# REAL-TIME SHORT-TERM SOLAR FORECASTING FOR EFFICIENT LOAD-DEMAND MANAGEMENT FOR MICROGRIDS



To create a wireless sensor network for solar photovoltaic (PV) data acquisition and subsequently implement a hybrid online prediction model for short-term solar irradiance forecasting with minimal data required from the sensor network.

To perform irradiance predictions to alert the system owner through the utilisation of historical and real-time data.



Accurate solar irradiance forecasting is crucial for PV system efficiency due to solar's intermittent nature. The team has developed a low-cost, low-power remote sensor-based data acquisition system for large-scale PV systems. We use Espressif Simple Protocol -

**Project by: Ryan Kun Keat Peng** Bachelor of Engineering with Honours in Electrical Power Engineering (Year 3)



#### **Developed Online Prediction Framework**



Network of Wi-Fi (ESP-NOW) and Long Range Wide Area Network (LoRaWAN) protocols for data exchange. ESP-NOW handles short-range communication, while LoRaWAN handles long-range, low-power IoT communication.

Our self-power system monitors up to 12 voltage and temperature channels and 4 current, irradiance, ambient temperature, and humidity strings of PV panels. We employ 2.4GHz ESP-NOW for IoT node communication, with a transceiver node forwarding data via LoRaWAN. The system maintains a sub-3% sensor measurement error and averages an RSSI of -105dBm in non-line-of-sight conditions.

We collect offline and online feature data, with real-time environmental details as inputs for our online prediction model. Sensor data like panel temperature, ambient temperature and humidity, and irradiance feed into machine learning (ML) and deep learning (DL) models for single-variable (univariate) and multi-variable (multivariate) analysis. Well-trained model parameters and real-time data are used for online predictions, requiring careful parameter tuning.

Initially, we performed univariate single-step irradiance forecasting using various algorithms. Long Short-Term Memory (LSTM) and Random Forest (RF) outperformed XGBoost, multilayer perceptron (MLP), and convolutional neural network (CNN). Notably, a lag between prediction and observation persisted in historical data-based forecasting. Subsequently, we introduced multivariate inputs and compared offline and online methods using time-series graphs.

The online approach outperformed offline predictions, correcting errors caused by real-time weather deviations. Our online LSTM-based model achieved the best accuracy with mean absolute error (MAE) of 20.97, root mean square error (RMSE) of 41.49, and R-squared (R2) of 0.95.

We enhanced the online prediction model by incorporating time features to capture temporal patterns and seasonal fluctuations. These improvements facilitate accurate predictions.

In summary, the online method surpasses offline predictions, with a 25% RMSE improvement. These findings will be applied to the operation of the SIT Punggol campus microgrid, contributing to Singapore's transition to a greener, more resilient energy future.

#### Numerical Comparison and Performance Improvement of Using the Developed Online Model

•••						
	Univ	ARIATE SINC	GLE STEP FC	DRECAST RES	SULT	
Method	XGBo	ost Rand	lom Forest	t MLP	LSTM	CNN
MAE	34.33	3	33.56	35.35	34.31	36.13
RMSE	70.8		71.38	71.36	70.57	75.16
R2	0.83		0.85	0.85	0.86	0.84
PA	NEL TEMPE	RATURE, AM	BIENT TEMP	PERATURE A	ND HUMIDI	ry CDDL
	Method	XGBoost	Random Forest	MLP	LSTM	CNN
Offline	MAE	38.25	31.05	42.53	41.88	42.4
	RMSE	77.99	59.35	80.51	82.07	81.40
	R2	0.79	0.9	0.81	0.81	01110
		22.04	27.70			0.77
	MAE	22.84	27.78	30.04	20.97	0.77 31.85
Online	MAE RMSE	22.84 45.83	27.78 52.83	30.04 53.41	20.97 41.49	0.77 31.85 56.52

### Offline Multivariate Single-step Prediction Result



## **Online Multivariate Single-step Prediction Result**





- 1. 1 complete hardware and software-based data acquisition system testbed.
- 2. 1 deep learning-based online prediction model.
- 3. 1 paper submitted to IEEE conference.