

## Introduction and Background

- Data monitoring and communication infrastructure are the cornerstones of power system projects such as offshore wind farms.
- Types of communications
- |  |   |
|--|---|
| Local communication with the control centers     | Communication b/w onshore and offshore substations                              |
| Energy management, Active/reactive power control | fault detection/ protection info, predictive maintenance, wind power prediction |
- The main objective of this research is to develop a wireless sensor network-based Internet of Things (IoT) platform for sensing, data collection, analysis, and storage.
  - In remote areas where sensing nodes are isolated from communication networks, the platform would monitor offshore wind turbine operating conditions like current, voltage, wind speed, and vibration.
  - This proposed control and data acquisition system should be able to collect data with a high timestep resolution.

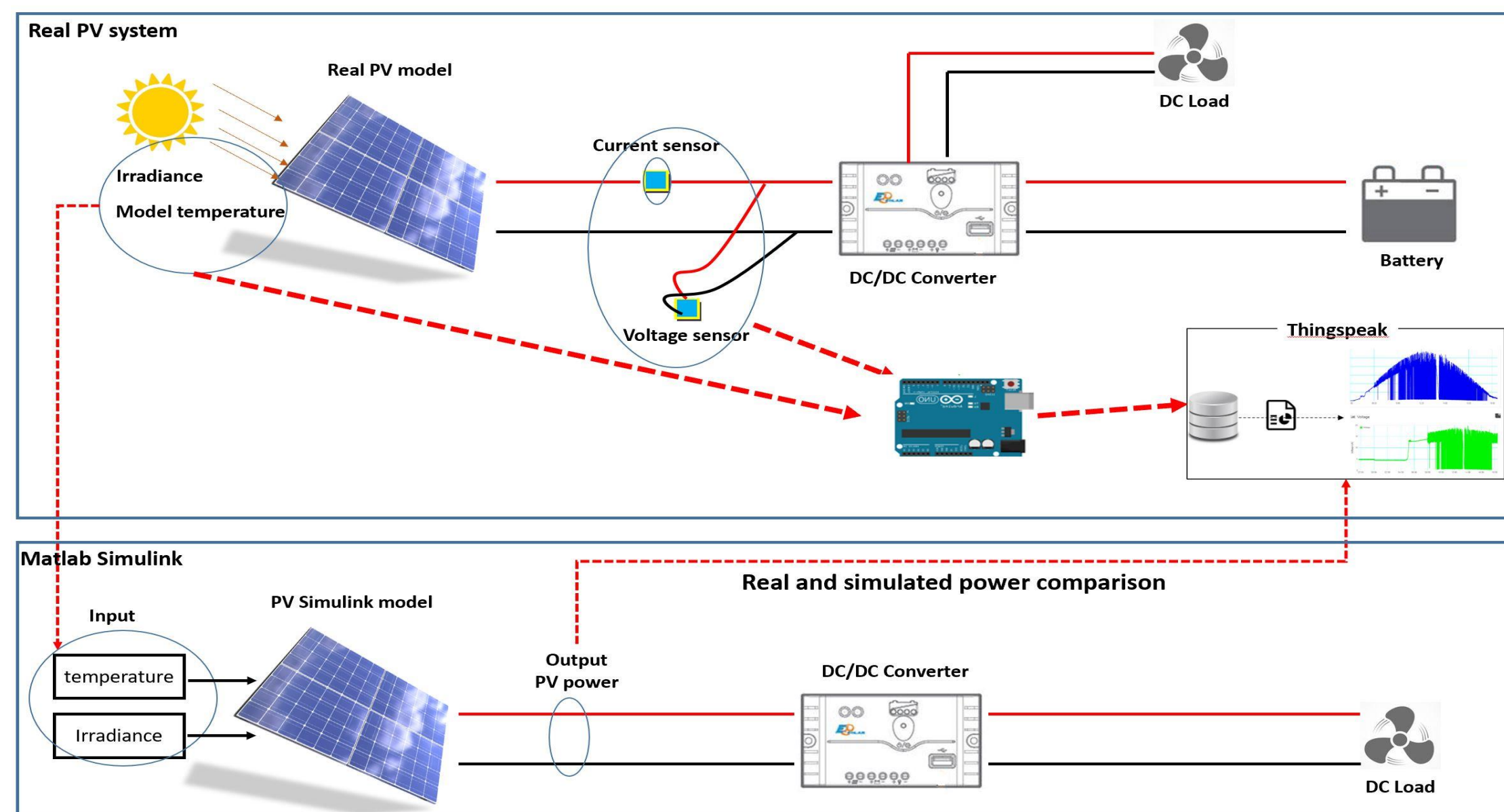


Fig1: Representation of System deployment

## Experimental Methods

- This research is conducted on Solar Photovoltaic system that can be deployed on offshore wind turbines.
- The prototype is developed by integrating a set of sensors (e.g., INA169 current sensor, voltage sensor, DHT11 sensor- temperature and humidity, Pyranometer- irradiance) to collect data from the real PV system, while the data is stored on a remote ThingSpeak platform using ESP8266 Wi-Fi module for wireless communication(Fig.1).
- By adjusting the light intensity with a Dimmer plug, the PV system is subjected to data collection at different irradiance levels in relation to power output.

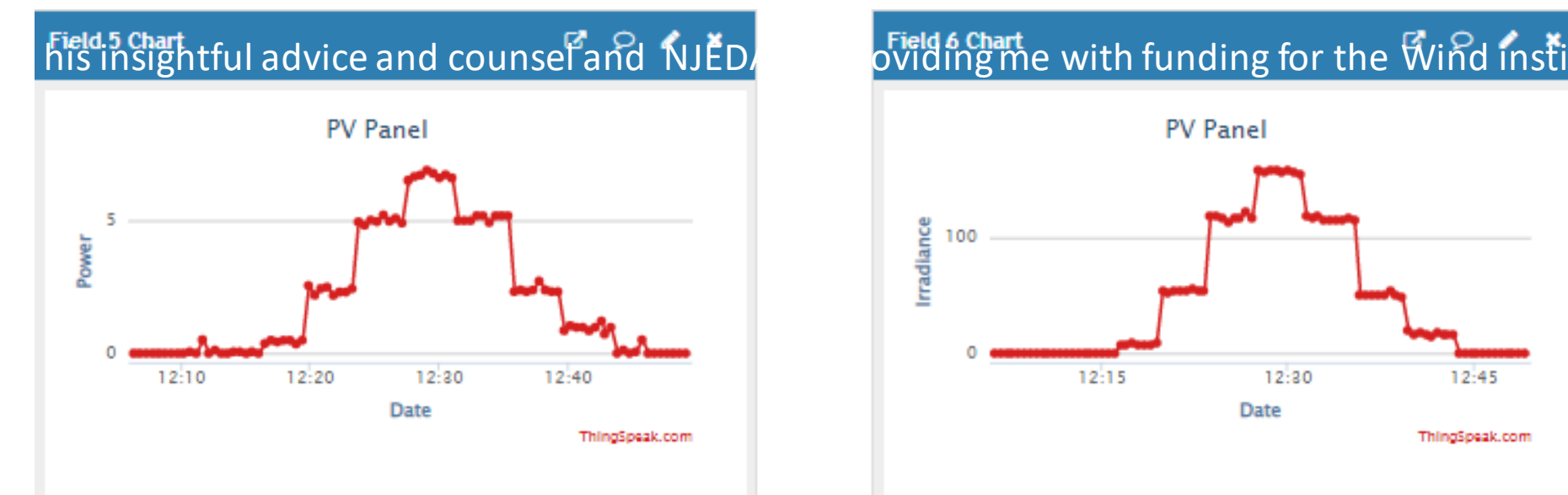


Fig2: Graph showing change in W for corresponding W/m<sup>2</sup>

- By comparing collected data to the MATLAB/Simulink virtual system, a real-time IoT/big data platform is developed (Fig1).
- Data with and without faults are collected.
- Induced partial shading, open circuit, and short circuit faults manually in the actual system (Fig5).
- Using the LSTM Deep learning method for Waveform Segmentation, the data is labeled, trained and tested for fault detection.

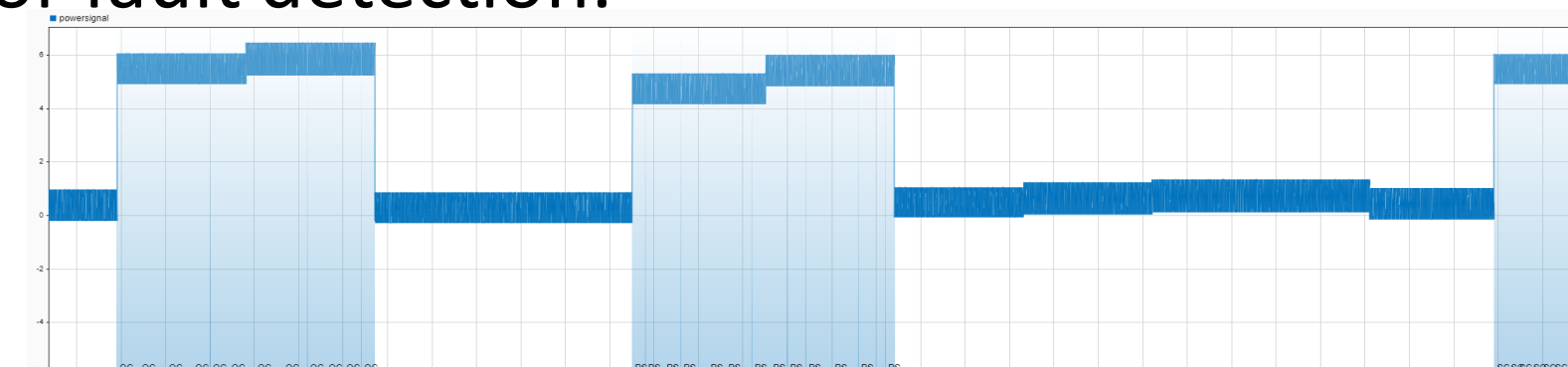


Fig3: Labeled signal with faults

## Results

True Class \ Predicted Class	OC	PS	SC	No fault
OC	58.4%	22.3%	50.6%	0.1%
PS	14.2%	62.8%	25.7%	0.1%
SC	27.4%	14.3%	23.6%	0.1%
No fault	0.0%	0.6%	0.1%	99.7%

Fig4: Confusion Matrix

- Using the raw Power signal as the network's input, only about 62% of partial shading faults, 58% of open circuit faults, and 23% of short circuit faults were depicted accurately(Fig4).
- And yielded an overall accuracy of 89% with a loss of 0.2% across all output classes(Table1).

Training Parameters	Values
Accuracy(%)	89
Loss	0.2
Epoch	10
Learning rate	1e-05

Table1: Training parameters of Deep Learning Model

## Discussion

### Conclusion:

- This proposed approach detected and diagnosed system faults, which is essential for system reliability and performance.
- Monitoring and maintaining systems are made more efficient and cost-effective by wireless IoT and deep learning algorithms, which can be scaled to increase renewable energy adoption.

### Future Scope:

- The system can be subjected to the collection of additional datasets containing various fault conditions, resulting in greater precision, more accurate training of the LSTM model.
- Incorporating digital twin technology into the system can aid in better R&D and greater efficiency.
- After the wind tunnel arrives in the lab, the IoT sensing platform will be modified for offshore wind energy scenario.