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A SIMULATION DRIVEN ANN-BASED INTELLIGENT FAULT DIAGNOSIS SYSTEM FOR A BUCK DC–DC CONVERTER

J Lokesh* and G.A. Rathy**

*Government Polytechnic College,
Kadathur, Dharmapuri,
Chennai, Tamil Nadu, INDIA
Email Id: lokeshnova@gmail.com

**National Institute of Technical Teachers Training and Research,
Chennai, Tamil Nadu, India

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ABSTRACT:

The bulk Buck DC–DC converters are extensively employed in modern power electronic systems as a result of their high efficiency and simple voltage step-down capability. They are commonly used in applications namelyElectric Vehicles (EV), Battery Management Systems (BMS), Renewable Energy Systems (RES), and Industrial Power Supplies (IPS). During prolonged operation, critical components including power switches, diodes, inductors, and capacitors are subjected to electrical and thermal stresses, which may result in performance degradation and unexpected failures. Early detection of such faults is essential for improving system reliability and minimizing maintenance costs. The present research proposes a novel fault detection method for a buck DC–DC converter using an Artificial Neural Network (ANN). The proposed model also continuously monitors the converter's voltage and current signals to discriminate between normal and faulty operating conditions. The ANN trained model can also be deployed on an embedded platform to enable intelligent online fault diagnosis with minimal computational complexity. The Experimental results reveal that the developed ANN approach achieves high accuracy of fault detection, indicating its suitability for real-time monitoring of buck converters in a wide range of power electronic applications. The proposed ANN-based fault diagnosis methodology is not limited to the buck converter and can be widespread to available other power electronic converter topologies by retraining the model with representative electrical features obtained under their respective operating conditions.

KEYWORDS: *Artificial Neural Network (ANN), Buck Converter, Fault Detection, DC-DC Converter.*

1.INTRODUCTION:

With the rapid deployment of DC-DC converters in day-to-day applications which serves as the power source of electronic system, the faults occurrence in such power switching components are also high. Finding such faults in components consumes huge time and also is quite tedious process. Faulty components are found only after they have failed. It is tedious to predict when or in which part the fault would occur on the long run. Faults usually occur in components which deals directly with the load current that flows in it. Most of the present strategies of finding

faults focuses on detecting only one fault. It is done either by processing the signals or by a model-based algorithm [1]. Present strategies such as the data mining [2][13], Deep Feedforward Network and Wavelet Compression [3] require intensive hardware to function. In this paper, the proposed system adopts an ANN model which is trained on numerical values of the voltage and current signals obtained rather than an image or a transformation. This makes the model lighter and faster in detecting the fault.

2. Materials and Method:

The complete workflow of the proposed fault detection system is shown in Figure 1. The voltage and current values from the converter that is to be diagnosed is obtained and the values are fed to the trained ANN model. The model then processes the input data and predicts the fault conditions. The model has been trained for fault conditions such as MOSFET open fault, Inductor degrading fault, Diode open fault.

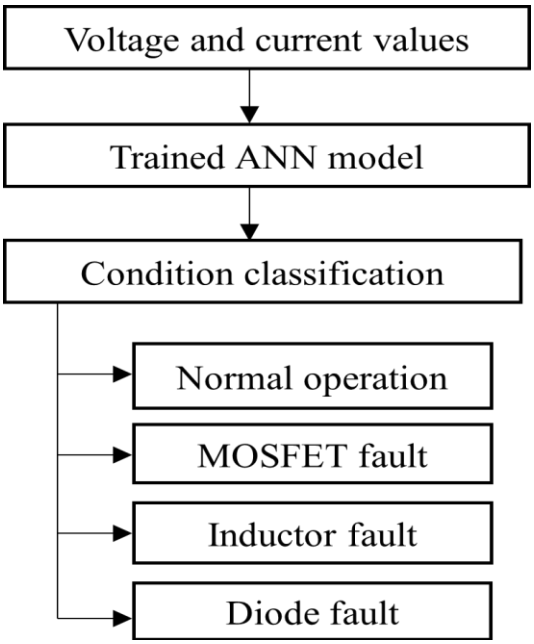

Figure 1: Proposed Architecture

2.1 Converter Model:

A buck converter was simulated for normal and three fault conditions. Under the normal operation, the converter is modeled to give an output voltage of 5volts with an input voltage of 12volts. At 20kHz frequency the MOSFET is made to switch and a load of 10 ohms is connected to it via an inductor of 1mH. A capacitor of 220µF is connected across the load to eliminated the voltage spikes. For the MOSFET open fault, the amplitude of the switching pulse produced from the pulse generator is made to be zero. Thus, making the MOSFET to become non operatable, which acts as an open switch. This brings the transfer of energy from the source to load to halt, making the output voltage and current through the inductor to zero. To simulate the diode open fault, the diode is removed from the circuit. This minimizes the transfer of energy from the source to load as the return path is been removed and the energy transfer happens only when the MOSFET closes. The inductor degrading condition is simulated by making the inductor value ten times lower than the normal operating condition.

2.2 Dataset preparation:

With a simulation run time of 0.5 seconds for each condition, the output voltage (V_{out}), output current (I_o), voltage across the switch (V_{sw}) was measured and the values were obtained in the matrix format. These parameters were chosen because most of the fault conditions directly influence these parameters.

Table 1: Dataset generated

Operating Condition	Value count
Normal Condition	42643
MOSFET open circuit	400001
Diode fault	242595
Inductor degradation	102236

The table 1 gives the value count for the corresponding condition. In a MOSFET open circuit fault, i.e. if the switching element has been damaged, the voltage across the switch would be the same as that of the source voltage, the output voltage would be zero and the corresponding load current would also be null. For the fault identification, each fault condition along with the normal condition, a key identifier was given for each set of values obtained.

2.3 ANN modeling:

The ANN model was developed using Tensorflow and Keras in python. Figure 2 shows the architecture of the developed ANN model. The model has four layers, in which two are hidden layers. Input layer has three neurons which processes the voltage and current parameters. The first hidden layer has 16 neurons with Rectified Linear Unit (ReLU). ReLU introduces non-linearity into the model and helps the network learn complex relationships in the dataset. The output layer uses the Softmax activation function, which converts the output values into probability distributions. The class with the highest likelihood is selected as the final forecast output. The table 2 shows the hyperparameters of the developed ANN model. The network uses Adam optimizer. The data set prepared is split into training and testing such as 80% and 20% of the model. The batch size is kept as 64 and epochs is taken as 20.

Table 2: Hyperparameters of developed ANN

Hyperparameter	Value

Network Type	Feedforward ANN
Input Features	3
Hidden Layers	2
Hidden Layer 1	16 neurons
Hidden Layer 2	12 neurons
Output Classes	4
Hidden Activation	ReLU
Output Activation	Softmax
Optimizer	Adam
Batch Size	64
Epochs	20
Training/Test Split	80: 20

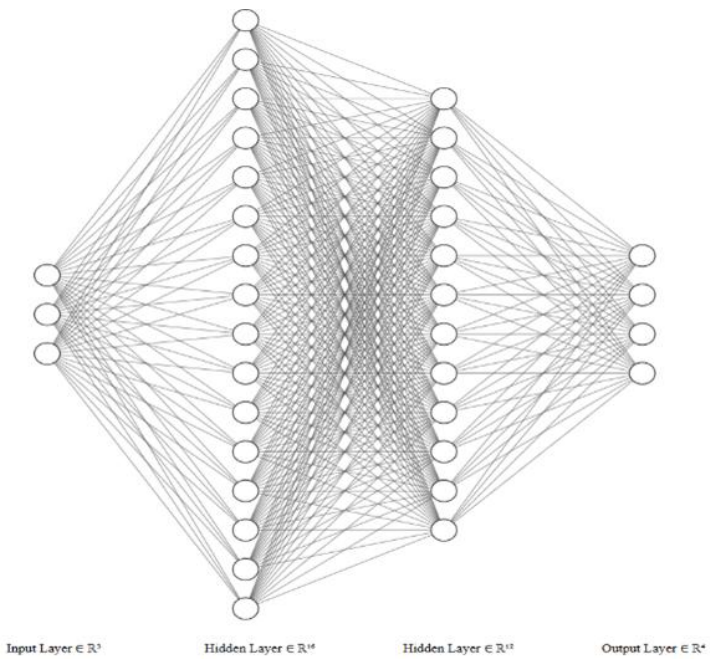

Figure 2: Architecture of ANN developed model

2.4 ANN mathematical model:

The ANN processes the input features through multiple layers consisting of neurons, weights, biases, and activation functions to generate the final output classification.

Let the input vector be represented as

$$X = [x_1, x_2, x_3] \quad (1)$$

where x_1, x_2,and $x_3$represents the three input parameters obtained from the dataset. These input values are first fed into the first hidden layer of the neural network. The neuron in eachhidden layer performs a weighted summation of the all-input signals and adds a bias term. The mathematical representation of this operation for the first hidden layer is given by

$$z_j^{(1)} = \sum_{i=1}^{3} w_{ij}^{(1)} x_i + b_j^{(1)} \qquad (2)$$

where $w_{ij}^{(1)}$represents the weight connecting the i^{th}input neuron to the j^{th}neuron in the first hidden layer, and $b_j^{(1)}$represents the bias associated with the j^{th}neuron. The computed value $z_j^{(1)}$is then passed through ReLU activation function to introduce nonlinearity in the network. The ReLU activation function can be expressed as

$$a_j^{(1)} = f(z_j^{(1)}) = \max(0, z_j^{(1)}) \qquad (3)$$

This activation function allows positive values to pass through while setting negative values to zero. Since the first hidden layer contains 16 neurons, this process is repeated for all neurons in that layer.The output of the first hidden layer becomes the input to the second hidden layer. Similar to the previous layer, each neuron computes a weighted sum of the incoming signals and adds a bias term. The mathematical expression (3) for the second hidden layer is

$$z_k^{(2)} = \sum_{j=1}^{16} w_{jk}^{(2)} a_j^{(1)} + b_k^{(2)} \qquad (4)$$

where $w_{jk}^{(2)}$ represents the weight connecting the j^{th}neuron of the first hidden layer to the k^{th}neuron of the second hidden layer, and $b_k^{(2)}$represents the corresponding bias. The output of this layer is again passed through the ReLU activation function, which can be written as

$$a_k^{(2)} = \max(0, z_k^{(2)}) \qquad (5)$$

The second hidden layer contains 12 neurons, which further process the extracted features from the previous layer and pass them to the output layer.The final layer of the neural network is the output layer, which contains four neurons corresponding to the four classes of converter operating conditions. The weighted summation in the output layer is given by

$$z_m^{(3)} = \sum_{k=1}^{12} w_{km}^{(3)} a_k^{(2)} + b_m^{(3)} \qquad (6)$$

where $w_{km}^{(3)}$represents the weight connecting the second hidden layer to the output layer and $b_m^{(3)}$represents the bias term of the output neuron.The output values are then passed through the Softmax activation function to convert them into probability values for multi-class classification. The Softmax function is mathematically represented as

$$P(y = m \mid X) = \frac{e^{z_m^{(3)}}}{\sum_{n=1}^{4} e^{z_n^{(3)}}} \qquad (7)$$

where $P(y = m \mid X)$represents the probability that the input sample belongs to class m. The class with the highest probability value is selected as the final predicted output of the neural

network.During the training process, the difference between the predicted output and the actual output is measured using the Sparse Categorical Cross-Entropy loss function, which is given by

$$L = -\log(P(y_{true})) \qquad (8)$$

This loss value is minimized by adjusting the weights and biases using the Adam optimization algorithm. The optimizer updates the network parameters iteratively using gradient descent and backpropagation so that the prediction error is gradually reduced.Thus, through repeated forward propagation and backpropagation over multiple epochs, the Artificial Neural Network learns the nonlinear relationship between the input parameters and the converter fault conditions, enabling accurate classification of different operating states of the converter system.

2.5 Results and Discussion:

The performance of the proposed Artificial Neural Network (ANN) model for converter fault detection was evaluated using several performance indicators including training accuracy, training loss, confusion matrix, Receiver Operating Characteristic (ROC) curve, and classification metrics such as precision, recall, and F1-score. The model was implemented and trained using the deep learning frameworks TensorFlow and Keras, while the evaluation metrics and classification report were generated using Scikit-learn. The final evaluation of the trained model shows an overall accuracy of 0.9996 (99.96%), which indicates that the neural network successfully classifies almost all the input samples correctly. The high accuracy value demonstrates the effectiveness of the proposed ANN architecture in identifying different converter fault conditions. Figure 3 shows the training accuracy graph of the model.

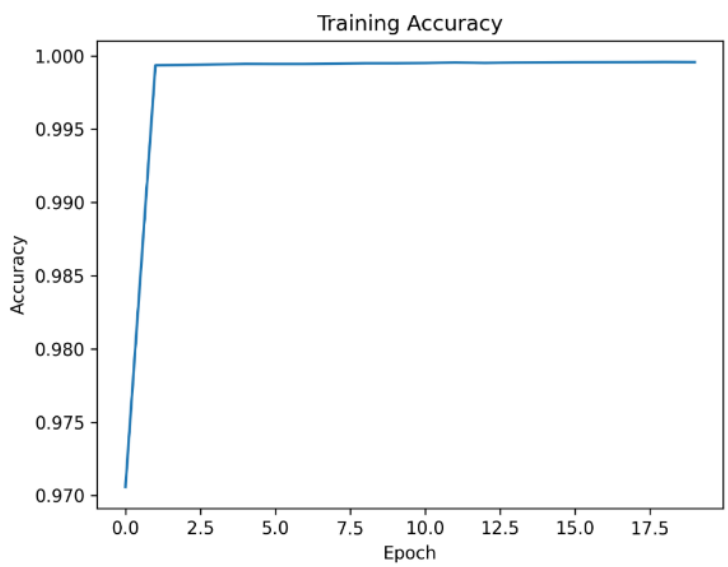

Figure 3: Accuracy of developed model

The final evaluated loss value of the trained model is 0.0014, which indicates a very small prediction error. This low loss value confirms that the model parameters such as weights and biases have been optimized efficiently through the backpropagation learning algorithm, resulting in accurate predictions. Figure 4 illustrates the training loss of the ANN model. The confusion

matrix in figure 5 shows that the highest values are located along the diagonal elements, indicating that the majority of samples are correctly classified.

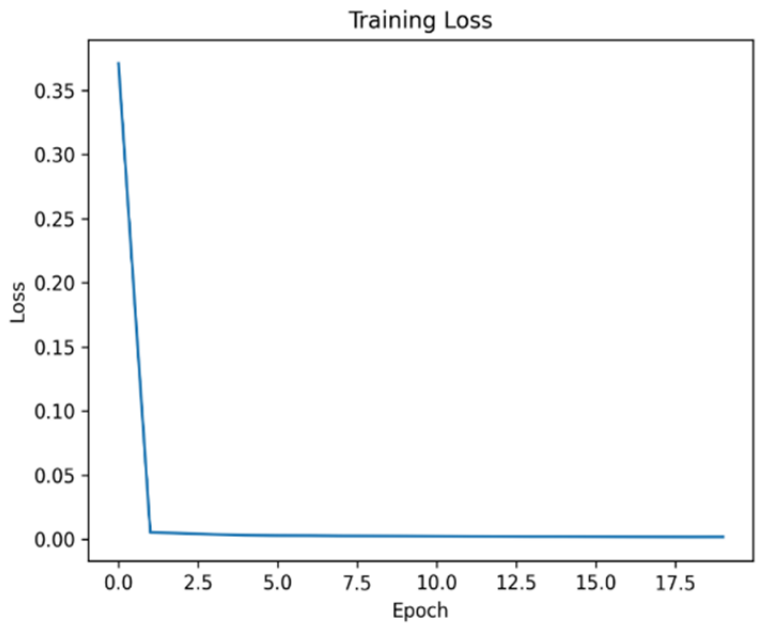

Figure 4: Training loss of developed model

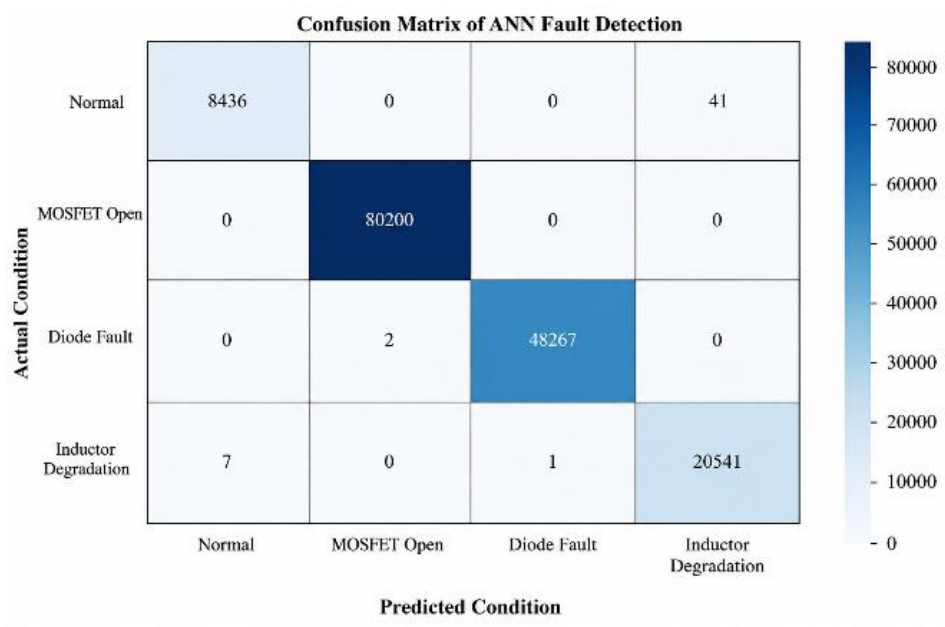

Figure 5: Confusion matrix

The very small number of off-diagonal elements demonstrates that the ANN model can effectively distinguish between different converter fault conditions.The ROC curves obtained for all four classes of fault condition are located very close to the top-left corner of the graph, indicating excellent classification performance. Figure 6 shows the ROC curve for the model.

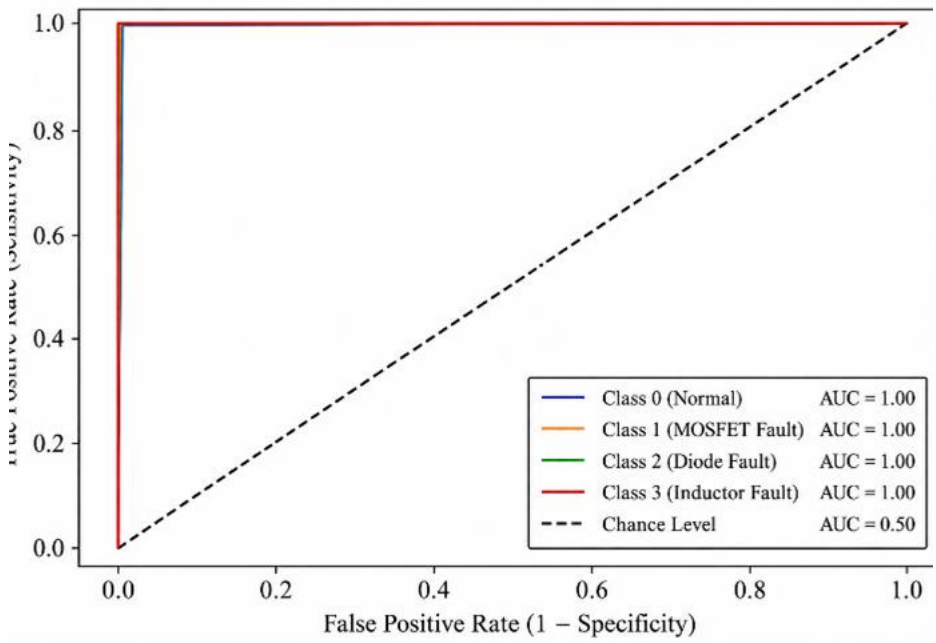

Figure 6: ROC Curve

The Area Under the Curve (AUC) value for all the classes is 1.00, which represents near-perfect classification capability. This result confirms that the proposed ANN model can effectively differentiate between normal operation and various fault conditions in the converter system. From table 3, the overall model performance shows an accuracy of 99.96%, with macro and weighted averages of precision, recall, and F1-score close to 1.00. These results confirm that the proposed ANN model achieves highly reliable fault classification.

Table 3: Performance metrics of developed model

Class	Precision	Recall	F1 Score	Support
Normal	1.00	0.99	1.00	8566
MOSFET Fault	1.00	1.00	1.00	79579
Diode Fault	1.00	1.00	1.00	48661
Inductor Fault	1.00	1.00	1.00	20635

3. CONCLUSION:

An intelligent fault detection system for power electronic converters was developed using an ANN and the power electronic converters are widely used in modern electrical systems,and faults occurring in components such as MOSFETs, diodes, and inductors can significantly affect system reliability and performance. Therefore, early detection and classification of such faults are essential for improving system safety and reducing maintenance time.The proposed method utilizes key electrical parameters as input features to train an ANN model capable of identifying different operating conditions of the converter. The trained model performance was analyzed using various evaluation techniques including accuracy of the training model, loss curves, confusion matrix, and ROC curve analysis. The obtained results demonstrate that the proposed ANN model attained a high classification accuracy of 99.96% with a very low loss value of 0.0014, indicating excellent prediction capability. The confusion matrix shows that the majority of the samples were correctly classified with minimal misclassification. Furthermore, the ROC

curves with an AUC value close to 1.00 confirm the strong ability of the model todifferentiate betweennormal operation and dissimilar fault conditions.From the results, the proposed ANN-based fault detection system offers an efficient and consistent solution for automated converter fault diagnosis. The developed approach can significantly improve system monitoring and enhance the operational reliability of power electronic systems.

4. REFERENCES:

1. Kumar, G.K. and Elangovan, D. (2020), "Review on fault-diagnosis and fault-tolerance for DC–DC converters", IET Power Electronics, vol.13, issue. 1, pp. 1-13, https://doi.org/10.1049/iet-pel.2019.0672

2. P. K. V, K. Gowrishankar, E. Sivanantham, K. S. Rao, N. Kiran and A. Vimal, "Detection of Early Fault in Power Electronic Converters through Machine Learning and Data Mining Techniques," *2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, Coimbatore, India, 2023, pp. 1438-1442, doi: 10.1109/ICAIS56108.2023.10073820.

3. Kou, L., Liu, C., Cai, G. W., & Zhang, Z. (2020). "Fault Diagnosis for Power Electronics Converters based on Deep Feedforward Network and Wavelet Compression". *Electric Power Systems Research*, vol. *185*,Article106370. https://doi.org/10.1016/j.epsr.2020.106370

4. V. Aviña-Corral, J. J. Rangel-Magdaleno, J. H. Barron-Zambrano, and S. Rosales-Nuñez, "Review of fault detection techniques in power converters: Fault analysis and diagnostic methodologies," Measurement, vol. 235, 2024. https://doi.org/10.1016/j.measurement.2024.114864

5. C. Liu, L. Kou, G. Cai, Z. Zhao, and Z. Zhang, "Review for AI-based open-circuit faults diagnosis methods in power electronics converters," 2022https://doi.org/10.48550/arXiv.2209.14058

6. S. Fouladi Panah et al., "Machine Learning Fault Diagnostic Techniques in Power Converters: A Review," 2025. https://dx.doi.org/10.2139/ssrn.6837686

7. S. Kim and K. Kim, "ANN design of multiple open-switch fault diagnosis for three-phase PWM converters," IET Power Electronics, vol. 13, no. 16, pp. 3562–3572, 2020.

8. X. Tan, Y. Zhang, and H. Wang, "Artificial neural network-based fault diagnosis of power electronic converters," IEEE Transactions on Industrial Electronics, 2020

9. J. Ko, H. Kim, and J. Lee, "Artificial neural network-based diagnosis for converter faults using current signatures," IEEE Transactions on Power Electronics, 2012.

10. S. Ou *et al.*, "Physics-Informed Neural Network for Parameter Identification: A Buck Converter Case Study," 2025.https://doi.org/10.48550/arXiv.2504.20528

11. C. Liu, L. Kou, G. Cai, Z. Zhao, and Z. Zhang, "Review for AI-Based Open-Circuit Faults Diagnosis Methods in Power Electronics Converters," 2022.

12. K. A. Mahafzah, M. A. Al-Nabi, M. Alkhawaldeh, and A. Al-Hinai, "Artificial-Intelligence-Based Open-Circuit Fault Diagnosis in VSI-Fed PMSMs: A Comprehensive Review," Sustainability, vol. 14, no. 24, Art. 16683, 2022

13. El-Naeem, K.S.A., A. Nayel, M., Abdelrahem, M. et al. Detecting Open-Circuit Faults in Power Electronic Converters Using Continuous Wavelet Transform and Convolutional Neural Networks for Simultaneous Charging Systems. Arab J Sci Eng 51, 10823–10845 (2026). https://doi.org/10.1007/s13369-025-10780-z

14. Chu KSK, Chew KW, Chang YC, Morris S. An Open-Circuit Fault Diagnosis System Based on Neural Networks in the Inverter of Three-Phase Permanent Magnet Synchronous Motor (PMSM). *World Electric Vehicle Journal*. 2024; 15(2):71. https://doi.org/10.3390/wevj15020071