Design and Implementation of Smart Monitoring Device

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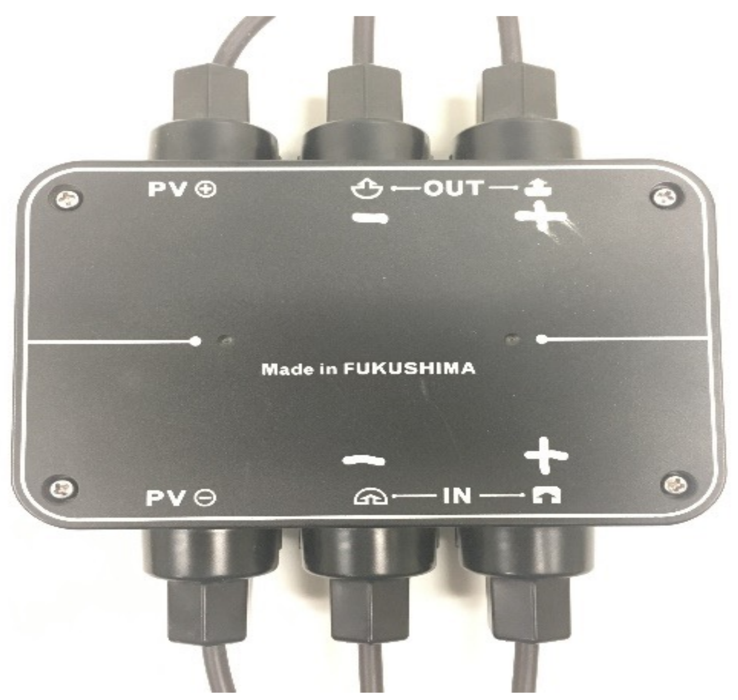
SOLAR FACILITY AT ASU

Solar Monitoring Facility at the ASU Research Park.

- PV array consists of 104 PV panels.
- Each panel has a smart monitoring device.
- SMDs sense current, and voltage. They have sensors, and actuators.

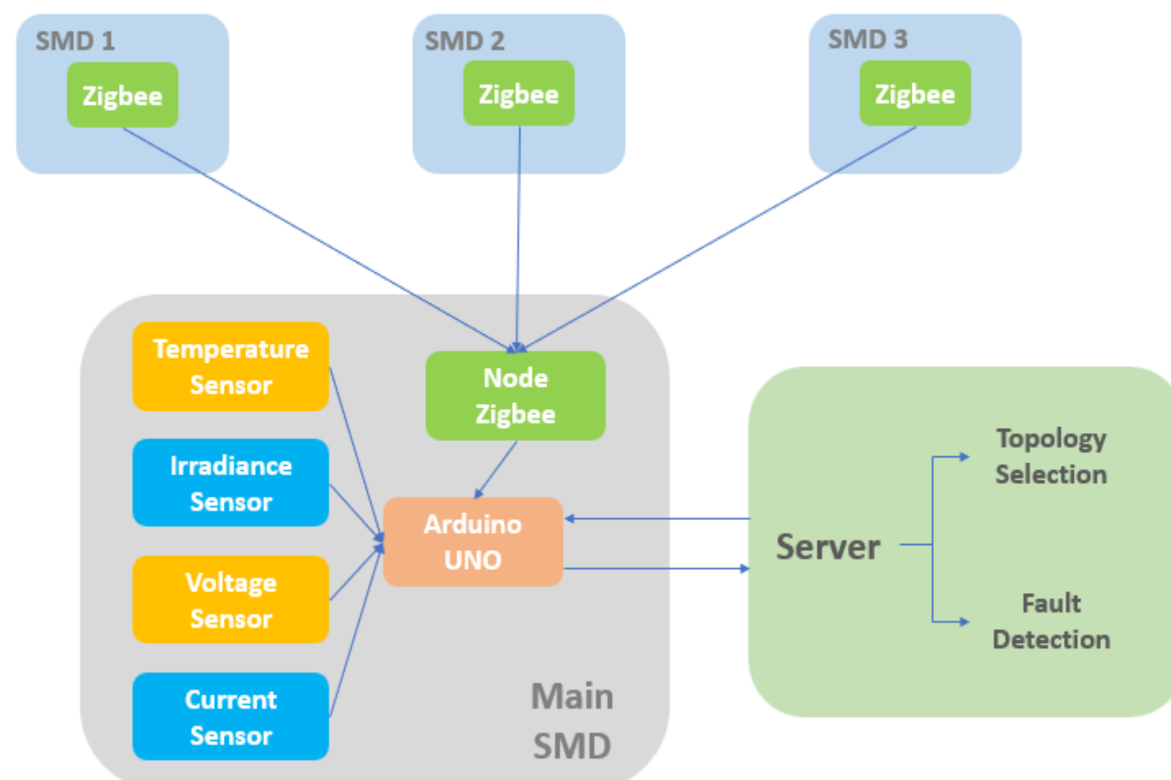
DISADVANTAGES OF AN EXISTING SMD



Existing SMD

- Can not measure the value of Temperature and Irradiance with the Current SMD
- Multiple software are being used
- Slow Transmission Rate
- Only performs series, parallel or series-parallel topology reconfiguration
- Safety Concerns (It can not predict faults)

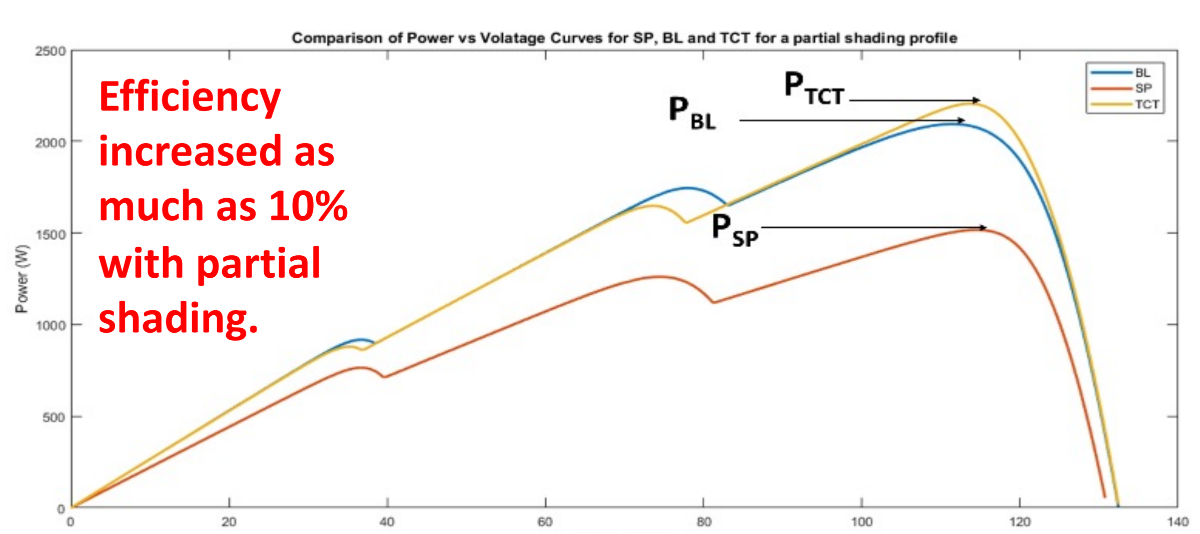
PROPOSED SMD DESIGN



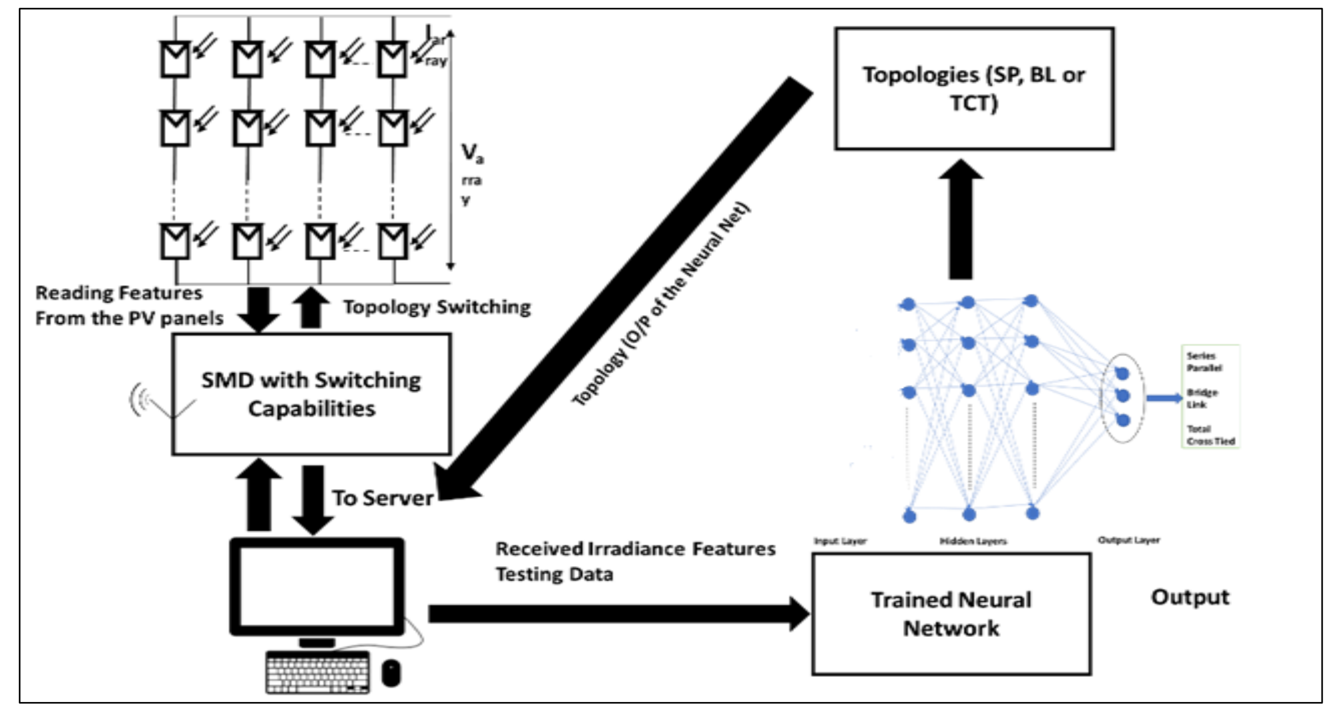
- Applications of Proposed New SMD
  1. Temperature, Voltage, Current and Irradiance data collection
  2. PV Array Control using Zigbee mesh Network
  3. Fault Detection using Neural Nets
  4. Topology Optimization

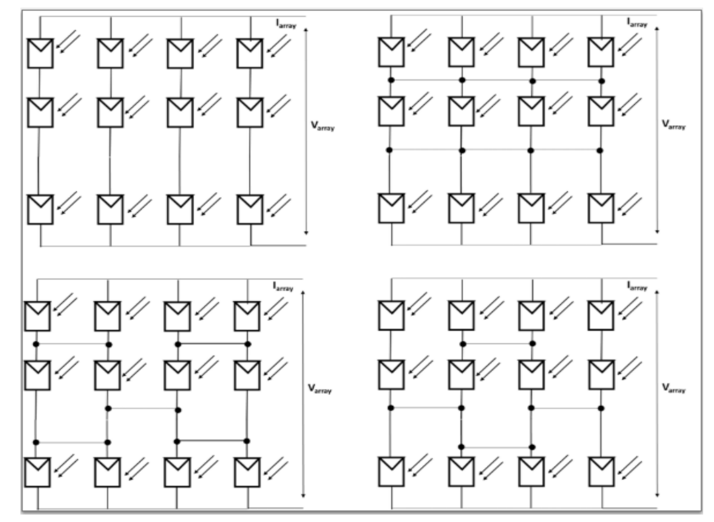
TOPOLOGY OPTIMIZATION

- **Need for Topology reconfiguration:** Depending upon partial shading, array topologies such as series parallel (SP), Bridge Link (BL) or HoneyComb (HC) and total cross tied (TCT) produce different maximum power points



TOPOLOGY SELECTION USING NEURAL NETS

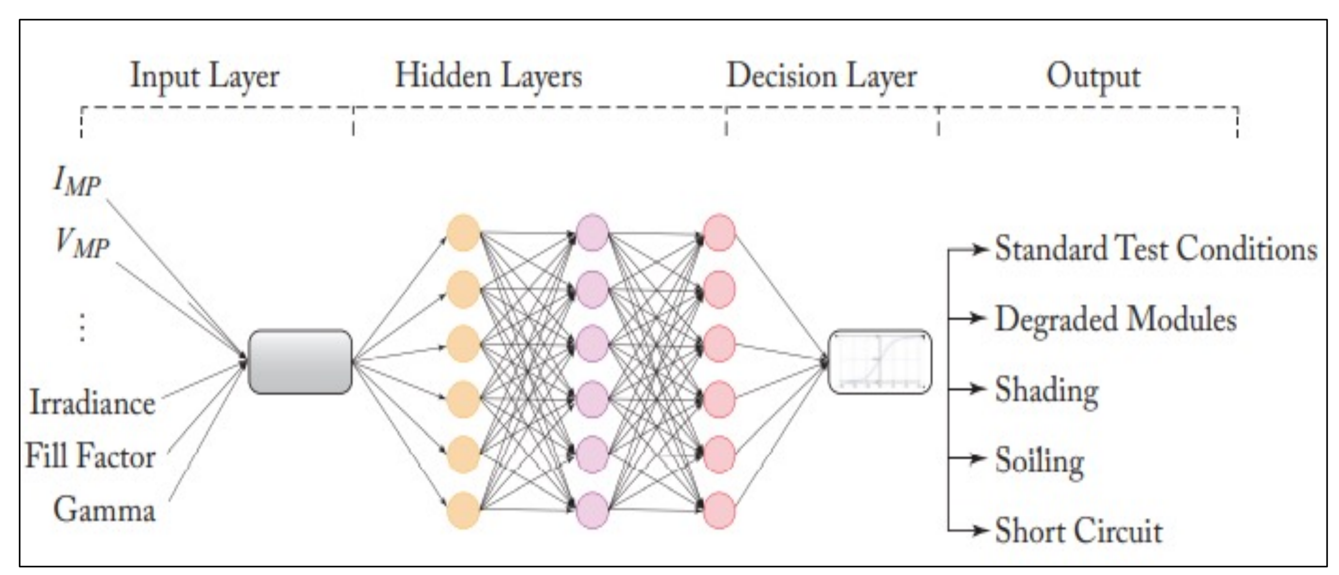




Topologies Considered
1. Series-Parallel
2. Total Cross Tied
3. Honeycomb
4. Bridge Link

FAULT DETECTION USING NEURAL NETS

- **Fault Detection**: 4 configurations (12S, 12P, 4S-3P, 3S-4P) to analyze 8 different faults.
- **Topology Optimization**: performance with partial shading. SP, TCT, BL, HC structures;
- **PV data** is used for training and testing.



- Real dataset from PV Watts.
- Fully Connected and Dropout Neural Nets with different probabilities used.
- Concrete Dropout reduces overfitting.
- Monte Carlo simulation and K-fold cross validation performed.

FAULT DETECTION RESULTS

Architecture	Train Accuracy(%)	Test Accuracy(%)	Test Accuracy Change	RPN weighted Accuracy
Fully Connected	91.62	89.34	Baseline	85.20
Concrete Dropout	91.45	89.87	+0.5%	85.25
Dropout p=0.1	89.71	89.34	0%	84.53
Dropout p=0.2	89.29	89.13	-0.21%	84.53
Dropout p=0.3	88.92	88.77	-0.57%	84.56
Dropout p=0.4	87.38	88.77	-2.14%	82.39
Dropout p=0.5	85.51	85.42	-3.92%	79.55
RFC	100	86.32	-3.02%	87.57
KNN	87.15	85.76	-3.58%	73.82
SVM	83.51	83.29	-6.05%	79.30

Comparison of various classifiers used for fault classification in PV Arrays. We note that the concrete dropout architecture performs best in terms of accuracy due to an optimized hyperparameter search within the architecture.

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[5] **Provisional Patents:** Topology: US 62/808,677 / Fault Detection: US 62/843,821

ACKNOWLEDGEMENTS

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