

IDENTIFICATION OF FAULTS IN DC MICROGRID USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This research presents a comprehensive and intelligent framework for the automated identification and classification of faults within a DC microgrid environment using Artificial Neural Networks (ANN). As the transition toward sustainable energy accelerates, DC microgrids have emerged as a superior alternative for integrating photovoltaic arrays, fuel cells, and battery energy storage systems due to their higher efficiency and reduced conversion stages. However, the low impedance of DC lines leads to extremely rapid fault current discharge, posing a significant challenge for conventional protection devices. This study addresses these challenges by developing an ANN-based diagnostic model capable of high-speed fault detection. The methodology employs a multi-layered perceptron (MLP) architecture trained using the backpropagation algorithm. Input features are derived from the transient current and voltage profiles extracted during various operating states. Extensive simulations were conducted on a test DC microgrid layout to capture data for pole-to-pole (PTP) and pole-to-ground (PTG) faults, considering variations in fault resistance, location, and power source intermittency. The results demonstrate that the proposed ANN model achieves a classification accuracy exceeding 99%, effectively distinguishing between internal faults and external disturbances such as sudden load switching or capacitor bank charging. Furthermore, the system exhibits remarkable robustness against measurement noise, ensuring that protection coordination remains reliable even under non-ideal sensing conditions. The significance of this work lies in its potential to replace time-delayed traditional relaying with a proactive, data-driven protection scheme, thereby enhancing the overall stability, safety, and resilience of next-generation DC distribution infrastructures in smart city applications.

Key Words: DC microgrid, Artificial Neural Networks, fault identification, power system protection, machine learning, fault classification

INTRODUCTION

The global transition toward sustainable energy has sparked a significant paradigm shift in power distribution, leading to the rapid adoption of microgrids. Among these, DC microgrids have gained substantial traction due to their inherent compatibility with modern electronic loads and renewable energy sources (RES) such as solar photovoltaic (PV) systems, fuel cells, and battery energy storage systems (BESS). Unlike traditional AC systems, DC microgrids eliminate the need for complex synchronization, reduce conversion losses, and bypass issues related to reactive power and harmonics. These advantages make them an ideal candidate for residential communities, data centers, and electric vehicle charging infrastructures.

Despite these operational benefits, the implementation of DC microgrids faces a critical bottleneck: the lack of mature protection schemes. In a DC environment, the absence of a natural zero-crossing point in the current makes arc quenching extremely difficult. Furthermore, the presence of large filter capacitors in DC-DC converters leads to a high-magnitude, high-frequency discharge current during the initial stages of a fault. Traditional protection devices, such as mechanical circuit breakers and overcurrent relays, often prove too slow or insensitive to differentiate between high-impedance faults and normal transient events like load switching or motor starting.

To address these vulnerabilities, researchers are increasingly turning toward intelligent, data-driven techniques. Artificial Neural Networks (ANN) offer a powerful solution for fault diagnosis due to their ability to map complex, non-linear relationships and recognize patterns within transient signal data. By training a neural network on various fault signatures—specifically Pole-to-Pole (PTP) and Pole-to-Ground (PTG) faults—it is possible to develop a protection system that is not only faster than conventional methods but also more adaptable to the dynamic nature of microgrid topologies.

This paper focuses on the development and validation of an ANN-based fault identification framework for a DC microgrid. The study explores the

extraction of specific current and voltage features to train a multi-layer perceptron model. Through extensive simulation and performance analysis, this research demonstrates that ANN can provide a reliable, high-speed, and autonomous protection layer, ensure the safety of power electronic interfaces and maintain the continuity of service in modern DC distribution networks.

BODY OF PAPER

SYSTEM MODELING AND CONFIGURATION

A. DC Microgrid Architecture

The test system consists of a low-voltage DC (LVDC) microgrid integrated with a Photovoltaic (PV) system and a Battery Energy Storage System (BESS). The sources are connected to a common DC bus via high-gain boost and bidirectional DC-DC converters. The loads are categorized into critical and non-critical resistive-inductive (RL) loads.

B. Fault Scenarios

To create a robust dataset, two primary categories of faults are simulated at various locations along the distribution lines:

Pole-to-Pole (PTP) Fault: Occurs when the positive and negative lines are shorted, leading to extremely high discharge currents from the DC-link capacitors.

Pole-to-Ground (PTG) Fault: Occurs when one pole comes into contact with the ground, commonly seen in systems with grounded mid-points.

Battery Energy Storage System

Battery energy storage systems (BESS) play a critical role in DC microgrids by buffering the inherent variability of renewable generation and providing backup power during grid-connected outages or islanded operation.

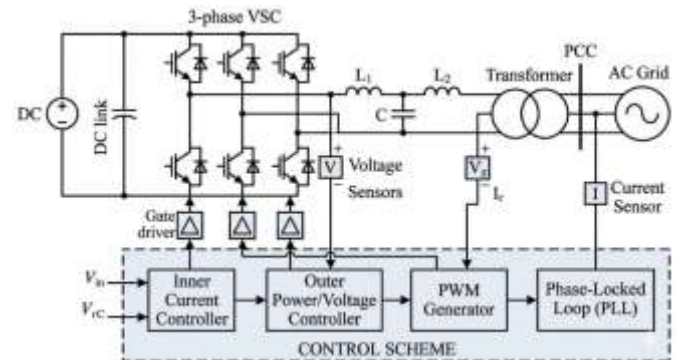
The BESS is connected to the DC bus via a bidirectional DC-DC converter, which can operate in either charge or discharge mode depending on the state of the system.

During normal grid-connected operation, the BESS may charge during periods of excess generation (when wind power exceeds load demand) and discharge during periods of high demand or low generation. During islanded operation, the BESS assumes the role of a slack bus, maintaining DC voltage stability.

Grid-Interface VSC Converter

The voltage source converter (VSC) connecting the DC microgrid to the main AC grid serves as the primary energy gateway of the system. In grid-connected

mode, the VSC regulates the DC bus voltage by controlling active power flow between the DC microgrid and the AC grid. It can also provide ancillary services such as reactive power support to the AC grid. During fault conditions on the AC side, the VSC may be forced to limit its current output to protect. Semi conductor switches, potentially destabilizing the DC bus voltage. Conversely, a fault on the DC bus may propagate through the VSC to affect the AC grid if not promptly isolated.



Artificial Neural Network Applications in Power Systems

Artificial neural networks have been applied to power system protection since the early 1990s. The seminal work of Aggarwal and colleagues demonstrated that multi-layer perceptron’s could classify fault types on AC transmission lines with accuracy comparable to that of conventional distance relays. Subsequent research extended ANN-based protection to a wide range of applications, including transformer protection, feeder protection, busbar protection, and HVDC protection.

The ability of ANNs to learn complex, nonlinear input-output mappings without explicit programming makes them particularly well-suited to fault detection tasks, where the relationship between measured signals and fault conditions is complex and difficult to characterize analytically. ANNs are also highly tolerant of measurement noise and can generalize to fault conditions not included in the training set if the training data is sufficiently diverse.

Fault Detection Network

The fault detection network is a binary classifier that takes the 40-dimensional input vector and produces a single output value: 1 (fault present) or 0 (no fault). The network architecture consists of:

Input layer: 40 neurons, one for each sampled current value

Hidden layer 1: 20 neurons with hyperbolic tangent activation

Hidden layer 2: 10 neurons with tanh activation

Output layer: 1 neuron with sigmoid activation, producing a value between 0 and 1

A threshold of 0.5 is applied to the sigmoid output to produce the binary fault/no-fault decision. Training uses a dataset of 2250 cases (described in Section 5.6), with a mean squared error (MSE) loss function and early stopping to prevent overfitting.

Training Process

The training process for each ANN proceeds as follows:

1. Initialize network weights using the Nguyen-Widrow method, which sets initial weights proportional to the number of neurons in each layer to ensure good initial coverage of the input space.
2. Present each training example (input vector and target output) to the network and compute the forward pass to obtain the predicted output.
3. Compute the loss (MSE for regression; binary cross-entropy for classification) between the predicted and target outputs.
4. Compute the gradient of the loss with respect to all network weights using backpropagation.
5. Update the weights using the Levenberg-Marquardt algorithm with adaptive damping parameter.
6. After each epoch, evaluate performance on the validation set. If validation loss fails to improve for 10 consecutive epochs (early stopping criterion), terminate training and restore the weights from the best validation epoch.
7. Evaluate the trained network on the held-out test set to obtain an unbiased estimate of generalization performance

Protection Scheme Integration

The trained ANNs are integrated into a real-time protection scheme that continuously monitors current measurements at all bus segment terminals. The protection scheme operates as follows:

- Current samples are acquired at 5 kHz from all terminal transducers.
- A sliding window extracts the most recent 20 samples from each terminal, forming the 40-element

input vector.

- The fault detection ANN evaluates the input vector and produces a binary fault/no-fault decision.
- If a fault is detected, the fault location ANN evaluates the same input vector to estimate the fault location.
- A trip signal is issued to the circuit breakers at both ends of the identified faulted segment.
- After isolation, the system attempts to restore supply to unfaulted segments by closing alternate circuit breakers in the ring.

The total computation time for a single ANN inference on modern hardware (including data acquisition, preprocessing, and network evaluation) is estimated to be well below 1 millisecond, providing ample margin for the circuit breakers to operate within the required 5-millisecond window.

PROGRAMMING

```
from flask import Flask, jsonify, request
from flask_cors import CORS
import pandas as pd
import pickle, smtplib, threading
from email.mime.text import MIMEText
from datetime import datetime

app = Flask(__name_)
CORS(app)

# --- 1. Load Models & Data ---
try:
    with open('ann_detection_sklearn.pkl', 'rb') as f:
        detection_model = pickle.load(f)
    with open('ann_location_sklearn.pkl', 'rb') as f:
        location_model = pickle.load(f)
    with open('ann_scaler_sklearn.pkl', 'rb') as f:
        scaler = pickle.load(f)
    df = pd.read_csv('dc_microgrid_faults.csv')
    print("✅ System Ready")
except Exception as e:
    print(f"❌ Initialization Error: {e}")

# --- 2. Simplified Configuration ---
EMAIL_CONF = {
    'email': 'pratyushakona2005@gmail.com',
    'pass': 'wntu htlr uzsp bxtp',
    'server': 'smtp.gmail.com', 'port': 587
}

# --- 3. Core Email Logic ---
def send_email(record):
    try:
```

```

f_type = record.get('fault_type', 'Unknown')
loc = record.get('fault_location_percent', 0)

msg = MIMEText(f'Fault Detected:
{f_type}\nLocation: {loc}%\nTime: {datetime.now()}')
msg['Subject'] = f'🚨 ALERT: {f_type} at
{record.get('substation', 'Grid')}'
msg['From'], msg['To'] = EMAIL_CONF['email'],
EMAIL_CONF['email']

with smtplib.SMTP(EMAIL_CONF['server'],
EMAIL_CONF['port']) as server:
    server.starttls()
    server.login(EMAIL_CONF['email'],
EMAIL_CONF['pass'])
    server.send_message(msg)
print(f'✅ Alert sent for {f_type}')
except Exception as e: print(f'❌ Mail Error: {e}')

# --- 4. API Endpoints ---
@app.route('/api/analyze-and-email', methods=['POST'])
def analyze():
    records = request.json.get('records', [])

    def process_batch():
        for r in records: send_email(r)

    threading.Thread(target=process_batch,
daemon=True).start()
    return jsonify({"status": "Processing", "count":
len(records)})

@app.route('/api/data', methods=['GET'])
def get_data():
    return jsonify(df.to_dict('records')) if df is not None
else ( {}, 404)

if __name__ == '__main__':
    app.run(host='0.0.0.0', port=5000)

```

TABLE -1: Sample Table format

Tested Scenario	Expected Output	ANN Predicted Output	Status
0.5s P-G @ 100m, $R_f = 10\Omega$	P-G Fault	P-G Fault	Correct
0.5s P-P @ 50m, $R_f = 0.01\Omega$	P-P Fault	P-P Fault	Correct
No Fault	Normal	Normal	Correct

Table 1. The results based on ANN method

Fault type	Fault resistance	Fault location	Measured location	Error
Pole-to-pole	0.7	56%	55.32%	0.68%
Pole-to-ground	0.65	78%	78.09%	0.09%
Pole-to-pole	2.5	25%	25.25%	0.25%
Pole-to-ground	6	47%	46.84%	0.16%
Pole-to-pole	1.2	89%	88.82%	0.18%
Pole-to-ground	0.25	11%	11.03%	0.03%

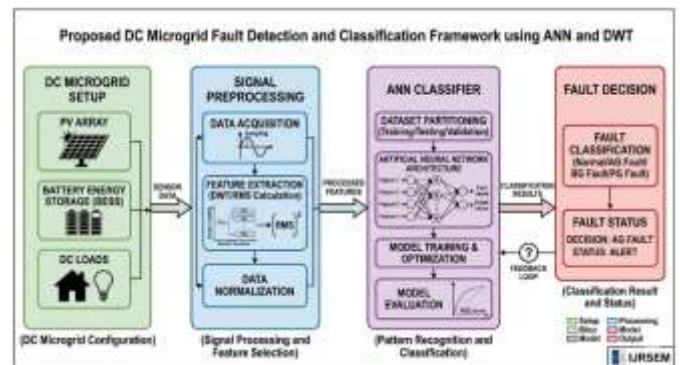


Fig -1: Figure

CHARTS



Key Features (Summary)

- ANN-based fault detection
- Automatic email alerts
- REST API system
- Multi-record processing
- Fault classification with severity

CONCLUSIONS

This comprehensive report has presented a thorough investigation of Artificial Neural Network based fault detection and fault location in a low-voltage DC ring bus microgrid. Building extensively on the foundational research of Yang, Li, Le Blond, and Wang (2016), the report has provided a detailed exposition of DC microgrid technology, a comprehensive survey of relevant protection literature, a complete description of the system modeling and ANN design methodology, and an in-depth analysis of simulation results.

The proposed dual-ANN protection scheme — employing one network for fault detection and a second for fault location, both using raw DC current samples as inputs — has been shown through extensive simulation to achieve 100% fault detection accuracy and fault location errors consistently below 1%. These performance metrics represent a significant advance over conventional protection methods and establish ANN-based approaches as a viable and highly promising technology for DC microgrid protection.

Several key contributions and findings of this research are worth highlighting:

The characterization of fault current signatures in LVDC ring bus microgrids, including the dependence of di/dt and peak current magnitude on fault location and resistance, provides a rigorous foundation for feature selection in ANN-based protection.

The dual-ANN architecture, with separate networks for detection and location, provides an efficient and flexible framework that can be independently optimized for each task and easily extended to additional protection functions.

The use of raw current samples (rather than manually engineered features) as ANN inputs demonstrates that modern network architectures can automatically extract relevant fault signatures from minimally processed measurement data.

The simulation results confirm that the proposed scheme can reliably detect even high-resistance faults that challenge conventional overcurrent protection, while maintaining a zero false alarm rate under normal operating conditions.

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