International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE)

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 7.122|

|| Volume 9, Issue 5, May 2020 ||

Feature Extraction and FIS Scheme for fault Detection in PV System

Supriya A.Wadekar[1], Poonam R. Patil[2]

Assistant Professor(Lecturer), Department of Electrical Engineering, DKTE Textile and Engineering Institute, Ichalkaranji, Kolhapur, Maharashtra, India[1]

Assistant Professor(Lecturer), Department of General Engineering, DKTE Textile and Engineering Institute, Ichalkaranji, Kolhapur, Maharashtra, India[2]

ABSTRACT: Demand of Photovoltaic (PV) power plants is increasing day by day due to their advantages such as long life of PV panel, easy maintenance, off-grid installation, and ability to connect to utility grid which have portrayed a bright future for the use of PV system in the world. These rapid developments have revealed certain technical issues such as module failures,Line to Line(LL) faults, Line to ground(LG) faults, cable faults etc., that if unresolved, may hamper economic and environmental benefits of PV technology. The proposed fault detection scheme is based on a pattern recognition approach that employs a multi-resolution signal decomposition technique to extract the necessary features, based on which a fuzzy inference system(FIS) determines if a fault has occurred. In this paper MSD is used to extract the necessary features, and an FIS, that based on the generated features, determines if a fault has happened has been discussed.

KEYWORDS: PV system Faults, Fault detection, Ground fault, Line to line fault,Multi-resolution signal decomposition MSD.

I. INTRODUCTION

Due to the rapid deployment of renewable energy plants, such as the (PV) systems, especially the large-scale grid-connected PV systems for the generation of electricity, the development of effective and economical techniques to ensure their long-lasting reliable performance becomes of paramount importance. Typical faults in a PV system include the irradiance change, ground faults, line-line faults, arc faults and so on. The occurrence of faults can result in energy loss, system shutdown or even safety concerns. Therefore, efficient online monitoring and quick fault detection become an essential component of the PV system performance control.[1] Fault detection strategies designed for PV arrays must be able to diagnose and clear such faults to enhance the reliability and efficiency of solar power plants. The next section presents a brief description of the problem and a review of the existing fault detection methods in the technical literature. This paper then proposes a fault detection scheme for PV arrays based on multi-resolution signal decomposition (MSD) and fuzzy inference systems (FIS).

II.PV ARRAY CONFIGURATION

Fig. 1 illustrates one of the most widely used configurations of a grid-connected PV system [3], [4], which consists of the PV array, a DC/DC converter and a centralized inverter. The PV array consists of multiple PV panels connected in series in a string, to provide the necessary voltage level, and multiple strings in parallel, to achieve the required output power [5].Output power characteristics of PV arrays as a function of output voltage, for different irradiance levels. The output power increases until the output voltage reaches the maximum power point (MPP_i), where the voltage of the arrays is V_{MPPi}, and decreases thereafter. This curvechanges as irradiance level changes, e.g., due to clouds passing over. Therefore, for PV systems, maximum power point tracking (MPPT) methods are employed to maximize the PV array output power at different irradiance levels. Typically, the MPPT algorithm is implemented by the DC/DC converter by maintaining the PV output voltage at V_{MPPi}. The inverter controls its DC-link voltage to track the reference $V_{dc,ref}$(Fig. 1), forcing the output AC voltage of the inverter to match the grid voltage level. In addition, the output reactive power is also controlled by the inverter.[2]

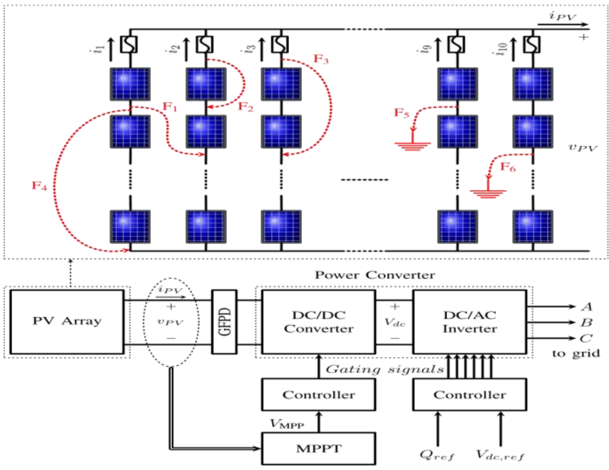

Fig. 1. A typical PV array configuration (with 10×10 solar panels) [2]

III. THE PROPOSED FAULT DETECTION ALGORITHM

The proposed fault detection method is based on a pattern recognition technique using a signal processing approach. Fault detection based on signal processing has been widely used in power systems [6], [7]. MSD is used to extract the necessary features, and an FIS, that based on the generatedfeatures, determines if a fault has happened. MSD is based on the wavelet transformation and uses a series of highand low-pass filters successively to extract the low-frequency components (approximation, *A*), and the high-frequency components (details, *D*) of the signal [8], [9]. Discrete wavelet transformation is typically used with digital signal processing platforms.

FIS is a fuzzy-logic-based decision making system. The inputs, or feature spaces in the case of this paper, are first fuzzified by linguistic descriptions and the associated membership functions. These fuzzified outputs are then aggregated based on fuzzy rules and eventually defuzzified, i.e., the output will be a single scalar [10], [11]. Based on the magnitude of this output, the occurrence and type of the fault are determined. This algorithm is designed focusing on detecting LL and LG faults, which are major failures that result in output losses in a PV system [12]. Other schemes might be employed in parallel for detecting other types of faults. The proposed process is the result of numerous simulation studies and extensive signal analyses and is described below.

A. FEATURE EXTRACTION

1) Features 1 and 2 (f_1 and f_2): In the proposed method, to make the scheme scalable, $i_{PV}$and $v_{PV}$are measured and normalized by the short-circuit current and the open-circuit voltage of the PV array under STC (short-circuit current and open-circuit voltage of a PV panel are usually provided in the datasheets by manufacturers), and are denoted by $i^n_{PV}(t)$ and $v^n_{PV}(t)$, respectively. Then, the following two signals are defined:

$$y(t) = -\frac{i^n_{pv}(t)}{v^n_{pv}(t)} \quad (1)$$

$$y(t) = \frac{di^n_{pv}(t)}{dv^n_{pv}(t)} \quad (2)$$

where$di^n_{PV}(t)$ and $dv^n_{PV}(t)$ represent the difference between two successive samples of $i^n_{PV}(t)$ and $v^n_{PV}(t)$, respectively. $y(t)$ and $y(t)$ are then decomposed into 6-level details $D_{y(t)}(1)$,..., $D_{y(t)}(6)$ and $D_{y(t)}(1)$,..., $D_{y(t)}(6)$ At the moment of fault inception, amplitudes of the details of $y(t)$ and $y(t)$ increase significantly. To differentiate fault and normal cases, the details of $y(t)$ and $y(t)$ are used to obtain s_1 and s_2, where

$$s_1 = \sum_{i=1}^{6} \left[D_{y(t)}(i) \right]^2 \quad (3)$$

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 7.122|

|| Volume 9, Issue 5, May 2020 ||

$$s_2 = \sum_{i=1}^{6} \left[D_{y'(t)}(i) \right]^2 \tag{4}$$

Fig. 4(a) shows that during faults, s_1 and s_2 both have a higher power content. To extract f_1 and f_2 two successive moving windows, with a length of L samples, are formed .The features are defined as the sum of these samples in the leading window divided by that of the lagging window, which is mathematically expressed as

$$f_j = \frac{\sum_{i=k-L+1}^{k} s_j[i]}{\sum_{i=k-2L}^{k} s_j[i]}, \; j = 1,2 \tag{5}$$

where$k$ is the current sample.

2) *Feature 3 (f_3):* The third feature used in the proposed algorithm is obtained from the normalized equivalent conductance of the PV array, which is calculated based on $i^n_{PV}$and v^n_{PV}, and the real-time irradiance, *IRR*. Due to the nonlinFear characteristics of PV arrays and the fast reaction of MPPT, when the irradiance increases, the operational voltage does not change significantly, while the output current of the array increases proportionally to the irradiance level. Therefore, the normalized equivalent conductance, which is defined by $i^n_{PV}/v^n_{PV}$is proportional to the irradiance level [13]. In order to make the detecting algorithm more accurate and to eliminate the impact of irradiance, $i^n_{PV}/v^n_{PV}$is normalized once more by dividing the original value by the real-time irradiance level, *IRR*W/m^2, to obtain f_3:

3)

$$f_3 = \frac{i^n_{pv}}{v^n_{pv} X I_{RR}} \tag{6}$$

As shown in Fig. 5, subsequent to the fault, f_3 manifests a temporary dip to zero, which provides a distinctive feature to differentiate fault and normal cases.

4) *Feature 4 (f_4):* The forth feature used in the proposed algorithm is a flag that signals the change of open-circuit voltage of the PV array. This feature is especially helpful for faults with large mismatch percentages. In this case, as described before, during the transient state, the PV array will have an output current of zero with a new lower open-circuit voltage. By detecting this, f_4 is defined as

5)

$$f_4 = \begin{cases} 1 \;\; if \;\; v^{oc}_{fault} \;\; is \;\; \det ected \\ 0 \;\; if \;\; v^{oc}_{fault} \;\; is \; not \;\; \det ected \end{cases} \tag{7}$$

It should be noted that while $f_4 = 1$ is a definite fault indicator, $f_4 = 0$ is inconclusive, and decision making in this case mainly relies on the other features.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 7.122|

|| Volume 9, Issue 5, May 2020 ||

Table no 1 Fuzzy Rules

Event	Feature			
	f1	f2	f3	f4
LL	H	VH	L	0
	H	H	----	1
LG	H	VH	----	----
	M	VH	H	----
	--	VH	VH	----
Normal	----	VH	H	0
	----	VH	M	0

IV. FAULT DETECTION PROCEDURE

FIS is employed for the decision making stage of the proposed fault detection method. Under extreme cases, such as faults that occur in a low irradiance condition or with high impedance, the boundaries of the feature levels between fault and normal cases cannot be precisely defined, which would greatly lower the accuracy of conventional crisp classifiers with binary outputs (1 or 0). FIS is an ideal platform for dealing classification problems with noisy, imprecise or incomplete information [14]. It provides a nonlinear input-output mapping method that converts a vector, which consists of features, into a scalar.

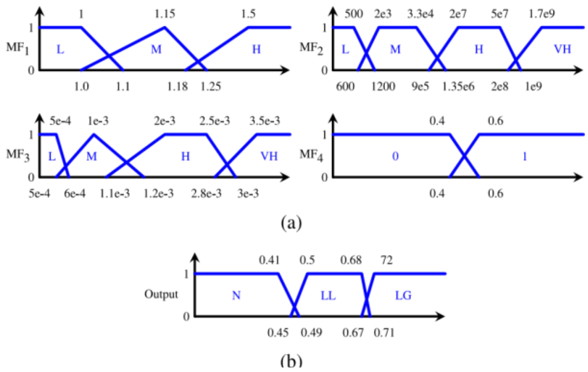

Fig. 2. (a) FIS membership functions for the extracted features, (b) output membership function

Membership functions are illustrated in Fig. 2 (a), and the output fuzzy sets are shown in Fig. 6 (b). Fuzzified results are then fed to the Mamdani FIS engine that determines the results of the detection according to the rule base, which is obtainedby analyzing the characteristics of the extracted features under different fault conditions, as listed in Table I, where "-" means "do not care". By using "if-then" expressions, the rule base describes the reasoning relations between the input fuzzified feature space and the output fuzzy sets. The aggregation process then combines the output of each rule into a single fuzzy set. Using the centroid method, which is widely used in FIS applications, the outputs of aggregation are then defuzzified into crisp results within 0 and 1, where the interval (0, 0.4] represents the case "Normal", (0.4, 0.7] represents "LL fault", and (0.7, 1) represents "LG fault".

V. CONCLUSION

In this paper methodology for faults that usually occur on the DC side of PV arrays and the challenges of detecting such faults.Fault detection scheme for PV arrays based on multi-resolution signal decomposition (MSD) and fuzzy inference systems (FIS).MSD is based on the wavelet transformation and uses a series of high and low-pass filters successively to extract the low-frequency components and the high-frequency components of the signal, Discrete wavelet transformation is typically used with digital signal processing platforms.FIS is a fuzzy-logic-based decision making system. The inputs, or feature spaces in the case of this paper, are first fuzzified by linguistic descriptions and the associated membership functions. These fuzzified outputs are then aggregated based on fuzzy rules and eventually defuzzified., i.e. the output will be a single scalar.

REFERENCES

1 Leian Chen, Shang Li, And Xiaodong Wang" Quickest Fault Detection In Photovoltaic Systems" IEEE Transactions On Smart Grid, Vol. 9, No. 3, May 2018

2 Zhehan Yi, Amir H. Etemadi "Fault Detection for Photovoltaic Systems Based on Multi-Resolution Signal Decomposition and Fuzzy Inference Systems" IEEE transactions on smart grid, vol. 8, no. 3, may 2017

3 E. Romero-Cadaval, B. Francois, M. Malinowski, and Q.-C. Zhong, "Grid-connected photovoltaic plants: An alternative energy source, replacing conventional sources," *IEEE Ind. Electron. Mag.*,vol.9,no.1, pp.18–32,Mar. 2015.

4 H. Abu- Rub, M. Malinowski, and K. Al-Haddad, "Power electronics for renewable energy systems, transportation, and industrial applications,"in*Photovoltaic Energy Conversion System*.Chichester,U.K.:Wiley,2014.

5 S.B.Kjaer,J.K.Pedersen,andF.Blaabjerg,"Areviewofsingle-phase grid-connected inverters for photovoltaic modules," *IEEE Trans. Ind. Appl.*,vol. 41,no.5,pp.1292–1306,Sep./Oct. 2005.

6 A. H. Etemadi and M. Sanaye-Pasand, "High-impedance fault detection using multi-resolution signal decomposition and adaptive neural fuzzy inference system," *IET Gener. Transm. Distrib.*, vol. 2, no. 1, pp.110–118, Jan.2008.

7 F.B.Costa,"Fault-inducedtransientdetectionbasedonreal-timeanalysisofthewaveletcoefficientenergy," *IEEE Trans. Power Del.*,vol.29, no.1,pp.140–153, Feb.2014.

8 J.Barros,R.I.Diego,andM.deApraiz,"Applicationsofwavelettransform for analysis of harmonic distortion in power systems: A review," *IEEE Trans. Instrum. Meas.*vol.61,no.10,pp.2604–2611,Oct.2012.

9 O.RioulandM.Vetterli,"Waveletsandsignalprocessing," *IEEE Signal Process. Mag.*,vol.8,no.4,pp.14–38, Oct. 1991.

10 P. Hajek and V. Olej, "Defuzzification methods in intuitionistic fuzzy inference systems of Takagi-Sugeno type: The case of corporate bankruptcy prediction," in *Proc. 11th Int. Conf. Fuzzy Syst. Knowl. Discov. (FSKD)*,Xiamen, China,Aug.2014,pp.232–236.

11 D.Gayme,S.Menon,C.Ball,D.Mukavetz,andE.Nwadiogbu,"Fault detection and diagnosis in turbine engines using fuzzy logic," in *Proc. 22nd Int. Conf. North Amer. Fuzzy Inf. Process. Soc. (NAFIPS)*,Chicago, IL,USA, Jul. 2003,pp.341–346.

12 M. K. Alam, F. Khan, J. Johnson, and J. Flicker, "A comprehensive review of catastrophic faults in PV arrays: Types, detection, and mitigation techniques," *IEEE J. Photovolt.*, vol. 5, no. 3, pp.982–997, May 2015

13 M.S.Salim,J.M.Najim,andS.M.Salih,"Practicalevaluationofsolar irradianceeffectonPVperformance," Energy Sci. Technol.,vol.6,no.2, pp.36–40,2013.

14 O. Cordón, M. J. del Jesus, and F. Herrera, "A proposal on reasoning methods in fuzzy rule-based classification systems," *Int. J. Approx. Reason.*,vol. 20,no.1,pp.21–45,1999.