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INTELLIGENT PROTECTION of MICROGRID



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I. Introduction

□ Microgrid (MG) :

- Effective way to integrate the increasing penetration of distributed energy resources (DERs)
- Small scale medium or low voltage distribution network
- Normally work in grid-tied mode
- Can operate in Islanded mode → Faults in main utility

□ Benefits of Microgrids:

- Reduce the power losses
- Provide uninterrupted service to customers
- Improve reliability & power quality
- Reduced emissions of greenhouse gases

I. Introduction

A. **Challenges** associated with microgrid operation

- ❑ **MG operation is different from traditional distribution networks:**
 - Bi-directional power flow in the feeders
 - Continuous switching between radial and looped topologies
 - Various operating scenarios → Grid-tied mode, and Islanded mode
- ❑ **The complex and multi-mode operation → protection and control challenges**
- ❑ **MG Protection can be divided into two sub-problems**
 - Anti-islanding protection/Islanding detection
 - Fault protection
 - Detection
 - Classification
 - Location of faults

I. Introduction

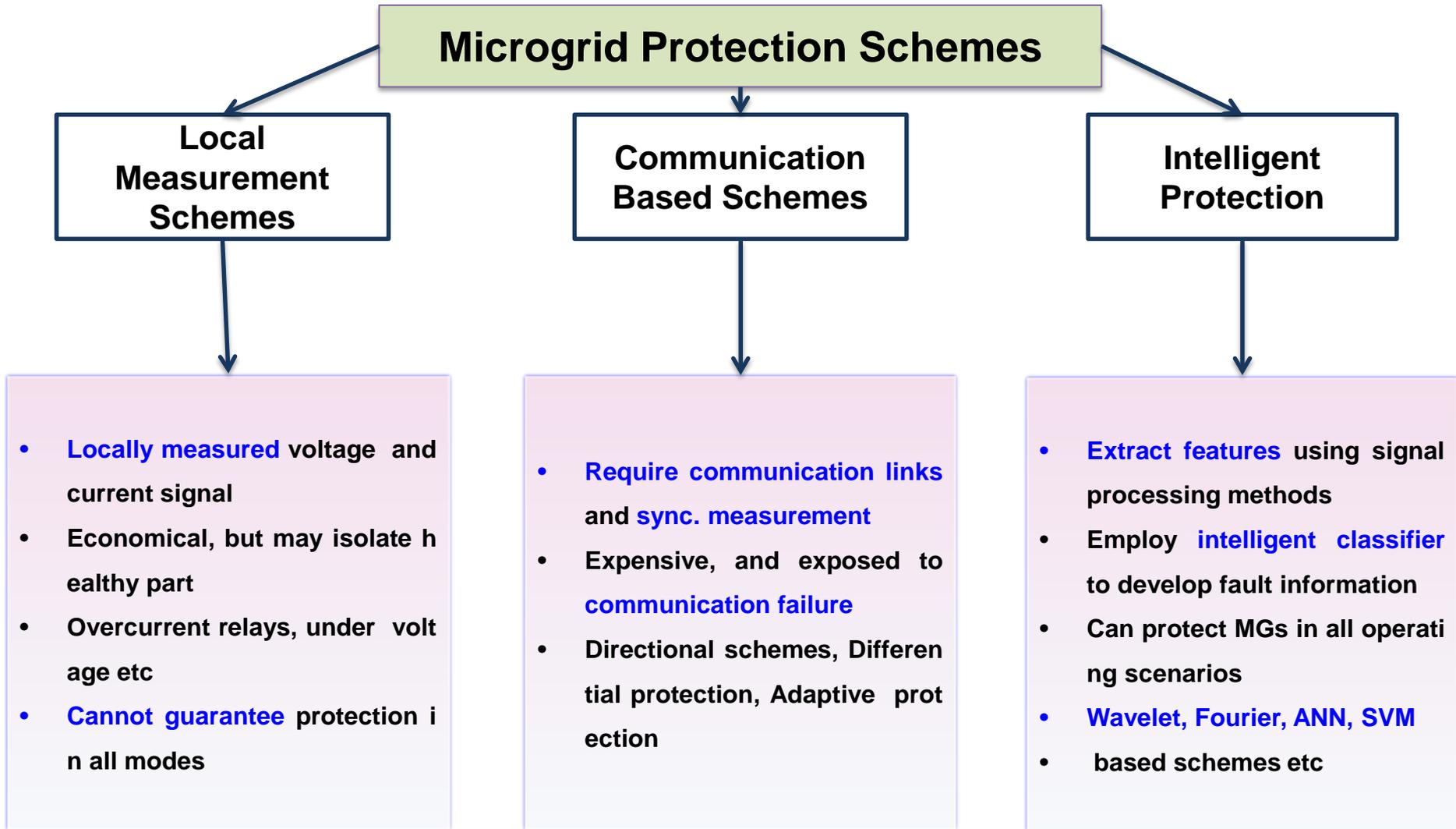
B. Problem statement

□ Fault protection:

- **Bidirectional power flow** in the MG feeders
- Different **fault current level** in different operating modes
- **Microgrid switching** between radial and looped topologies
- **Protection methods** of distribution network → **Not applicable** to MG

II. Research trend and previous work

A. Existing microgrid protection schemes



II. Research trend and previous work

B. Problems of existing microgrid protection schemes

- ❑ **Local protection schemes cannot guarantee protection in both modes of operation**
- ❑ **Communication-based scheme**
 - Required synchronized measurement
 - Exposed to communication failure
- ❑ **Intelligent schemes**
 - Use fixed basis function to extract fault features
 - Cannot provide fault phase information
 - Did not consider the time-sequence of fault current signal
 - Most of the intelligent schemes have been developed for low voltage MG
 - Prone to communication failure

III. Contributions

- ❑ **Intelligent Scheme:** A Novel intelligent islanding detection and fault protection scheme for MGs based on **empirical wavelet transforms** (EWT) and **long short-term memory network** (LSTM) is proposed
- ❑ **Adaptive Feature Extraction:** Unlike existing methods, the proposed scheme **extracts the features** using **signal-adaptive filter banks**. The wavelet filter banks in the EWT are built based on the information contained in the input signals
- ❑ **Extension of EWT concept for islanding detection:** The EWT concept is **extended to islanding detection problems** to calculate the features from the three-phase voltage signals
- ❑ **Long short-term temporal features:** The proposed scheme uses LSTM to extract the long and short-term temporal dependencies within the voltage signal
- ❑ **Comprehensive Method:** The proposed method can protect MGs in all operating modes and can detect islanding events with small non-detection zone
- ❑ **The method can work in noisy conditions and does not use communication**

IV. Background theory

A. Empirical Wavelet Transform (EWT):

❑ EWT designs signal-dependent adaptive wavelet-filters, which decompose a signal into empirical mode

- The empirical modes (Ems) are centered around a specific frequency with a compact frequency support

❑ The empirical wavelet and scaling function are:

$$\Psi_i(\omega) = \begin{cases} 1, & \text{if } |\omega| \leq (1 - \omega)\omega_i \\ \cos(\frac{\pi}{2}\beta(\gamma, \omega_i)), & \text{if } (1 - \omega)\omega_i \leq |\omega| \leq (1 + \omega)\omega_i \\ 0, & \text{Otherwise} \end{cases} \quad (1)$$

$$\varphi_i(\omega) = \begin{cases} 1, & \text{if } (1 + \omega)\omega_i \leq |\omega| \leq (1 - \omega)\omega_{i+1} \\ \cos(\frac{\pi}{2}\beta(\gamma, \omega_{i+1})), & \text{if } (1 - \omega)\omega_{i+1} \leq |\omega| \leq (1 + \omega)\omega_{i+1} \\ \sin(\frac{\pi}{2}\beta(\gamma, \omega_i)), & \text{if } (1 - \omega)\omega_i \leq |\omega| \leq (1 + \omega)\omega_i \end{cases} \quad (2)$$

$\beta(x)$ is an arbitrary $C^k([0, 1])$ function

ω = frequency

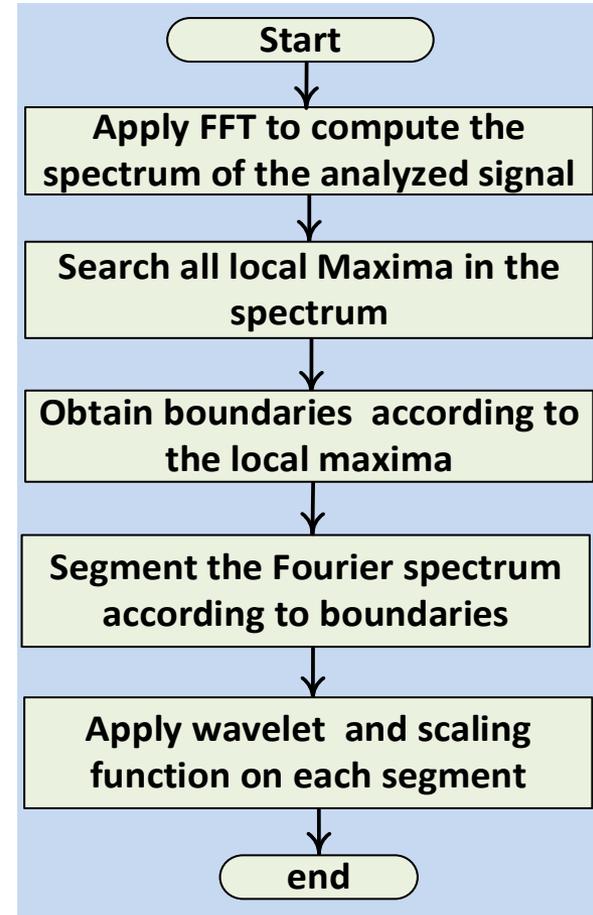


Fig.1a Flowchart of EWT

IV. Background theory

A. Empirical Wavelet Transform (EWT) – Cont.

$$\beta(\gamma, \omega_i) = \alpha \left(\frac{|\omega| - (1 - \gamma)\omega_i}{2\gamma\omega_i} \right) \quad (3) \quad \gamma < \min_i \left(\frac{\omega_{i+1} - \omega_i}{\omega_{i+1} + \omega_i} \right) \quad (4)$$

- After obtaining empirical scaling and empirical wavelet function, the empirical modes are calculated using:

$$f_0(t) = W_f^\varepsilon(0, t) * \phi_1(t) \quad (5) \quad W_f^\varepsilon(0, t) : \text{Approximation coefficients}$$

$$f_k(t) = W_f^\varepsilon(k, t) * \psi_k(t) \quad (6) \quad W_f^\varepsilon(k, t) : \text{Detail coefficients}$$

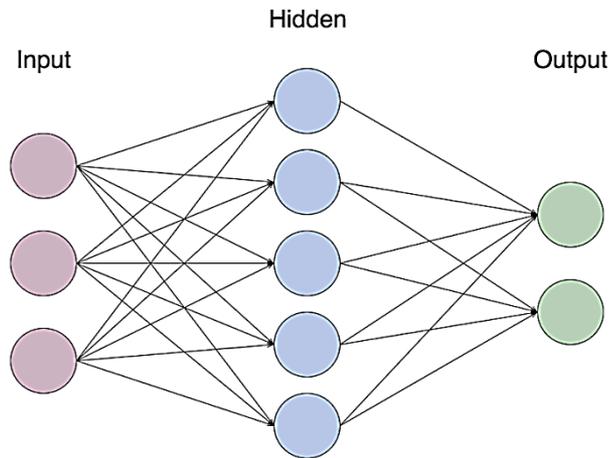
k : Number of modes

- First three modes contains most of the signal information
 - This study considers first three modes only
- Hilbert transform → Instantaneous **amplitude** of each empirical mode
→ Instantaneous **frequency** of each empirical modes

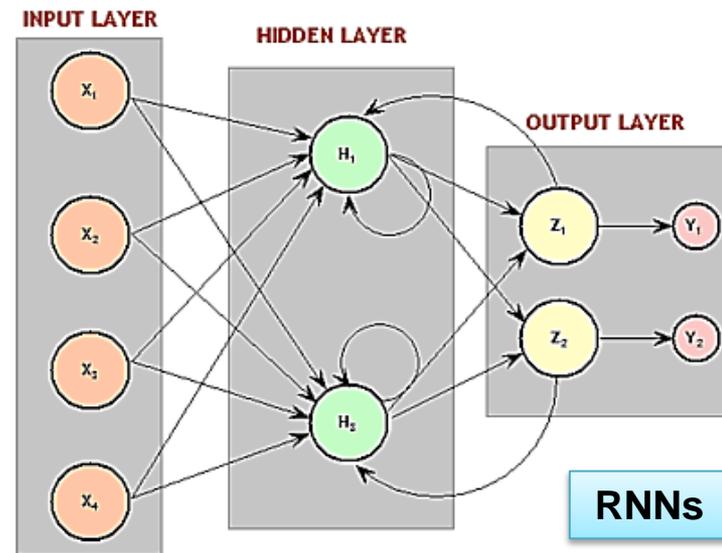
IV. Background theory

B. Long short-Term Memory network (LSTM)

- ❑ LSTMs are a type of recurrent neural network (RNN)
- ❑ RNNs receive inputs, update the hidden states depending on the previous computations, and make predictions for every element of a sequence
- ❑ RNNs are a neural network with memory



Simple Artificial Neural Networks



RNNs

IV. Background theory

B. Long short-Term Memory network (LSTM) – Cont.

- ❑ An LSTM is a special kind of **RNN architecture**, capable of learning long-term dependencies
- ❑ **LSTM networks** outperform RNNs and Hidden Markov Models
- ❑ This is due to **the multiplicative gate units** that learn to open and close access to the constant error flow
- ❑ LSTM networks introduce **a new structure** called a **memory cell**
- ❑ **The memory cells** store the previous information and help in learning long term features from the input
- ❑ **The short term feature** learning capability is an **inherited property** of RNNs

IV. Background theory

B. Long short-Term Memory network (LSTM) – Cont.

□ Comprises of memory units

- **Memory cell** stores the temporal state of the network
- **Input gate** regulate input to update the cell
- **Forget gate** decides about the information to be discarded from previous memory
- **Output gate** controls the information to be taken as output from the current state of memory cell

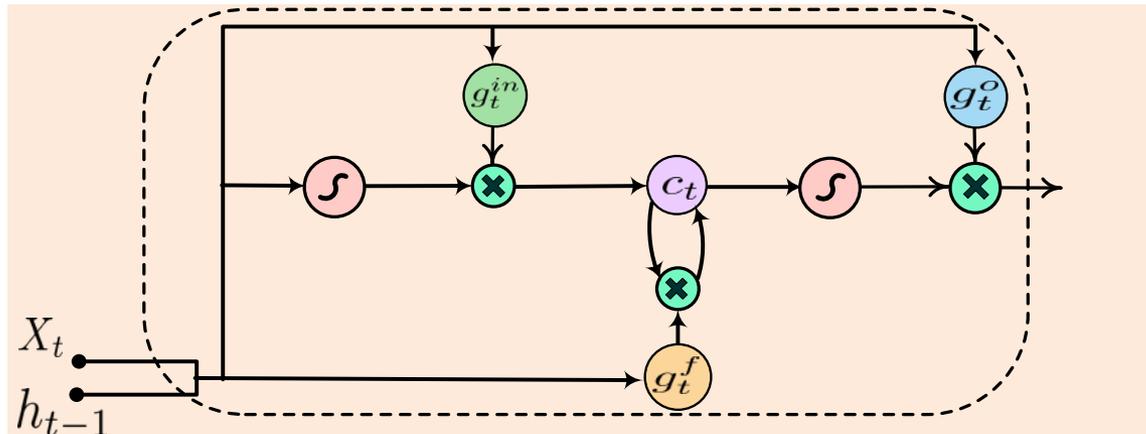


Fig. 2. LSTM memory unit

V. Proposed MG protection scheme

- ❑ **Input:** Three-phase current Signal
- ❑ **EWT → Features extraction**
- ❑ **Three units**
 - Fault **detection** unit
 - Fault **classification** unit
 - Triggered in case of unbalanced fault
 - Fault **location estimation** unit
 - Activated after fault detection
- ❑ **Each unit → EWT based LSTM network**
- ❑ **Finally, the generated fault information can be employed for fault isolation and recovery**

V. Proposed MG protection scheme

A. Feature extraction

- ❑ First, EWT is used to decompose each phase current into EMs
- ❑ Then, the following features are extracted from the first three EMs of each phase
 1. Minimum value
 2. Maximum value
 3. Root-mean square (RMS)
 4. Energy
 5. Standard deviation
 6. Coefficient of variation
 7. Kurtosis
 8. Entropy
- ❑ For each cycle of the three-phase current 72 feature are extracted
 - $3 \text{ (empirical modes)} \times 8 \text{ (features)} \times 3 \text{ (phases)} = 72$
- ❑ The generated features are later inputted into the LSTM networks of each unit to develop the fault information

V. Proposed MG protection scheme

B. Fault detection unit

- ❑ **Input:** one cycle of **Three-phase currents**
- ❑ **Output:** Three 0,1 indicators (no-fault, unbalanced fault, and three-phase fault)
- ❑ **Dropout** helps in **mitigating** overfitting
- ❑ **LSTM layers** extract the **temporal dependencies** from the fault signals

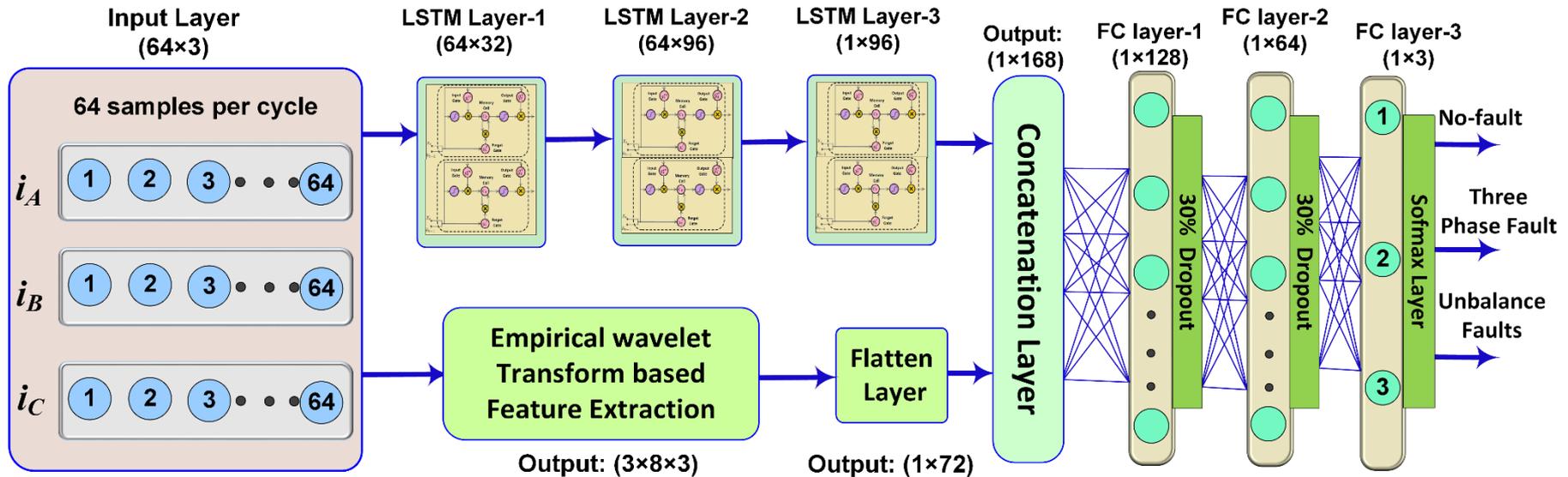


Fig. 3. Fault detection unit

V. Proposed MG protection scheme

C. Fault classification unit

❑ Triggered:

- If the fault detection unit detects **an unbalanced fault** in the MG

❑ Structure is same except last FC layer

❑ Last FC layer :

- Six 0-1 indicators
- represent **the status** of each unbalanced fault

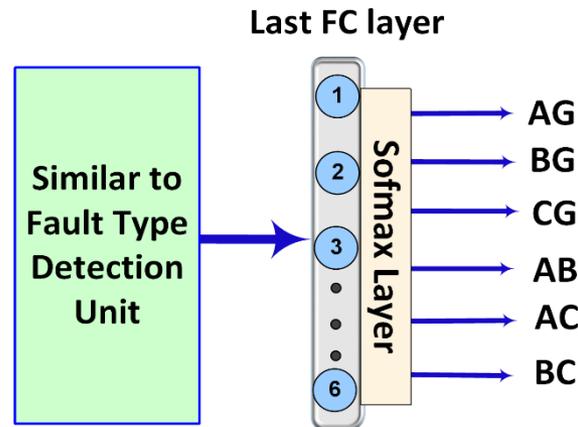


Fig. 4. Fault classification unit

V. Proposed MG protection scheme

D. Fault location estimation unit

❑ Activated:

- If the fault detection unit **detected** an unbalanced/three-phase fault

❑ Structure is same except last FC layer

❑ Last FC layer:

- Regression Task

❑ Output:

- estimated fault location

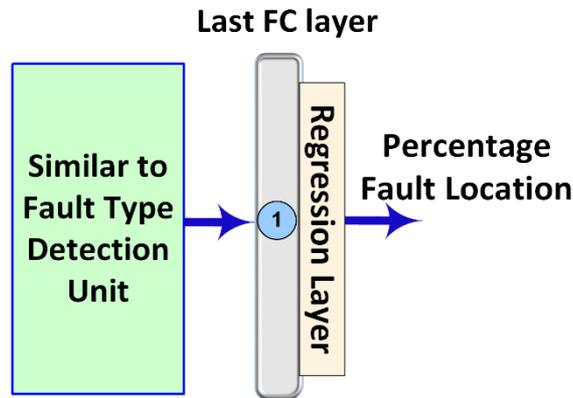


Fig. 5. Fault Location unit

VI. Simulation results

A. IEC microgrid test system

Table 1. Conditions for simulating fault conditions

Parameter Details	Count
Fault on different distribution lines (DL-1, DL-2, DL-3, DL-4, and DL-5).	5
Fault at different locations (20%, 35%, 50%, 65% and 80%).	5
Fault resistances (0.1, 20, 45, and 75).	4
Fault inception angle (0°, 45°, 90°, and 180°).	4
Topology (radial and looped).	2
Operating modes (grid-tied /islanded).	2
Types of Fault	10
Total Fault Cases	16000

Table 2. Conditions for simulating no-fault conditions

Parameter Details	Count
Abrupt load change.	6
Operating mode (Grid-tied/islanded mode)	2
Topology (radial/looped).	2
Capacitor switching at load buses and PCC.	6
Various DER penetration levels	2
Total no-fault cases	288

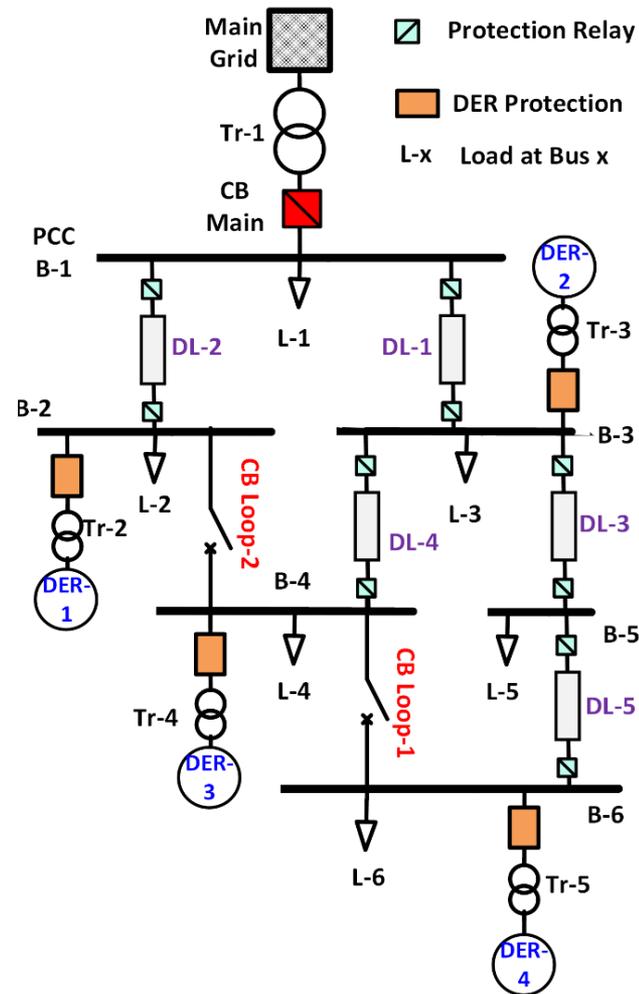


Fig. 6. A standard IEC MG test system

VI. Simulation results

B. EWT decomposition

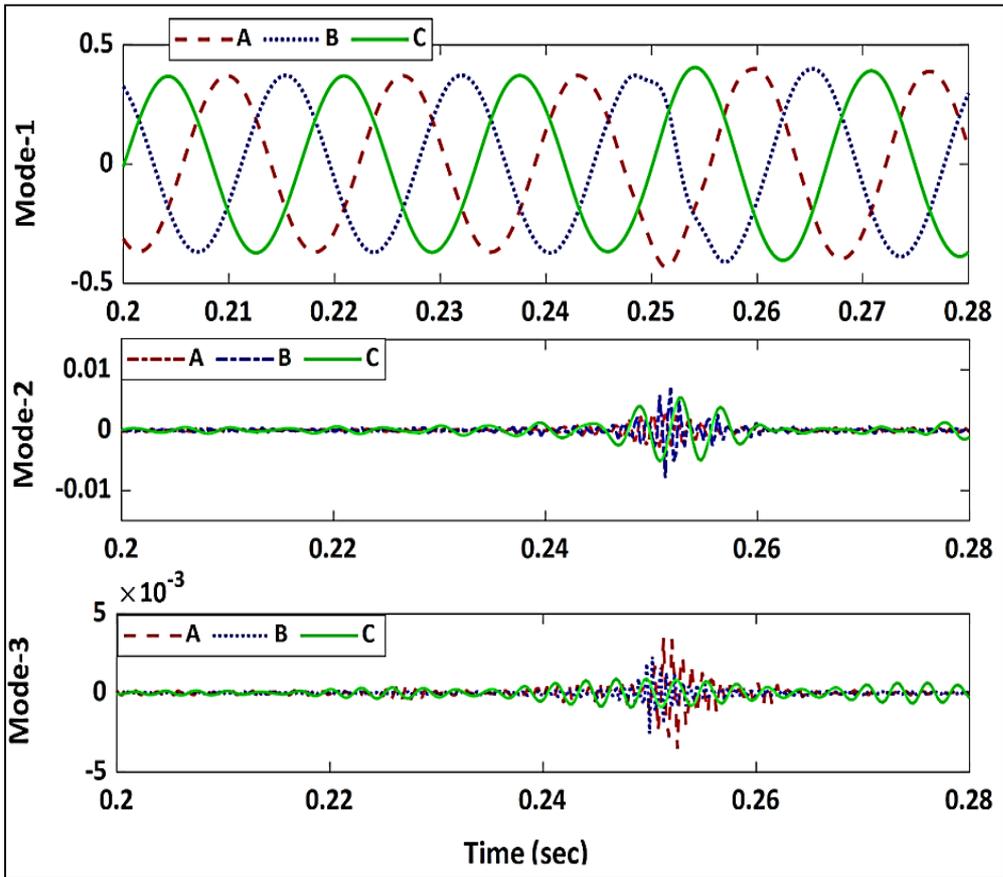


Fig. 7. First three empirical mode of three-phase current during capacitor bank switching at 0.25

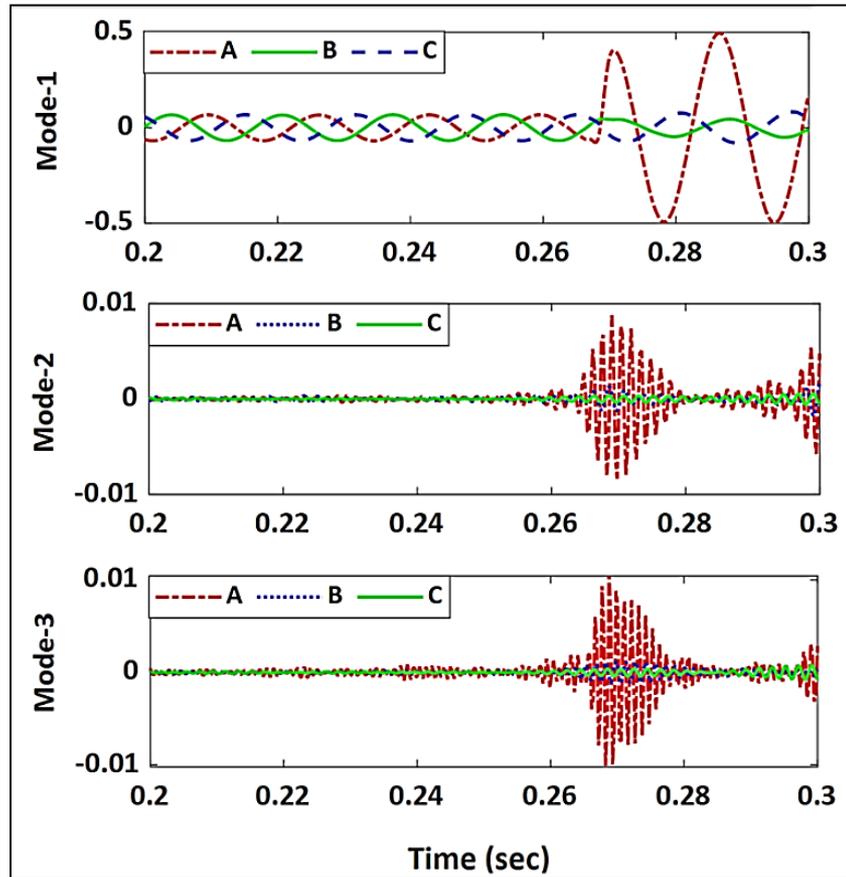


Fig. 8. First three empirical mode of three-phase current when a AG fault hits the MG at 0.27sec

VI. Simulation results

C. Fault detection unit

Predicted Fault Type	TP	240 9.6%	4 0.2%	0 0.0%	98.4% 1.6%
	UF	0 0.0%	2155 86.6%	0 0.0%	100% 0.0%
	NF	0 0.0%	1 0.0%	88 3.5%	98.9% 1.1%
		100% 0.0%	99.8% 0.2%	100% 0.0%	99.8% 0.2%
	TP	UF	NF		
	Actual Fault Type				

(a)

Predicted Fault Type	TP	238 9.7%	4 0.2%	0 0.0%	98.3% 1.7%
	UF	2 0.1%	2156 88.3%	0 0.0%	99.9% 0.1%
	NF	0 0.0%	0 0.0%	43 1.8%	100% 0.0%
		99.2% 0.8%	99.8% 0.2%	100% 0.0%	99.8% 0.2%
	TP	UF	NF		
	Actual Fault Type				

(b)

Fig. 9. Confusion Matrices of the testing dataset of **fault detection unit** during: (a) grid-tied mode, (b) islanded mode

VI. Simulation results

D. Fault classification unit

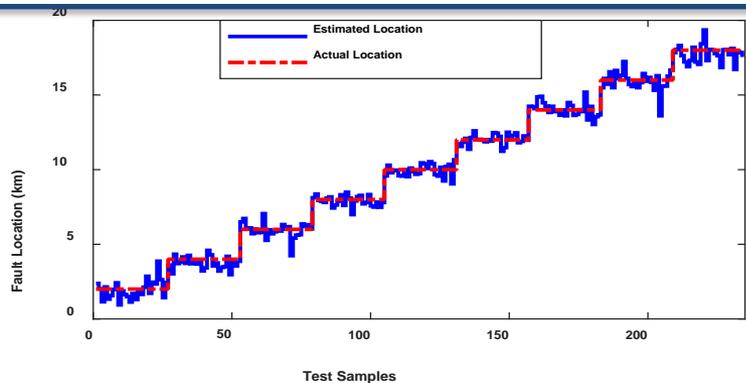
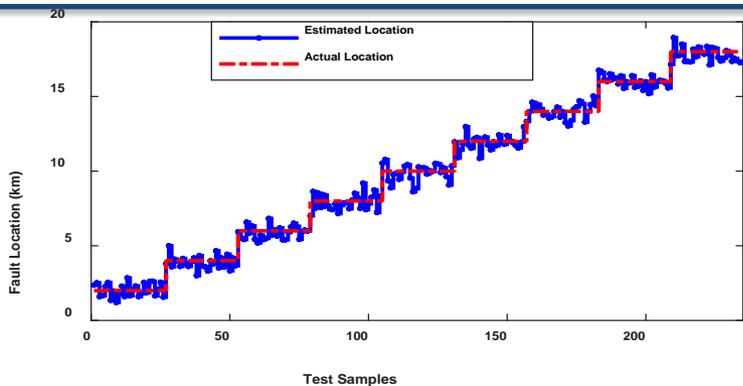
Predicted Fault Class	AG	238 11.0%	3 0.1%	1 0.0%	3 0.1%	5 0.2%	2 0.1%	94.4% 5.6%
	BG	0 0.0%	237 11.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	CG	1 0.0%	0 0.0%	239 11.1%	0 0.0%	0 0.0%	0 0.0%	99.6% 0.4%
	AB	1 0.0%	0 0.0%	0 0.0%	477 22.1%	0 0.0%	0 0.0%	99.8% 0.2%
	AC	0 0.0%	0 0.0%	0 0.0%	0 0.0%	474 21.9%	1 0.0%	99.8% 0.2%
	BC	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.0%	477 22.1%	99.8% 0.2%
			99.2% 0.8%	98.8% 1.2%	99.6% 0.4%	99.4% 0.6%	98.8% 1.2%	99.4% 0.6%
		AG	BG	CG	AB	AC	BC	
		Actual Fault Class						

(b)

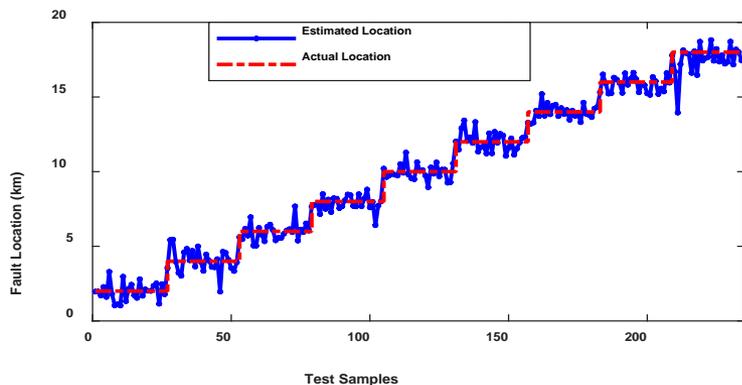
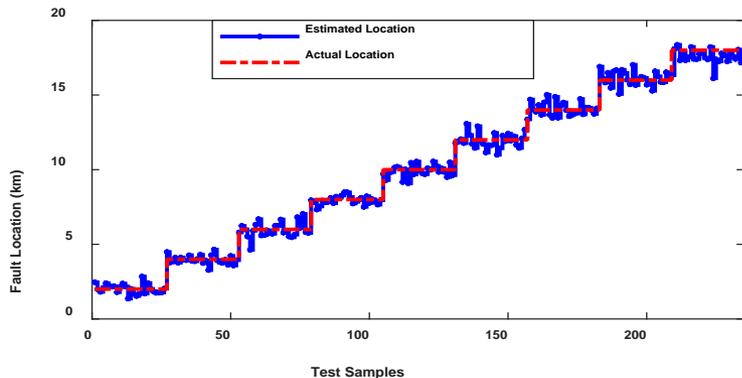
Fig. 10. Confusion Matrices of the testing dataset of **fault classification unit** during: (a) grid-tied mode, (b) islanded mode

VI. Simulation results

E. Fault location unit



(b)



(d)

Fig. 11. Comparison of the **actual fault location** vs **estimated fault location**:
(a) For DL-1, (b) For DL-2, (c) For DL-3, and (d) For DL-4

VI. Simulation results

F. Comparison with existing schemes

Table 5: Comparison with existing fault detection schemes in **grid-tied mode**

Scheme	Dependability	Security	Accuracy
Support vector machine [12]	99.60%	97.06%	98.33%
Decision Tree[12]	99.80%	98.24%	99.02%
Proposed Scheme	99.96%	100.0%	99.97%

$$\text{Dependability} = \frac{\text{Total fault cases predicted}}{\text{Actual fault cases}}$$

$$\text{Security} = \frac{\text{Total nofault cases predicted}}{\text{Actual nofault cases}}$$

Table 6: Comparison with existing fault detection schemes in **Islanded mode**

Scheme	Dependability	Security	Accuracy
Support vector machine [12]	100.0%	98.06%	99.03%
Decision Tree [12]	99.60%	99.35%	99.47%
Proposed Scheme	99.97%	100.0%	99.97%

VII. Conclusions

- ❑ A novel **intelligent islanding detection** and **fault protection** for MGs based on **EWT** and **LSTM** was **proposed**
- ❑ The proposed scheme **extracted the features** from the power system signals using **signal adaptive wavelet filters**
- ❑ **Long-term temporal features** within a cycle were extracted using **LSTM networks**
- ❑ **Extensive simulation** were performed to verify the proposed schemes
- ❑ The results showed that the **proposed schemes** provided **better performance** as compared to existing IDMs and MG protection techniques
- ❑ The proposed schemes **does not require** any **communication link** for their operation

Thank you for your attention !

