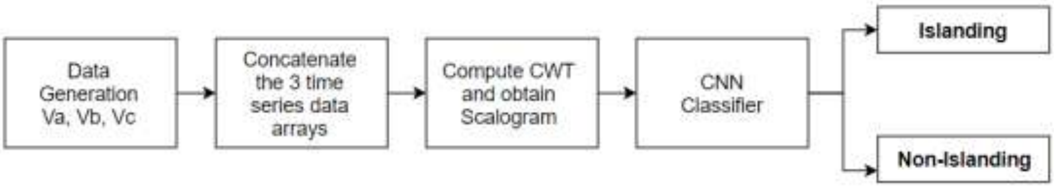

Figure 4. Block diagram for the proposed IDM

5.2 The Proposed CNN Design

The developed Convolutional Neural Network model carries out the selection of features, extraction of features, and classification. The basic architecture of the CNN model has three convolutional blocks. This structure was decided upon by virtue of preliminary testing and review of literature. The structure of the CNN model is depicted graphically in figure 5.

Figure 5. Basic structure CNN structure for the proposed model

Images layer supplied to the input layer should have equal dimensions. After a preliminary testing input image size of 64 x 64 was adopted.

The convolutional layer carries out convolution during a set of filters known as kernels. For any image $I\ [x, y]$ and filter $f\ [x, y]$ the convolution operation is given as:

$$\mathrm{f}\,[\mathrm{x,y}] \times \mathrm{I}[\mathrm{x,y}] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} \mathrm{f}[\mathrm{n}_1, \mathrm{n}_2]\mathrm{I}\,[\mathrm{x}-\mathrm{n}_1, \mathrm{y}-n_2] \quad (1)$$

The batch normalization layer speeds up training and reduces sensitivity, thereby optimizing the model. It is not compulsory, but it helps the model converge faster and improves validation accuracy.

The rectified linear unit layer is an activation layer, which is the layer that contains the activation function. The operation of the layer is given as follows

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (2)$$

It returns zero for negative input values and returns the input value itself when it is positive.

The max-pooling layer uses a window to partition images and pull the maximum value from each partition. In essence, it downsamples the input images and performs dimensionality reduction. It multiplies the input by weight in addition to a bias factor.

$$Z = f\left(\sum_{i=1}^{N} x_i + w_i + b \right) \tag{3}$$

The fully connected layer generates a vector that is used to carry out classification. This vector is centered on the yield of other layers. Classification begins at this layer.

The softmax layer converts the vector representation from the previous layer into a set of probabilities for all possible classes. The operation of this layer is given as:

$$X_i = \frac{e^{Z_i}}{\sum_{j=1}^{n} e^{Z_j}} \tag{4}$$

The classification output layer gives the final classification. For the developed model, this layer has only two possible output classes (islanding and non-islanding).

To arrive at an optimum design, the hyper-parameters of the CNN model needs to be carefully selected to give the best detection accuracy. These hyper-parameters include the number of filters, type of solver (learning algorithm), learning rate, filter size, pooling window size, pooling window stride, and the maximum number of epoch. In this study, SGDM is the selected solver. It has advantages over other solvers, and it is often selected ahead of even more complex learning algorithms. The other hyper-parameters are selected using the design value approach. The approach involves testing several possible values to see which one gives the best result. The selected hyper-parameter values for the optimum CNN-based islanding detection model are presented in this article's result and discussion section.

6. Results and Discussion

In this study, the voltage at the PCC is used to classify islanding and non-islanding events. For every event simulated, voltage data obtained was converted to scalogram images using CWT. For an event, the whole simulation takes 0.1s, and the switching that triggers the event type occurs at 0.05s.Figure6 shows the voltage waveform at the PCC and the corresponding scalogram image for a sample motor switching event.

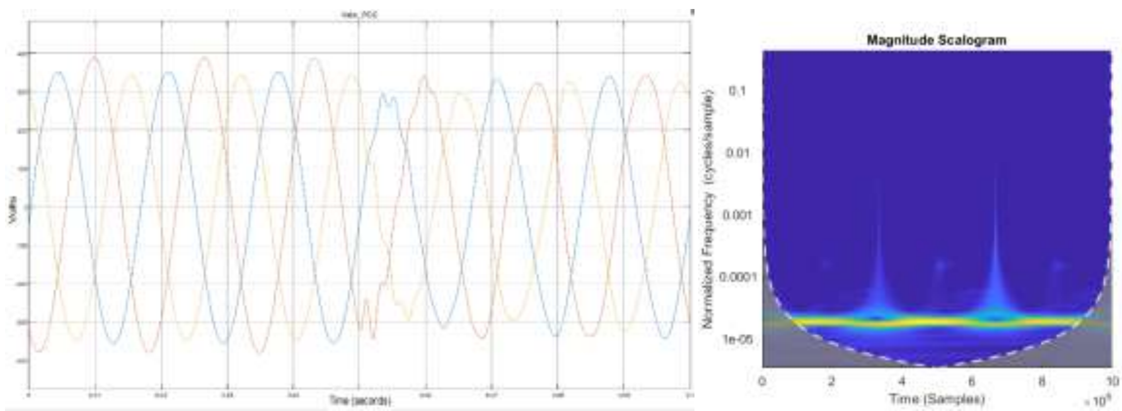

Figure 6. Generated data for sample motor switching event

IOP Conf. Series: Earth and Environmental Science **993** (2022) 012021 doi:10.1088/1755-1315/993/1/012021

Pre-processing is carried out for each event image data generated to ensure the training and testing processes run without errors. This process involves resizing, normalization, and variation. The CNN islanding detection model was developed using MATLAB. The model is made up of an input layer, three blocks of convolution (a convolutional layer, a batch normalization layer, an activation layer, and a pooling layer), a fully connected layer, a softmax layer, and a classification layer. The classification output layer has two possible output classes (islanding and non-islanding). The data set used to train and validate the CNN islanding detection model is made up of 1500 images; 750 islanding and non-islanding events each, as seen in Table 1. 60% of the data for each class is used to train while 40% was used to validate the model. To arrive at the optimum CNN architecture, design value approach is adopted in updating the hyper-parameters. Figure 7 shows the correlation between the validation and the maximum number of epoch, and figure 8 shows the correlation between validation accuracy and learning rate for different sizes of filter.

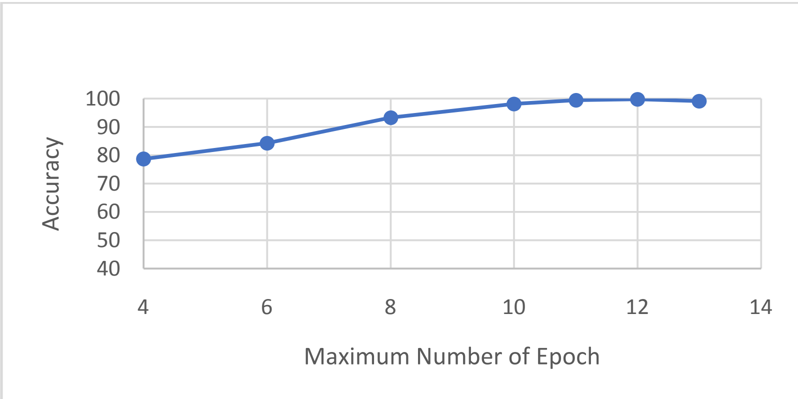

Figure 7. Accuracy vs maximum number of epoch

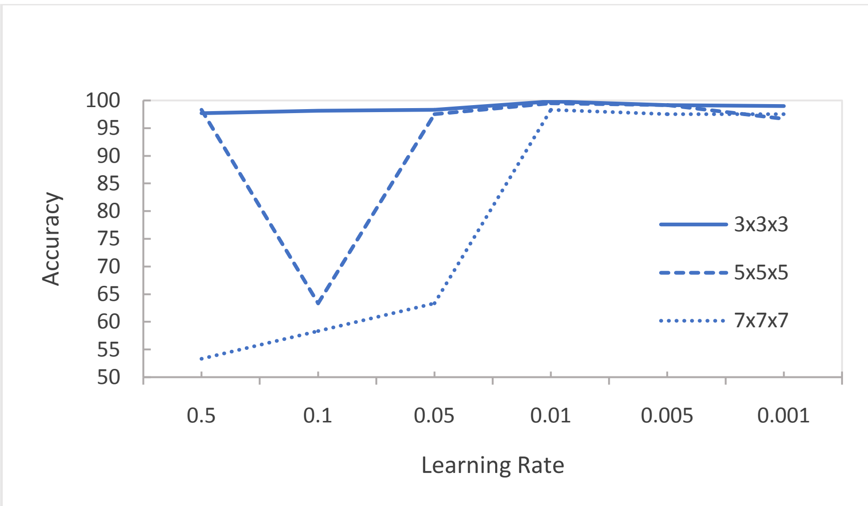

Figure 8. Accuracy and learning rate using different filter sizes

Figure 9 shows the architecture design summary and the values of hyperparameters that led to the optimum model.

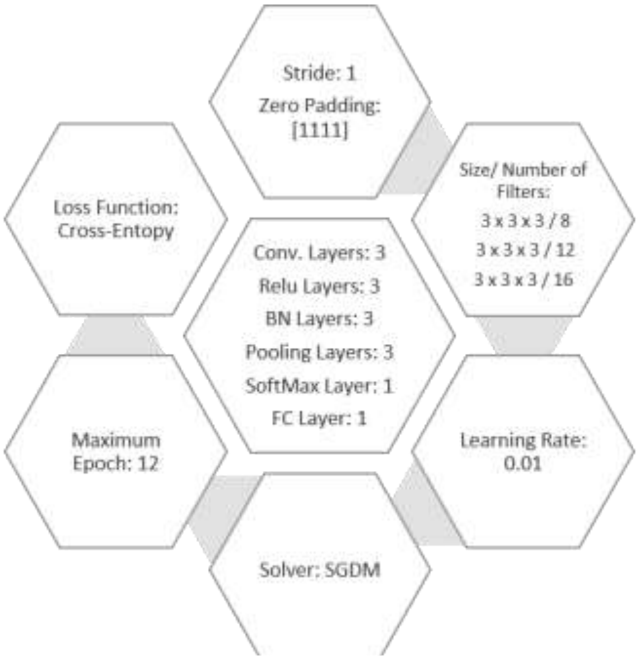

Figure 9. CNN design Summary

To assess the developed model's performance, the confusion matrix for the model is generated and analyzed. Figure10 shows the confusion matrix for the developed islanding detection model

Output Class			
	299 49.8%	0 0.0%	100% 0.0%
	1 0.2%	300 50.0%	99.7% 0.3 %
	99.7% 0.3 %	100% 0.0%	99.8% 0.2%

Target Class

Figure 10. Confusion matrix for the proposed IDM

From the confusion matrix, itis seen that out of the 300 islanding events used to validate the model, only one was misclassified as non-islanding. The detection accuracy is calculatedas follows:

$$Accuracy = \frac{299 + 300}{299 + 300 + 1 + 0}\ X\ 100 = 99.83\%$$

Figure 11. Final structure for the proposedCNN islanding detection model.

To investigate the model's noise susceptibility, the model is tested directly with noise laden test data comprising 300 islanding and 300 non-islanding events at SNR of 25dB and with another set at SNR of 30dB. Figures 12 & 13 show the confusion matrix for the islanding detection model when tested with noisy datasets of 25db SNR and 30dB SNR.

Output Class			
	296 49.3%	2 0.3%	99.3% 0.7%
	4 0.7%	298 49.7%	98.7% 1.3 %
	98.7% 1.3 %	99.3% 0.7%	99.0% 1.0%

Target Class

Figure 12. Confusion matrix with 25db SNR test data

Output Class			
	296 49.3%	1 0.2%	99.7% 0.3%
	4 0.7%	299 49.8%	98.7% 1.3 %
	98.7% 1.3 %	99.7% 0.3%	99.2% 0.8%

Target Class

Figure 13. Confusion matrix with 30db SNR test data

Accuracy of the proposed IDM with 25dB SNR test data is given as:

$$Accuracy = \frac{296 + 298}{296 + 298 + 4 + 2}\ X\ 100 = 99.00\%$$

Accuracy of the proposed IDM with 30dB SNR test data is given as:

$$Accuracy = \frac{296 + 299}{296 + 299 + 4 + 1}\ X\ 100 = 99.18\%$$

Compared to [15], where the CNN-based islanding detection model developed achieved a detection accuracy of 98.78, a noticeable performance improvement is observed. This could be attributed to the increase in dataset size and change in CNN architecture.

In [13], where deep learning was used, and [29], where SVM and neural network were used to carry out islanding detection, the models show significantly lower performance levels of 98.3% and 97%, respectively, compared to the model proposed in this study. This demonstrates the viability of the proposed model for islanding detection in power systems.

7. Conclusion

In this paper, a convolutional neural network model was proposed to detect islanding. The three-phase voltage signal at PCC was used as the detection parameter. In this method, the three-phase voltage signals are converted to a scalogram image for each event by applying CWT. A total of 1500 simulated events were used to create the data set. 750 islanding and 750 non-islanding events. 60% of the dataset was used to train the CNN model, and 40% was used to test. The model achieved a detection accuracy of 99.83%. This shows the efficacy of the model in handling islanding detection. Furthermore, the vulnerability of the model to noise was examined as the model was tested with 25dB and 30dB noise-laden datasets, and the model achieved a detection accuracy of 99.00% and 99.17%, respectively. This shows the great potential of CNN for islanding detection.

This innovative and intuitive solution would go along way in assisting protection engineers in keeping tabs on the power system. This method does not require any form of feature extraction, giving it some leverage over other intelligent-based methods.

For future consideration, it is recommended that the proposed method is tested on a power system containingmore than one DG. Also, the possible occurrence of multiple events simultaneously can be investigated to see its effect on the system.

Acknowledgment

The authors appreciate the Covenant University for conference support.

References

[1] The World Bank Group. Access to electricity (% of population) [Internet]. 2016. Available from: https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS
[2] Ayodele Benjamin.C E, Agbetuyi A, Oghorada O, Ogbeide K, Awelewa A, Afolabi A. Reliability

assessments of an islanded hybrid PV-diesel-battery system for a typical rural community in Nigeria. *Heliyon*. 2019 May 1;**5**:e01632.

[3] Reichl J, Cohen J, Moeltner K, Schmidthaler M. Electricity supply security, service valuation, and public perception of energy infrastructure. In 2016. p. 34–43.

[4] Al-Bataineh H, Kavasseri R G. Islanding Detection with Data Mining Methods - A Comparative Study. In: 2017 Ninth Annual IEEE Green Technologies Conference (GreenTech). 2017. p. 104–9.

[5] Chauhan N. Distributed Generation: Definition, Technology, Impact & Issues due to penetration. In 2013.

[6] Bayrak G, Kabalci E. Implementation of a new remote islanding detection method for wind–solar hybrid power plants. *Renew Sustain Energy Rev*. 2016 May 1;**58**:1–15. Available from: https://www.sciencedirect.com/science/article/pii/S136403211501610X?via%3Dihub

[7] Khamis A, Shareef H, Bizkevelci E, Khatib T. A review of islanding detection techniques for renewable distributed generation systems. *Renew Sustain Energy Rev*. 2013 Dec 1;**28**:483–93. Available from: https://www.sciencedirect.com/science/article/pii/S1364032113005650?via%3Dihub

[8] Basso T. IEEE 1547 and 2030 Standards for Distributed Energy Resources Interconnection and Interoperability with the Electricity Grid IEEE 1547 and 2030 Standards for Distributed Energy Resources Interconnection and Interoperability with the Electricity Grid. *Nrel*. 2014;(December):22.

[9] Kim M S, Haider R, Cho G J, Kim C H, Won C Y, Chai J S. Comprehensive review of islanding detection methods for distributed generation systems. *Energies*. 2019;**12**(5):1–21.

[10] Castillo A, Gayme D. Grid-scale energy storage applications in renewable energy integration: A survey. *Energy Convers Manag*. 2014 Nov 1;**87**:885–894.

[11] Tran S, Nguyen Duc T, Fujita G. Islanding Detection Method Based on Injecting Perturbation Signal and Rate of Change of Output Power in DC Grid-Connected Photovoltaic System. *Energies*. 2018 May 21;**11**:1313.

[12] Haider R, Kim C H, Ghanbari T, Bukhari S B A, Zaman M S uz, Baloch S, et al. Passive islanding detection scheme based on autocorrelation function of modal current envelope for photovoltaic units. *IET Gener Transm Distrib*. 2018;**12**(3):726–36.

[13] Kong X, Xu X, Yan Z, Chen S, Yang H, Han D. Deep learning hybrid method for islanding detection in distributed generation. *Appl Energy*. 2018;**210**(July 2017):776–85. Available from: https://doi.org/10.1016/j.apenergy.2017.08.014

[14] Merlin V L, Santos R C, Grilo A P, Vieira J C M, Coury D V., Oleskovicz M. A new artificial neural network based method for islanding detection of distributed generators. *Int J Electr Power Energy Syst*. 2016;**75**:139–51. Available from: http://dx.doi.org/10.1016/j.ijepes.2015.08.016

[15] Manikonda S K G, Gaonkar D N. IDM based on image classification with CNN. 2019;(2):1–6.

[16] Bignucolo F, Cerretti A, Coppo M, Savio A, Turri R. Impact of Distributed Generation Grid Code Requirements on Islanding Detection in LV Networks. *Energies*. 2017 Jan 26;**10**(2):156. Available from: http://www.mdpi.com/1996-1073/10/2/156

[17] Bhavani R, Prabha N R. A hybrid classifier for power quality (PQ) problems using wavelets packet transform (WPT) and artificial neural networks (ANN). *Proc 2017 IEEE Int Conf Intell Tech Control Optim Signal Process INCOS 2017*. 2018;**2018-Febru**:1–7.

[18] Cui Q, El-Arroudi K, Joós G. Islanding Detection of Hybrid Distributed Generation Under Reduced Non-Detection Zone. *IEEE Trans Smart Grid*. 2018;**9**(5):5027–37.

[19] Laghari J A, Mokhlis H, Karimi M, Bakar A H A, Mohamad H. Computational Intelligence based techniques for islanding detection of distributed generation in distribution network: A review.

Energy Convers Manag. 2014 Dec 1;**88**:139–52. Available from: https://www.sciencedirect.com/science/article/pii/S0196890414007481?via%3Dihub
[20] Reigosa D, Briz F, Charro C B, Garcia P, Guerrero J M. Active Islanding Detection Using High-Frequency Signal Injection. *IEEE Trans Ind Appl*. 2012;**48**(5):1588–97.
[21] Samantaray S R, Pujhari T M, Subudhi B D. A new approach to islanding detection in distributed generations. In: 2009 International Conference on Power Systems. 2009. p. 1–6.
[22] Samantaray S R, Samui A, Babu B C. S-transform based cumulative sum detector (CUSUM) for islanding detection in Distributed Generations. In: 2010 Joint International Conference on Power Electronics, Drives and Energy Systems & 2010 Power India. 2010. p. 1–6.
[23] Pigazo A, Liserre M, Mastromauro R A, Moreno V M, Dell'Aquila A. Wavelet-Based Islanding Detection in Grid-Connected PV Systems. *IEEE Trans Ind Electron*. 2009;**56**(11):4445–55.
[24] Merlin V L, Santos R C, Pavani A P G, Coury D V, Oleskovicz M, Vieira J C M. A methodology for training artificial neural networks for islanding detection of distributed generators. In: 2013 IEEE PES Conference on Innovative Smart Grid Technologies (ISGT Latin America). 2013. p. 1–6.
[25] Samet H, Hashemi F, Ghanbari T. Minimum non detection zone for islanding detection using an optimal Artificial Neural Network algorithm based on PSO. *Renew Sustain Energy Rev*. 2015;**52**:1–18.
[26] Puthenpurakel S P. Identification and Classification of Microgrid Disturbances in a Hybrid Distributed Generation System Using Wavelet Transform. 2016;
[27] Matic-Cuka B, Kezunovic M. Islanding detection for inverter-based distributed generation using support vector machine method. *IEEE Trans Smart Grid*. 2014;**5**(6):2676–86.
[28] Kumari S, Bhalja B, Maheshwari R P. A new SVM based islanding detection scheme in the presence of distributed generation. *2017 7th Int Conf Power Syst ICPS 2017*. 2018;352–7.
[29] Faqhruldin O N, El-Saadany E F, Zeineldin H H. A Universal Islanding Detection Technique for Distributed Generation Using Pattern Recognition. *IEEE Trans Smart Grid*. 2014;**5**(4):1985–92.
[30] Bitaraf H, Sheikholeslamzadeh M, Ranjbar A M, Mozafari B. A novel SVM approach of islanding detection in micro grid. *2012 IEEE Innov Smart Grid Technol - Asia, ISGT Asia 2012*. 2012;1–5.
[31] Khamis A, Shareef H, Mohamed A, Bizkevelci E. Islanding detection in a distributed generation integrated power system using phase space technique and probabilistic neural network. *Neurocomputing*. 2015;**148**:587–99. Available from: http://dx.doi.org/10.1016/j.neucom.2014.07.004
[32] Saikia H J, Mohanty S. A fuzzy logic based controller for Loss of Mains detection. In: 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON). 2017. p. 376–81.
[33] Dash P K, Padhee M, Panigrahi T K. A hybrid time-frequency approach based fuzzy logic system for power island detection in grid connected distributed generation. *Int J Electr Power Energy Syst*. 2012;**42**(1):453–64. Available from: http://dx.doi.org/10.1016/j.ijepes.2012.04.003
[34] Sejdic E, Djurovic I, Stankovic L. Quantitative Performance Analysis of Scalogram as Instantaneous Frequency Estimator. *Signal Process IEEE Trans*. 2008 Sep 1;**56**:3837–45.
[35] Abd-Elkader A G, Allam D F, Tageldin E. Islanding detection method for DFIG wind turbines using artificial neural networks. *Int J Electr Power Energy Syst*. 2014;**62**:335–43. Available from: http://dx.doi.org/10.1016/j.ijepes.2014.04.052