Abstract

Line-line (LL) electrical faults occurring on the DC side of photovoltaic (PV) arrays can lead to diminished output power and decreased lifespan of PV systems. The intensity of LL faults is influenced by the quantity of modules affected by the fault and the resistivity along the fault path. To prevent these impacts, this research first classifies LL faults using a deep Q-network (DQN), followed by the main procedure for estimating the resistance of LL faults (Rf) to accurately assess the fault's severity. A regression-focused model called Bayesian neural network (BNN) is introduced and optimized to predict Rf across a continuous range of 0–100 Ω. Additionally, BNN offers a confidence measure (uncertainty) for that estimation. The features derived from the current-voltage (I-V) curve of the PV array are influenced by five distinct points. The outcomes of the study demonstrate a high level of accuracy in detecting faults, classifying them, and estimating the resistance of the faults.

Research Contributions

• For the first time, we used a wide range of resistante in LL faults for detecting as a fault resistance estimation model.

• A Bayesian neural network implemented to estimate resistance in photovoltaic array.

Proposed Method

Fig. 1 illustrates the overall flowchart of the LL faults resistance estimation phase that we propose. As depicted in Fig. 1, the initial step involves gathering data samples from five specific points along the I–V curve of the PV array and extracting relevant features. The dataset undergoes normalization, after which LL faults are identified and categorized into four different classes, labeled M1 to M4, where index represents the number of involved modules in the LL fault. For this classification task, a deep Q-network reinforcement learning model has been created. At this stage, LL faults are prepared for the crucial phase, which is the estimation of fault resistance. Our goal is to predict the resistance values of LL faults to develop a comprehensive severity assessment scheme. To achieve this, we propose a Bayesian neural network (BNN) that is trained across a continuous range of Rf (0–100 Ω) to effectively predict various unseen Rf values during the testing phase.

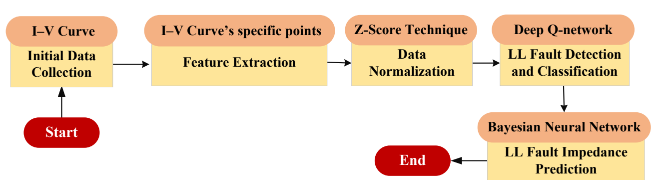


Fig. 1. The graphical process of the proposed method.

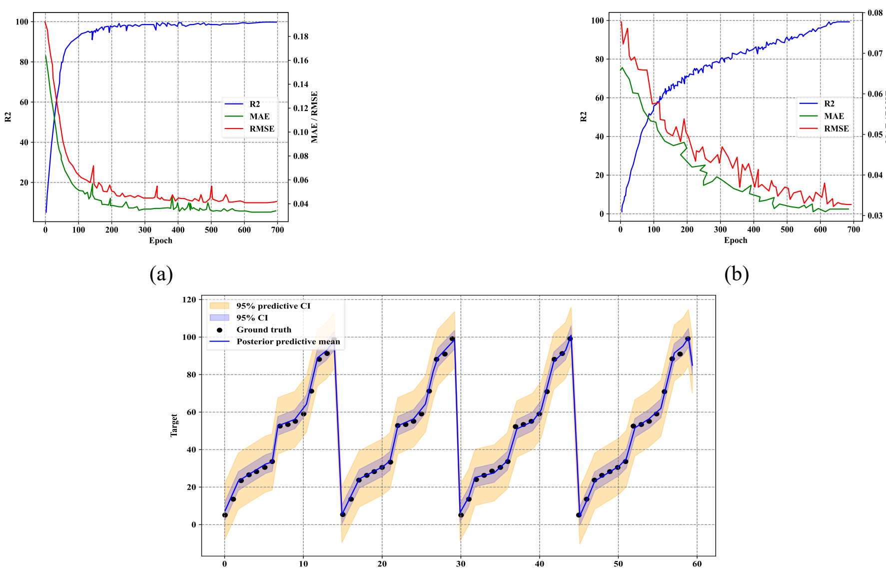
Result

The results demonstrate a maximum classification accuracy of 100% and an R^2 value of 99.2% for the regression task during testing.

Table 1

The reports of evaluation metrics in BNN.

	R^2	MAE	RMSE	Coverage	Average CI Width
Train	99.77%	0.031	0.032	94.63%	0.1583 ± 0.0637
Validation	99.28%	0.034	0.042	94.31%	0.2348 ± 0.0079
Test	99.2%	0.054	0.076	94.2%	0.1248 ± 0.0504



(a) (b) (c)

Fig. 2. (a) Training process (b) Validation process (c) Testing process.