



University of HUDDERSFIELD

University of Huddersfield Repository

Dhimish, Mahmoud, Holmes, Violeta, Mehrdadi, Bruce, Dales, Mark and Mather, Peter

Photovoltaic fault detection algorithm based on theoretical curves modelling and fuzzy classification system

Original Citation

Dhimish, Mahmoud, Holmes, Violeta, Mehrdadi, Bruce, Dales, Mark and Mather, Peter (2017) Photovoltaic fault detection algorithm based on theoretical curves modelling and fuzzy classification system. *Energy*, 140 (1). pp. 276-290. ISSN 0360-5442

This version is available at <http://eprints.hud.ac.uk/id/eprint/33464/>

The University Repository is a digital collection of the research output of the University, available on Open Access. Copyright and Moral Rights for the items on this site are retained by the individual author and/or other copyright owners. Users may access full items free of charge; copies of full text items generally can be reproduced, displayed or performed and given to third parties in any format or medium for personal research or study, educational or not-for-profit purposes without prior permission or charge, provided:

- The authors, title and full bibliographic details is credited in any copy;
- A hyperlink and/or URL is included for the original metadata page; and
- The content is not changed in any way.

For more information, including our policy and submission procedure, please contact the Repository Team at: E.mailbox@hud.ac.uk.

<http://eprints.hud.ac.uk/>

Photovoltaic Fault Detection Algorithm Based on Theoretical Curves Modelling and Fuzzy Classification System

Mahmoud Dhimish, Violeta Holmes, Bruce Mehrdadi, Mark Dales, Peter Mather

Department of Computing and Engineering, University of Huddersfield, Huddersfield, United Kingdom

Abstract

This work proposes a fault detection algorithm based on the analysis of the theoretical curves which describe the behaviour of an existing grid-connected photovoltaic (GCPV) plant. For a given set of working conditions, solar irradiance and PV modules' temperature, a number of attributes such as voltage ratio (VR) and power ratio (PR) are simulated using virtual instrumentation (VI) LabVIEW software. Furthermore, a third order polynomial function is used to generate two detection limits (high and low limit) for the VR and PR ratios obtained using LabVIEW simulation tool.

The high and low detection limits are compared with real-time long-term data measurements from a 1.1kWp GCPV system installed at the University of Huddersfield, United Kingdom. Furthermore, samples that lies out of the detection limits are processed by a fuzzy logic classification system which consists of two inputs (VR and PR) and one output membership function.

The obtained results show that the fault detection algorithm can accurately detect different faults occurring in the PV system. The maximum detection accuracy of the algorithm before considering the fuzzy logic system is equal to 95.27%, however, the fault detection accuracy is increased up to a minimum value of 98.8% after considering the fuzzy logic system.

Keywords: *Photovoltaic Faults, Fault Detection, Fuzzy Logic, PV Hot Spot Detection, LabVIEW.*

1. INTRODUCTION

Despite the fact that Grid-Connected Photo-Voltaic (GCPV) systems have no moving parts, and therefore usually require low maintenance, they are still subject to various failures and faults associated with the PV arrays, batteries, power conditioning units, utility interconnections and wiring [1 and 2]. It is especially difficult to shut down PV modules completely during faulty conditions related to PV arrays (DC side) [3]. It is therefore required to create algorithms to facilitate the detection of possible faults occurring in GCPV systems [4].

There are existing fault detection techniques for use in GCPV plants. Some use satellite data for fault prediction as presented by M. Tadj et al [5], this approach is based on satellite image for estimating solar radiation data and predicting faults occurring in the DC side of the GCPV plant. However, some algorithms do not require any climate data, such as solar irradiance and modules' temperature, but instead use earth capacitance measurements in a technique established by Taka-Shima et al [6].

37 Some fault detection methods use an automatic supervision based on the analysis of the output power for
38 the GCPV system. A. Chouder & S. Silvestre et al [7], presented a new automatic supervision and fault
39 detection technique which use a standard deviation method ($\pm 2\sigma$) for detecting various faults in PV
40 systems such as faulty modules in a PV string and faulty maximum power point tracking (MPPT) units.
41 However, S. Silvestre et al [8] presented a new fault detection algorithm based on the evaluation of the
42 current and output voltage indicators for analyzing the type of fault occurred in PV systems installations.

43 A photovoltaic fault detection technique based on artificial neural network (ANN) is proposed by W.
44 Chine et al [9]. The technique is based on the analysis of the voltage, power and the number of peaks in
45 the current-voltage (I-V) curve characteristics. However, [10 and 11], proposed a fault detection algorithm
46 which allows the detection of seven different fault modes on the DC-side of the GCPV system. The
47 algorithm uses the t-test statistical analysis technique for identifying the presence of systems fault
48 conditions.

49 Other fault detection algorithms focus on faults occurring on the AC-side of GCPV systems, as proposed
50 by R. Platon et al [12]. The approach uses $\pm 3\sigma$ statistical analysis technique for identifying the faulty
51 conditions in the DC/AC inverter units. Moreover, hot-spot detection in PV substrings using the AC
52 parameters characterization was developed by [13]. The hot-spot detection method can be further used
53 and integrated with DC/DC power converters that operates at the subpanel level. Nevertheless, the hot
54 spot mitigation due to the impact of micro cracks is described in [14].

55 A comprehensive review of the faults, trends and challenges of the grid-connected PV systems is
56 explained by M. Obi & R. Bass, M. Alam et al and A. khamis et al [15-17].

57 Currently, fuzzy logic systems widely used with GCPV plants. R. Boukenoui et al [18] proposed a new
58 intelligent MPPT method for standalone PV system operating under fast transient variations based on
59 fuzzy logic controller (FLC) with scanning and storing algorithm. Furthermore, [19] presents an adaptive
60 FLC design technique for PV inverters using differential search algorithm.

61 B. Abdesslam et al [20] proposed a neuro-fuzzy classifier for fault detection and classification in PV
62 systems, the approach is suitable for detection faulty conditions such as detected bypass diodes and
63 blocking diodes faults. Furthermore, [21] proposed a cascaded fuzzy logic based arc fault detection in PV
64 modules using an analog-digital converter (ADC) contained in micro controllers.

65 Since many fault detection algorithms use statistical analysis techniques such as [7, 10, 11 and 12], this
66 work proposes a fault detection algorithm that does not depend on any statistical approaches in order to
67 classify faulty conditions in PV systems. Furthermore, some existing fault detection techniques such as
68 [22 and 23] use a complex power circuit design to facilitate the fault detection in GCPV plants. However,
69 the proposed fault detection algorithm depends only on the variations of the voltage and the power, which
70 makes the algorithm simple to construct and reused in wide range of GCPV plants.

71 In this work, we present the development of a fault detection algorithm which allows the detection of
72 possible faults occurring on the DC-side of GCPV systems. The algorithm is based on the analysis of
73 theoretical voltage ratio (VR) and power ratio (PR) for the examined GCPV system. High and low
74 detection limits are generated using 3rd order polynomial functions which are obtained using the simulated
75 data of the VR and PR ratios. Subsequently, if the theoretical curves are not capable to detect the type of
76 the fault occurred in the GCPV system, a fuzzy logic classifier system is designed to facilitate the fault
77 type detecting for the examined PV system. A software tool is designed using Virtual Instrumentation
78 (VI) LabVIEW software to automatically display and monitor the possible faults occurring within the

79 GCPV plant. A LabVIEW VI is also used to log the measured power, voltage and current data for the
80 entire GCPV system, more details regarding the VI LabVIEW structure is presented in [24].

81 The main contribution of this work is the theoretical implementation of a simple, fast and reliable GCPV
82 fault detection algorithm. The algorithm does not depend on any statistical techniques which makes it
83 easier to facilitate and detect faults based on theoretical curves analysis and fuzzy logic classification
84 system. In practice, the proposed fault detection algorithm is capable of localizing and identifying faults
85 occurring on the DC-side of GCPV systems. The types of fault which can be detected are based on the
86 size of the GCPV plant, which will be discussed in the next section. The algorithm is based on a six layer
87 method working sequentially as shown in Fig. 1.

88 This paper is organized as follows: Section 2 describes the methodology used which includes the PV
89 theoretical power curve modelling and the proposed fault detection algorithm, while section 3 explains
90 the validation and a brief discussion of the proposed fault detection algorithm. Finally, section 4 describes
91 the conclusion and future work.

92 2. METHODOLOGY

93 2.1 Photovoltaic Theoretical Power Curve Modelling

94 The DC side of the GCPV system is modelled using the 5-parameter model. The voltage and current
95 characteristics of the PV module can be obtained using the single diode model [25] as shown in (1).

$$96 \quad I = I_{ph} - I_o \left(e^{\frac{V+IR_s}{nsV_t}} - 1 \right) - \left(\frac{V+IR_s}{R_{sh}} \right) \quad (1)$$

97 Where I_{ph} is the photo-generated current at STC, I_o is the dark saturation current at STC, R_s is the
98 module series resistance, R_{sh} is the panel parallel resistance, ns is the number of series cells in the PV
99 module and V_t is the thermal voltage and it can be defined based on (2).

$$100 \quad V_t = \frac{AKT}{q} \quad (2)$$

101 Where A the ideal diode factor, k is Boltzmann's constant and q is the charge of the electron.

102 The five parameter model is determined by solving the transcendental equation (1) using Newton-
103 Raphson algorithm [26] based only on the datasheet of the available parameters for the examined PV
104 module that was used in this work as shown in Table 1. The power produced by the PV module in Watts
105 can be easily calculated along with the current (I) and voltage (V) that is generated by equation (1),
106 therefore:

$$107 \quad P_{theoretical} = I \times V \quad (3)$$

108 The Power-Voltage (P-V) curve analysis of the tested PV module is shown in Fig. 2. The maximum
109 power and voltage for each irradiance level under the same temperature value can be expressed by the P-
110 V curves.

111 The purpose of using the analysis for the P-V curves, is to generate the expected output power of the
112 examined PV module, therefore, it can be used to predict the error between the measured PV data and the
113 theoretical power and voltage performance.

114 The proposed PV fault detection algorithm can detect various fault in the GCPV plants such as:

- 115 • Partial shading (PS) condition effects the GCPV system
- 116 • 1 Faulty PV module and PS
- 117 • 2 Faulty PV modules and PS
- 118 • 3 Faulty PV modules and PS
- 119 ○
- 120 ○
- 121 ○
- 122 • (n-1) Faulty PV modules and PS, where n is the total number of PV modules in the GCPV
- 123 installation.

124 In this paper, faulty PV module corresponds to a short-circuited PV module. Moreover, A briefly
125 explanation of the proposed fault detection algorithm is presented in section 2.2 and section 2.3.

2.2 Proposed Fault Detection Algorithm: Theoretical Curves Modelling

126 The main objective of the fault detection algorithm is to detect and determine when and where a fault has
127 occurred in the GCPV plant.

128 The first layer of the fault detection algorithm passes the measured irradiance level and photovoltaic
129 module's temperature to VI LabVIEW software in order to generate the expected theoretical P-V curve as
130 described previously in section 2.1. This layer is shown in Fig. 3.

131 To determine if a fault has occurred in a GCPV system, two ratios have been identified. The theoretical
132 Power ratio (PR) and the theoretical voltage ratio (VR) have been used to categorize the region of the
133 fault. It is necessary to use both ratios because:

- 134 1. Both ratios are changeable during faulty conditions in the PV systems
- 135 2. When the power ratio is equal to zero, the voltage ratio can still have a value regarding the
136 voltage open circuit of the PV modules

137 The power and voltage ratios are given by the following expressions:

$$138 \quad PR = \frac{P_{G,T}}{P_{G,T} - nP_0} \quad (4)$$

$$139 \quad VR = \frac{V_{G,T}}{V_{G,T} - nV_0} \quad (5)$$

140 Where $P_{G,T}$ is the theoretical output power generated by the GCPV system at specific G (irradiance) and
141 T (module temperature) values, n is the number of PV modules, $V_{G,T}$ is the theoretical output voltage
142 generated by the GCPV system at specific G (irradiance) and T (module temperature) values and both
143 V_0 , P_0 are the maximum operating voltage and power at STC (G: 1000 W/m², T: 25 °C) respectively.

144 The number of faulty PV modules can be expressed by the number of PV modules in the examined PV
 145 string. For example, if the PV string comprises 5 photovoltaic modules connected in series, then, $n = 5$.

146 In reality, the internal sensors used to measure the voltage and current for a GCPV system have
 147 efficiencies of less than 100%. This tolerance rate must therefore be considered in the PR and VR ratio
 148 calculations. For this instance, the PR and VR values are divided into two limits:

- 149 1. High limit: where the maximum operating efficiency of the sensors is applied, therefore, the high
 150 limit for both PR and VR ratios is expressed by (4) and (5).
- 151 2. Low limit: where the efficiency (tolerance rate) of the sensors is applied. Both limits can be
 152 expressed by the following formulas:

$$153 \quad \text{PR Low limit} = \frac{P_{G,T}}{(P_{G,T} - nP_0)\eta_{\text{sensor}}} \quad (6)$$

$$154 \quad \text{VR Low limit} = \frac{V_{G,T}}{(V_{G,T} - nV_0)\eta_{\text{sensor}1}} \quad (7)$$

155 Where η_{sensor} is the efficiency of both the voltage and current sensor, while, $\eta_{\text{sensor}1}$ is the efficiency of
 156 the voltage sensor:

$$157 \quad \eta_{\text{sensor}} = \eta_{\text{sensor}1}(\text{Voltage Sensor efficiency}) + \eta_{\text{sensor}2}(\text{Current Sensor efficiency}) \quad (8)$$

158 The PR and VR high and low detection limits are evaluated for the examined GCPV system using various
 159 irradiance levels, as described in the third layer in Fig. 3. For this particular layer, the analysis of the PR
 160 vs. VR curves can be seen in the example shown next to layer 5, Fig. 3. This example shows the high and
 161 low detection limit for two case scenarios: one faulty PV module and two faulty PV modules, where both
 162 curves are created using 3rd order polynomial functions. The purpose of the 3rd order polynomial curves is
 163 to generate a regression function which describes the performance of the curves which are created by the
 164 theoretical points using VI LabVIEW software.

165 The overall GCPV fault detecting algorithm is explained in Fig. 3. Layer 5, shows the measured data vs.
 166 the 3rd order polynomial curves generated by VI LabVIEW software. The measured PR and measured VR
 167 can be evaluated using the following formula:

$$168 \quad \text{Measured PR vs. Measured VR} = \frac{P_{G,T}}{P_{\text{MEASURED}}} \text{ vs. } \frac{V_{G,T}}{V_{\text{MEASURED}}} \quad (9)$$

169 In case of which the measured PR vs. VR is out of range:

$$170 \quad F \text{ High limit} < \text{Measured PR vs. Measured VR} < F \text{ low limit}$$

171 Therefore, the fault detection algorithm cannot identify the type of the fault that has occurred in the
 172 GCPV plant. However, it can predict two possible faulty conditions which might have occurred in the
 173 GCPV system. As shown in Fig. 3, layer 5 example. The measured data 2 indicates two possible faulty
 174 conditions:

- 175 1. Faulty PV module and PS effects on the GCPV system
- 176 2. Two faulty PV modules and PS effects on the GCPV system

177 Therefore, out of region samples is processed by a fuzzy logic classifier as shown in Fig 3, layer 6.

178 The difference between the proposed theoretical curve modelling with other similar approaches described
179 by [7, 8, 9 and 10] is that the algorithm contains the number of PV modules in the GCPV system, also the
180 approach is using 3rd order polynomial function which can be used to plot a regression function that
181 describes the behavior of the faulty region and the design of a fuzzy logic fault classification which is
182 described in the next section (section 2.3).

2.3 Proposed Fault Detection Algorithm: Fuzzy Logic Classifier

183 Nowadays, fuzzy logic systems became more in use with PV systems. A brief overview of the recent
184 publications on fuzzy logic system design is presented by L. Suganthi [27]. From the literature reviewed
185 previously in the introduction, currently, there are a lack of research in the field of fuzzy logic
186 classification systems which are used in examining faulty conditions in PV plants. Therefore, in this
187 paper, a fuzzy logic classifier is demonstrated and verified experimentally.

188 Fig. 4 describes the overall fuzzy logic classifier system design. The fuzzy logic system consists of two
189 inputs: voltage ratio (VR) and the power ratio (PR), denoted in Fig. 4 as (A) and (B) respectively. The
190 membership function for each input is divided into five fuzzy sets described as: PS (partial shading
191 condition), 1 (one faulty PV module), 2 (two faulty PV modules), 3 (three faulty PV modules) and 4 (four
192 faulty PV modules). The fuzzy interface applies the approach of Mamdani method (min-max) managed
193 by the fuzzy logic system rule, stage 2 of the fuzzy logic system. After the rules application, the output is
194 applied to classify the fault detection type occurred in the GCPV plant.

195 A brief calculation of each membership function for VR, PR and the fuzzy logic membership output
196 function is reported in Fig. 5. The membership functions are based on the mathematical calculation of the
197 examined GCPV plant used in this work. The examined GCPV system which is used to evaluate the
198 performance of the fault detection algorithm is demonstrated briefly in section 3.1: experimental setup.
199 Both fuzzy logic system inputs VR and PR are evaluated at the maximum power and voltage of the
200 GCPV system which are equal to 1100Wp and 143.5V. In addition, the mathematical calculations
201 includes the PS conditions which might affect the performance of the entire PV system.

202 The fuzzy logic system rule are based on: if, and statement. Each case scenario is presented after the
203 fuzzy logic system rule as shown in Fig. 5. However, the output membership function is divided into 5
204 sets: PS (0 - 0.2), faulty PV module (0.2 - 0.4), two faulty PV modules (0.4 - 0.6), three faulty PV
205 modules (0.6 - 0.8) and four faulty PV modules (0.8 - 1.0).

206 Furthermore, the output surface for the fuzzy logic classifier system is plotted and presented by a 3D
207 fitting curve shown in Fig. 6. Where the x-axis presents the PR, y-axis presents VR and the fault detection
208 output classification is on the z-axis.

209 In order to generalize the proposed fuzzy logic classification systems, it is required to input the values of
210 the voltage and the power to the fuzzy interface system, and then, the faulty region could be calculated
211 using the formulas (4 & 5) for the variations of the power and voltage respectively. Additionally, the
212 output detection membership function could be extended up to the value of the PV modules connected in
213 series in each PV string separately and this extension in the membership function can be evaluated within
214 the region of 0 to 1 as the following:

215
$$1 / \text{number of series PV modules in the PV string}$$

216 **3. GCPV Fault Detection Algorithm Validation**

217 In this section, the performance of the proposed fault detection algorithm is verified. For this purpose, the
218 acquired data for various days have been considered using 1.1 kWp GCPV plant. The time zone for all
219 measurements is GMT.

220 **3.1 Experimental Setup**

221 The PV system used in this work consists of a GCPV plant comprising 5 polycrystalline silicon PV
222 modules each with a nominal power of 220 Wp. The PV modules are connected in series. The PV string
223 is connected to a Maximum Power Point Tracker (MPPT) with an output efficiency of not less than 95%.
224 The DC current and voltage are measured using the internal sensors which are part of the FLEXmax
225 MPPT unit. A battery bank is used to store the energy produced by the PV plant.

226 A Vantage Pro monitoring unit is used to receive the Global solar irradiance measured by the Davis
227 weather station which includes a pyranometer. A Hub 4 communication manager is used to facilitate
228 acquisition of modules' temperature using the Davis external temperature sensor, and the electrical data
229 for each PV string. VI LabVIEW software is used to implement data logging and monitoring functions of
230 the GCPV system. Fig. 7 illustrates the overall system architecture of the GCPV plant.

231 The real-time measurements are taken by averaging 60 samples, gathered at a rate of 1Hz over a period of
232 one minute. Therefore, the obtained results for power, voltage and current are calculated at one minute
233 intervals.

234 The SMT6 (60) P solar module manufactured by Romag, has been used in this work. The electrical
235 characteristics of the solar module are shown in Table 1. The standard test condition (STC) for these solar
236 panels are: Solar Irradiance = 1000 W/m², Module Temperature = 25 °C.

237 The fault detection algorithm has been validated experimentally over a 5 day period. On each day a
238 different fault case scenario was perturbed as shown in Fig. 8:

- 239 1. Day1: Normal operation mode and PS effects on the GCPV plant (no fault occurred in any of the
240 tested PV modules),
241 2. Day2: One faulty PV module and PS effects on the GCPV plant
242 3. Day3: Two faulty PV modules and PS effects on the GCPV plant
243 4. Day4: Three faulty PV modules and PS effects on the GCPV plant
244 5. Day5: Four faulty PV modules and PS effects on the GCPV plant

245 In all cases, faulty PV module stands for an in active PV module which means that this particular PV
246 module has been disconnected (short circuit) from the entire examined PV plant.

247 In order to test the effectiveness of the proposed fault detection algorithm, the theoretical and the
248 measured output power for each case scenario was logged and compared using VI LabVIEW software.

249 **3.2 Evaluation of the Proposed Theoretical Curves Modelling**

250 In this section, the performance of the fault detection algorithm (theoretical curves modelling) is verified
251 using normal operation mode and partial shading effects the GCPV system. Fig. 9 describes the
252 theoretical simulation vs. real time long term data measurement.

253 In order to apply a partial shading condition to the GPCV modules an opaque paper object has been used.
 254 The partial shading was applied to all PV modules at the same rate. Partial shading condition is increased
 255 during the test. In case of overcast scenario affecting the PV modules, the performance of the entire
 256 system will remain with a consistent output power, therefore, the faults or PS conditions could be
 257 identified using the purposed algorithm.

258 Fig. 10(A) shows the entire measured data vs. theoretical detection limits which are discussed previously
 259 in section 2.2. As can be noticed, most of the measured data lies within the high and low theoretical
 260 detection limits which are created using 3rd order polynomial function. The high and low detection limit
 261 functions are also illustrated in the Fig 10(A).

262 PR and VR ratios for this particular test is shown in Fig 10(B). Since the PS condition applied to the
 263 GPCV system is increasing, therefore, both VR and PR ratios are increasing slightly during the test.
 264 Moreover, both ratios can be measured using (9). Fig. 10(B) shows the efficiency of the GPCV plant.
 265 The efficiency is evaluated using (10).

$$266 \quad \text{Efficiency} = \frac{\text{Measured Output Power}}{\text{Theoretical Power}} \quad (10)$$

267 From Fig. 10(B), the efficiency of the GPCV system decreased while increasing the PS applied to the PV
 268 system. The detection accuracy (DA) for the proposed theoretical curves modelling algorithm is
 269 calculated using (11).

$$270 \quad \text{Detection accuracy (DA)} = \frac{\text{Total Number of Samples} - \text{Out of Region Samples}}{\text{Total Number of Samples}} \quad (11)$$

271 Using (11), the proposed algorithm has a detection accuracy equals to:

$$272 \quad \text{Detection accuracy for the partial shading condtion} = \frac{720 - 37}{720} = 0.9486 = 94.86\%$$

273 In this test, the theoretical curves modelling fault detection algorithm shows a significant success for
 274 detecting partial shading conditions applied to the GPCV plant. The detection accuracy rate can be
 275 increased using a fuzzy logic classification system. Therefore, out of region samples (samples which are
 276 away from the high and low detection limits) are processed by the fuzzy logic system.

277 In this paper, the MPPT unit is used to locate and acquired the output power at the global maximum
 278 power point (GMPP), therefore, all local maximum power points (LMPP) are not considered in the fault
 279 detection algorithm. Fig. 11(A) illustrates one examined case scenario which shows the percentage of the
 280 partial shading on each examined PV module. The output P-V curve of the PV system is shown in Fig.
 281 11(B). As can be noticed, the MPPT unit locates all LMPP and GMPP, however, the output of the MPPT
 282 unit is at the GMPP.

283 In order to detect all LMPPs and the GMPP obtained by the MPPT unit, it is required to further
 284 investigate MPPT techniques which is not one of the targets of this manuscript.

285 **3.3 Evaluation of the Proposed Fuzzy Logic Classification System**

286 This test is created to confirm the ability of the fault detection algorithm to detect faulty PV modules
287 occurring in the GCPV plant using theoretical curves modelling algorithm and fuzzy logic classification
288 system. Four different case scenarios have been tested:

- 289 A. Faulty PV module with partial shading condition
- 290 B. Two faulty PV modules with partial shading condition
- 291 C. Three faulty PV modules with partial shading condition
- 292 D. Four faulty PV module and partial shading condition

293 Each case scenario is examined during a time period of a full day as shown Fig. 8 (Day 2, 3, 4 and 5),
294 where the total number of samples for each examined day are equal to 720 samples. Fig. 10 shows the
295 theoretical curve limits vs. real-time long-term measured data. 3rd order polynomial function of the
296 theoretical high and low limits is plotted, while the minimum determination factor (R) is equal to 99.59%.

297 As can be noticed, the measured data for each test is plotted and compared with the theoretical curve
298 limits. Most of the measured data among the 4 day test period lies within the high and low detection
299 limits of the theoretical curves. However, in each day, several out of region samples have been detected as
300 shown in Fig. 12.

301 The detection accuracy (DA) for each case scenario is calculated using (11) and reported in Table 2. The
302 minimum and maximum DA is equal to 94.03% and 95.27% respectively before considering the fuzzy
303 logic classification system.

304 For each test including the test illustrated in section 3.2, out of region samples have been processed by the
305 fuzzy logic classification system. Fig. 13 describes the performance of the fuzzy logic system during each
306 test:

- 307 • Test 1: PS, described in section 3.2
- 308 • Test 2: One faulty PV module and PS
- 309 • Test 3: Two faulty PV modules and PS
- 310 • Test 4: Three faulty PV modules and PS
- 311 • Test 5: Four faulty PV modules and PS

312 It is evident that most of the samples are categorized correctly by the fuzzy classifier. For example, before
313 considering the fuzzy logic system, the DA for test 2 is equal to 95.27% while the DA increased up to
314 99.03% after taking into account the fuzzy logic classification system. This result is due to the detection
315 of the out of region samples. The results for this test is shown in Fig. 13, only 7 out of 34 processed
316 samples are detected incorrectly, while 27 samples have been detected correctly within an output
317 membership function between 0.2 and 0.4.

318 Table 2 shows number of out of region samples and the detection accuracy (DA) for each test separately.
319 The DA rate is increased up to a minimum value equals to 98.8%.

320 In this section, the evaluation for the theoretical curves modelling algorithm and the fuzzy logic system
321 are discussed and briefly explained. From the obtained results, it is confirmed that the fault detection
322 algorithm proposed in this article is suitable for detecting faulty conditions in PV systems accurately.

3.4 Evaluation of the Proposed Method Using Hot Spot Detection in PV Modules

This test is created to confirm the ability of the fault detection algorithm to detect hot spots in PV modules. The test was evaluated using two different PV modules which contains different hot spots. As shows in Fig. 14(A), the first PV module contains only one hot spot in the top right side of the PV module, however, the second tested PV module contains two adjacent hot spots. The thermal images were taken from FLIR i7 camera, which has a thermal sensitivity equals to 0.1 °C (32.18 °F).

The first PV module temperature is measured at 55.4 °F, while the hot spot has been detected at 60.2 °F. Same results obtained for the second PV module where the PV module temperature is approximately equals to 56.8 °F. However, the hot spots detected in the PV module have a temperature equal to 59.6 °F and 62.3 °F.

The theoretical curves modelling was used to evaluate the difference between a healthy PV module (PV module without hot spots) with the examined PV modules shown in Fig. 14(A) at the same environmental conditions. The results of this test is shown in Fig. 14(B). As can be noticed, the detection limits of the theoretical curves does only contain most of the PV data obtained from the healthy PV module. Furthermore, the measured data of the first PV module which contains only one hot spot shows an increase in the values of the VR and PR. This results is due to the decrease in the value of the voltage obtained from the PV module. The voltage from this particular PV module is decreased approximately about 2V. Therefore the overall VR and PR is increased as can be demonstrated by (12).

The second PV module has more drop in the value of the voltage due to the detection of two hot spots. The drop in the value of the voltage is estimated at 3.7V. As shown in Fig. 14(B), the measured data obtained from the second PV module show a significant increase in the values of the VR and PR. Therefore, the measured data is apart from the detection limits obtained by the fault detection algorithm.

$$\uparrow VR = \frac{V_{G,T \text{ theoretical}}}{\downarrow V_{G,T \text{ measured}} - nV_0} \quad \& \quad \uparrow PR = \frac{P_{G,T \text{ theoretical}}}{\downarrow P_{G,T \text{ measured}} - nP_0} \quad (12)$$

3.5 Discussion

In order to test the effectiveness of the proposed fault detection algorithm presented in this paper, the results obtained have been compared with multiple fault detection approaches. The common combination between the proposed algorithm in this paper and the research demonstrated by [5, 8 and 28] is the VR and PR equations. However, the VR and PR equations presented in this work have a different parameters such as:

1. VR and PR equations contain the number of modules that are examined in the GCPV plant, which is presented using the variable: n.
2. Both equations contain the voltage and current sensors uncertainly (sensor efficiency rate), which makes the algorithm easier to use with different PV installations.
3. The detection limits (high and low) is a novel idea which has not been presented by any other research article related to fault detection algorithms in PV systems.

Moreover, by using VR and PR ratios it was evident that the algorithm can detect up to (n-1) faulty PV modules and PS effects the GCPV plant, where n is equal to the number of PV modules in the examined GCPV installation. In this paper, a MPPT unit which has an output power of one single point (mostly, it is

361 equal to the GMPP), therefore, the detection algorithm is not capable of detecting and categorizing ALL
362 LMPP, since the examined PV system is using a MPPT unit without any enhancement of the output
363 power using an advanced MPPT techniques.

364 In [7 and 12] statistical analysis technique based on standard deviation limits are used to detect possible
365 faults in the GCPV plant, however, the presented techniques cannot identify the type of the fault occurred
366 in the PV system, therefore, it is necessary to create a new mathematical calculations of the entire GCPV
367 plant. In this paper, it is presented that the algorithm is based on the analysis of the theoretical curves
368 modelling using 3rd order polynomial functions, without the use of any statistical analysis approaches.

369 Furthermore, [10] experimented another statistical analysis technique called t-test. This algorithm is
370 capable to detect multiple faults in PV systems, however, the ratios used to monitor the performance of
371 the PV system does not contain any parameter for the number of PV modules and the uncertainty in the
372 internal voltage and current sensors used.

373 There are variety of fuzzy logic control systems used with PV applications. Three-phase three-level grid
374 interactive inverter with fuzzy based maximum power point tracking controller is presented by [29].
375 Additionally, some of the fuzzy logic classification systems were used with hybrid green power systems
376 as reported by S. Safari et al [30]. Furthermore, M. Tadj et al [5] presented a fuzzy logic technique which
377 is used to estimate the solar radiation, the proposed technique contains three membership functions:
378 cloudy sky, partial cloudy sky and clear sky. However, in this paper, a new attempt for using fuzzy logic
379 classification system to detect possible faults occurring in the PV plans. The main purpose of the fuzzy
380 logic presented in this work is to detect out of region samples (samples that lies away from the high and
381 low theoretical detection limits), and therefore, to increase the detection accuracy of the fault detection
382 algorithm. The fuzzy logic system can be reused with other GCPV plants by changing the parameters
383 which are shown in Fig. 5.

384 Overall comparison between this work and the research presented by [4, 7 & 8] are listed in Table 3. As
385 can be seen that this work is the only research contains a mathematical modelling technique (3rd order
386 polynomial functions) presented previously in Layer 3, Fig 3. Also this paper demonstrates a new
387 statistical technique which can be used in the detection of faulty conditions in PV systems called t-test
388 statistical method. Comparing to [4, 7 and 8], the proposed fault detection algorithm presented in this
389 research can detects all type of faults listed in Table 3 including: partial shading conditions, faulty PV
390 modules and evaluating the hot spots in PV modules. However, the algorithm cannot distinguish between
391 the investigated partial shading conditions occurred in the PV modules and hot spots.

392 The fault detection algorithm presented in this work contains some advantages and disadvantages such as:

393 **Advantages:**

- 394 • The fault detection algorithm can be used with wide range of PV installation, since it depends on
395 the analysis of the power and the voltage ratios.
- 396 • Multiple faults can be detected accurately, the minimum and maximum detection accuracy
397 obtained by the algorithm are equal to 98.8% and 99.31% respectively.
- 398 • The efficiency of the voltage and current sensor has been taken into account in the mathematical
399 modelling for the proposed fault detection algorithm.
- 400 • The fuzzy logic classification system is easy to be reused in other PV systems since it depends
401 only on the analysis of the VR and PR.
- 402 • Hot spot detection can also be evaluated using the proposed theoretical curves modelling.

403 **Disadvantages:**

- 404
- The algorithm depends on the voltage and the power ratios of the GCPV systems. Therefore, the accuracy of the algorithm depends on the instrumentation used in the PV plants.
 - The algorithm is not capable of detecting faults occurring in the bypass diodes, which are commonly used nowadays with PV systems. This problem in GCPV plants has been investigated by W. Chine [9].
 - The fault detection algorithm cannot detect any fault arising in the DC/AC inverter units which are commonly used with GCPV systems. This type of fault has been reported by R. Platon et al [12], G. Bayrak [23] and F. Deng et al [31].
- 405
406
407
408
409
410
411

412 **4. Conclusion**

413 In this work, a new GCPV fault detection algorithm is proposed. The developed fault detection algorithm
414 is capable of detecting faulty PV modules and partial shading conditions which affect GCPV systems.
415 The detection algorithm has been tested using 1.1kWp GCPV system installed at Huddersfield University,
416 United Kingdom.

417 The fault detection algorithm consist of six layers working in series. The first layer contains the input
418 parameters of the sun irradiance and PV modules' temperature, while the second layer generates the
419 GCPV theoretical performance analysis using Virtual Instrumentation (VI) LabVIEW software. Layer 3
420 identifies the power and voltage ratios, subsequently creates a high and low detection limits which will be
421 used in Layer 4 to apply the 3rd order polynomial regression model on the top of the PR and VR ratios.
422 The fifth layer consists of two parts: the input parameters of the examined GCPV systems and the 3rd
423 order polynomial detection limits. If the measured voltage ratio vs. measured power ratio lies away from
424 the detection limits, the samples will be processed by the last layer which contains the fuzzy logic
425 classification system.

426 The novel contribution of this research is that the fault detection algorithm depends on the variations of
427 the voltage and the power of the GCPV plant. Additionally, the PR and VR equations contains the
428 number of examined modules and the uncertainly of the voltage and current sensors used. Also, there are
429 a few fuzzy logic classification systems which are used with PV fault detection algorithms, therefore, this
430 research introduced a simple, reliable and quick fuzzy logic classification system which can be reused
431 with various GCPV plants. Finally, the PV theoretical curves modelling can be used to evaluate PV
432 modules which contain hot spots.

433 The results indicate that the fault detection algorithm is detecting most of the measured data within the
434 theoretical limits created using 3rd order polynomial functions. Furthermore, the maximum detection
435 accuracy of the algorithm before considering the fuzzy logic system is equal to 95.27%, however, the
436 fault detection accuracy is increased up to a minimum value of 98.8% after considering the fuzzy logic
437 system.

438 In future, it is intended to implement the proposed fault detection technique on a low cost microcontroller
439 based system. The system's fault detection capabilities will be enhanced further by using artificial
440 intelligence machine learning technique to predict possible faults occurring in the GCPV system using
441 artificial neural networks (ANN).

442 **5. Acknowledgment**

443 The authors would like to acknowledge the financial support to the University of Huddersfield, School of
444 Computing and Engineering.

445 **References**

- 446 [1] Bortolini, M., Gamberi, M., & Graziani, A. (2014). Technical and economic design of photovoltaic and
447 battery energy storage system. *Energy Conversion and Management*, 86, 81-92.
- 448 [2] Dhimish, M., Holmes, V., Mehrdadi, B., Dales, M., Chong, B., & Zhang, L. (2017). Seven indicators
449 variations for multiple PV array configurations under partial shading and faulty PV conditions. *Renewable*
450 *Energy*.
- 451 [3] Kadri, R., Andrei, H., Gaubert, J. P., Ivanovici, T., Champenois, G., & Andrei, P. (2012). Modeling of the
452 photovoltaic cell circuit parameters for optimum connection model and real-time emulator with partial
453 shadow conditions. *Energy*, 42(1), 57-67.
- 454 [4] Dhimish, M., Holmes, V., Mehrdadi, B., & Dales, M. (2017). Diagnostic method for photovoltaic systems
455 based on six layer detection algorithm. *Electric Power Systems Research*, 151, 26-39.
- 456 [5] Tadj, M., Benmouiza, K., Cheknane, A., & Silvestre, S. (2014). Improving the performance of PV systems
457 by faults detection using GISTEL approach. *Energy conversion and management*, 80, 298-304.
- 458 [6] Takashima, T., Yamaguchi, J., Otani, K., Oozeki, T., Kato, K., & Ishida, M. (2009). Experimental studies
459 of fault location in PV module strings. *Solar Energy Materials and Solar Cells*, 93(6), 1079-1082.
- 460 [7] Chouder, A., & Silvestre, S. (2010). Automatic supervision and fault detection of PV systems based on
461 power losses analysis. *Energy Conversion and Management*, 51(10), 1929-1937.
- 462 [8] Silvestre, S., Kichou, S., Chouder, A., Nofuentes, G., & Karatepe, E. (2015). Analysis of current and
463 voltage indicators in grid connected PV (photovoltaic) systems working in faulty and partial shading
464 conditions. *Energy*, 86, 42-50.
- 465 [9] Chine, W., Mellit, A., Lughy, V., Malek, A., Sulligoi, G., & Pavan, A. M. (2016). A novel fault diagnosis
466 technique for photovoltaic systems based on artificial neural networks. *Renewable Energy*, 90, 501-512.
- 467 [10] Dhimish, M., & Holmes, V. (2016). Fault detection algorithm for grid-connected photovoltaic plants. *Solar*
468 *Energy*, 137, 236-245.
- 469 [11] Dhimish, M., Holmes, V., Mehrdadi, B., & Dales, M. (2017). Multi-Layer Photovoltaic Fault Detection
470 Algorithm. *High Voltage*.
- 471 [12] Platon, R., Martel, J., Woodruff, N., & Chau, T. Y. (2015). Online Fault Detection in PV Systems. *IEEE*
472 *Transactions on Sustainable Energy*, 6(4), 1200-1207.
- 473 [13] Kim, K. A., Seo, G. S., Cho, B. H., & Krein, P. T. (2016). Photovoltaic Hot-Spot Detection for Solar Panel
474 Substrings Using AC Parameter Characterization. *IEEE Transactions on Power Electronics*, 31(2), 1121-
475 1130.
- 476 [14] Dhimish, M., Holmes, V., Mehrdadi, B., & Dales, M. (2017). The Impact of Cracks on Photovoltaic Power
477 Performance. *Journal of Science: Advanced Materials and Devices*.
- 478 [15] Obi, M., & Bass, R. (2016). Trends and challenges of grid-connected photovoltaic systems—A
479 review. *Renewable and Sustainable Energy Reviews*, 58, 1082-1094.

- 480 [16] Alam, M. K., Khan, F., Johnson, J., & Flicker, J. (2015). A Comprehensive Review of Catastrophic Faults
481 in PV Arrays: Types, Detection, and Mitigation Techniques. *IEEE Journal of Photovoltaics*, 5(3), 982-997.
- 482 [17] Khamis, A., Shareef, H., Bizkevelci, E., & Khatib, T. (2013). A review of islanding detection techniques
483 for renewable distributed generation systems. *Renewable and sustainable energy reviews*, 28, 483-493.
- 484 [18] Boukenoui, R., Salhi, H., Bradai, R., & Mellit, A. (2016). A new intelligent MPPT method for stand-alone
485 photovoltaic systems operating under fast transient variations of shading patterns. *Solar Energy*, 124, 124-
486 142.
- 487 [19] Mutlag, A. H., Shareef, H., Mohamed, A., Hannan, M. A., & Abd Ali, J. (2014). An improved fuzzy logic
488 controller design for PV inverters utilizing differential search optimization. *International Journal of*
489 *Photoenergy*, 2014.
- 490 [20] Belaout, A., Krim, F., & Mellit, A. (2016, November). Neuro-fuzzy classifier for fault detection and
491 classification in photovoltaic module. In *Modelling, Identification and Control (ICMIC), 2016 8th*
492 *International Conference on* (pp. 144-149). IEEE.
- 493 [21] Grichting, B., Goette, J., & Jacomet, M. (2015, June). Cascaded fuzzy logic based arc fault detection in
494 photovoltaic applications. In *Clean Electrical Power (ICCEP), 2015 International Conference on* (pp. 178-
495 183). IEEE.
- 496 [22] Chen, J. L., Kuo, C. L., Chen, S. J., Kao, C. C., Zhan, T. S., Lin, C. H., & Chen, Y. S. (2016). DC-Side
497 Fault Detection for Photovoltaic Energy Conversion System Using Fractional-Order Dynamic-Error-based
498 Fuzzy Petri Net Integrated with Intelligent Meters. *IET Renewable Power Generation*.
- 499 [23] Bayrak, G. (2015). A remote islanding detection and control strategy for photovoltaic-based distributed
500 generation systems. *Energy Conversion and Management*, 96, 228-241.
- 501 [24] Dhimish, M., Holmes, V., & Dales, M. (2017). Parallel fault detection algorithm for grid-connected
502 photovoltaic plants. *Renewable Energy*, 113, 94-111.
- 503 [25] McEvoy, A., Castaner, L., Markvart, T., 2012. *Solar Cells: Materials, Manufacture and Operation*.
504 Academic Press.
- 505 [26] Sera, D., Teodorescu, R., & Rodriguez, P. (2007). PV panel model based on datasheet values. Paper
506 presented at the 2392-2396. doi:10.1109/ISIE.2007.4374981
- 507 [27] Suganthi, L., Iniyar, S., & Samuel, A. A. (2015). Applications of fuzzy logic in renewable energy systems—
508 a review. *Renewable and Sustainable Energy Reviews*, 48, 585-607.
- 509 [28] Chine, W., Mellit, A., Pavan, A. M., & Kalogirou, S. A. (2014). Fault detection method for grid-connected
510 photovoltaic plants. *Renewable Energy*, 66, 99-110.
- 511 [29] Altin, N., & Ozdemir, S. (2013). Three-phase three-level grid interactive inverter with fuzzy logic based
512 maximum power point tracking controller. *Energy Conversion and Management*, 69, 17-26.
- 513 [30] Safari, S., Ardehali, M. M., & Sirizi, M. J. (2013). Particle swarm optimization based fuzzy logic controller
514 for autonomous green power energy system with hydrogen storage. *Energy conversion and*
515 *management*, 65, 41-49.
- 516 [31] Deng, F., Chen, Z., Khan, M. R., & Zhu, R. (2015). Fault detection and localization method for modular
517 multilevel converters. *IEEE Transactions on Power Electronics*, 30(5), 2721-2732.

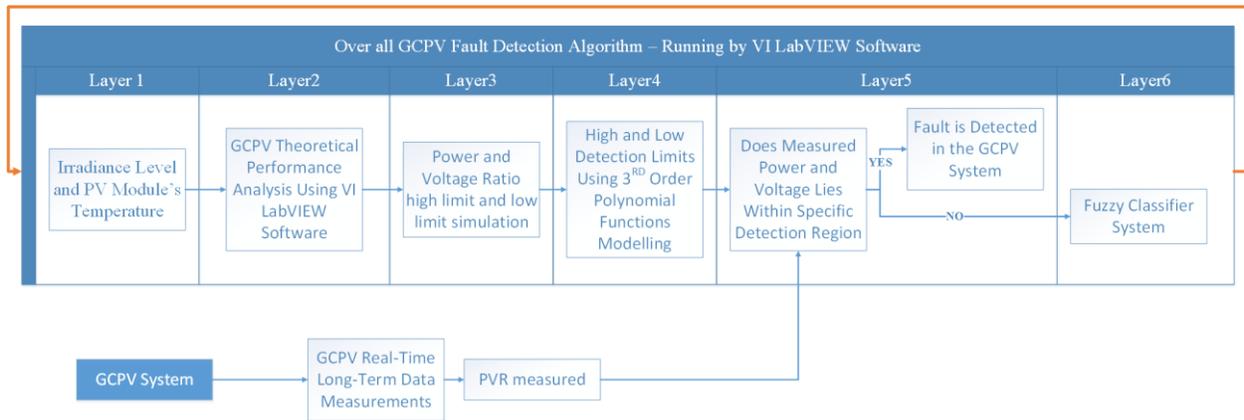


Fig. 1. Over all GCPV fault detection algorithm Layers

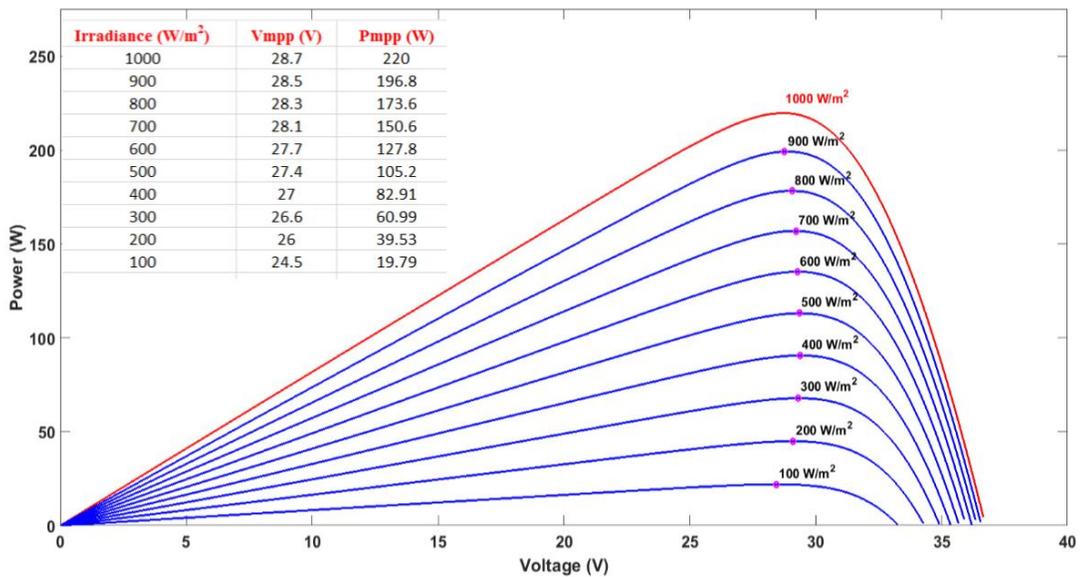


Fig. 2. P-V curve modelling under various irradiance levels

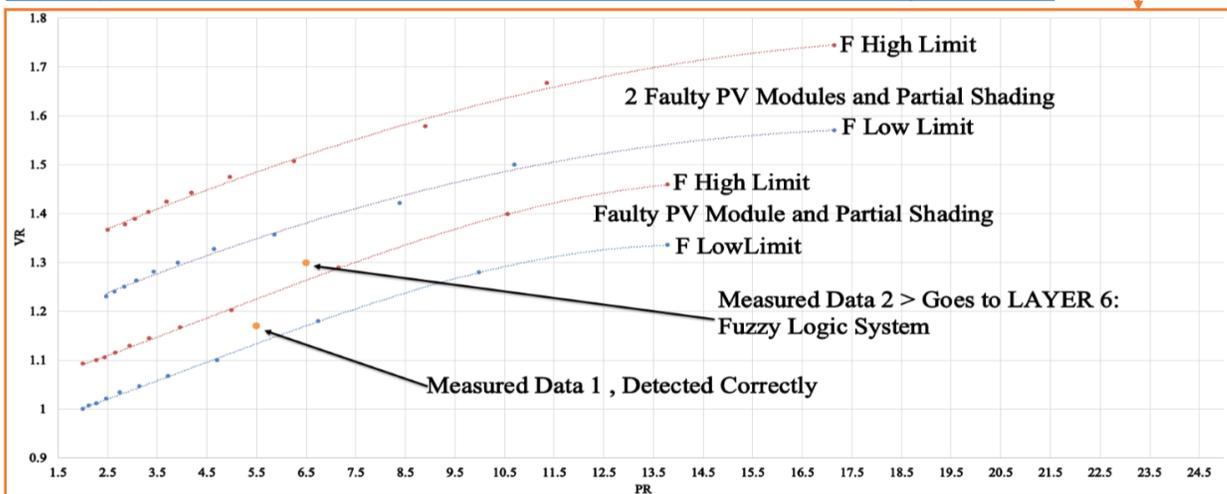
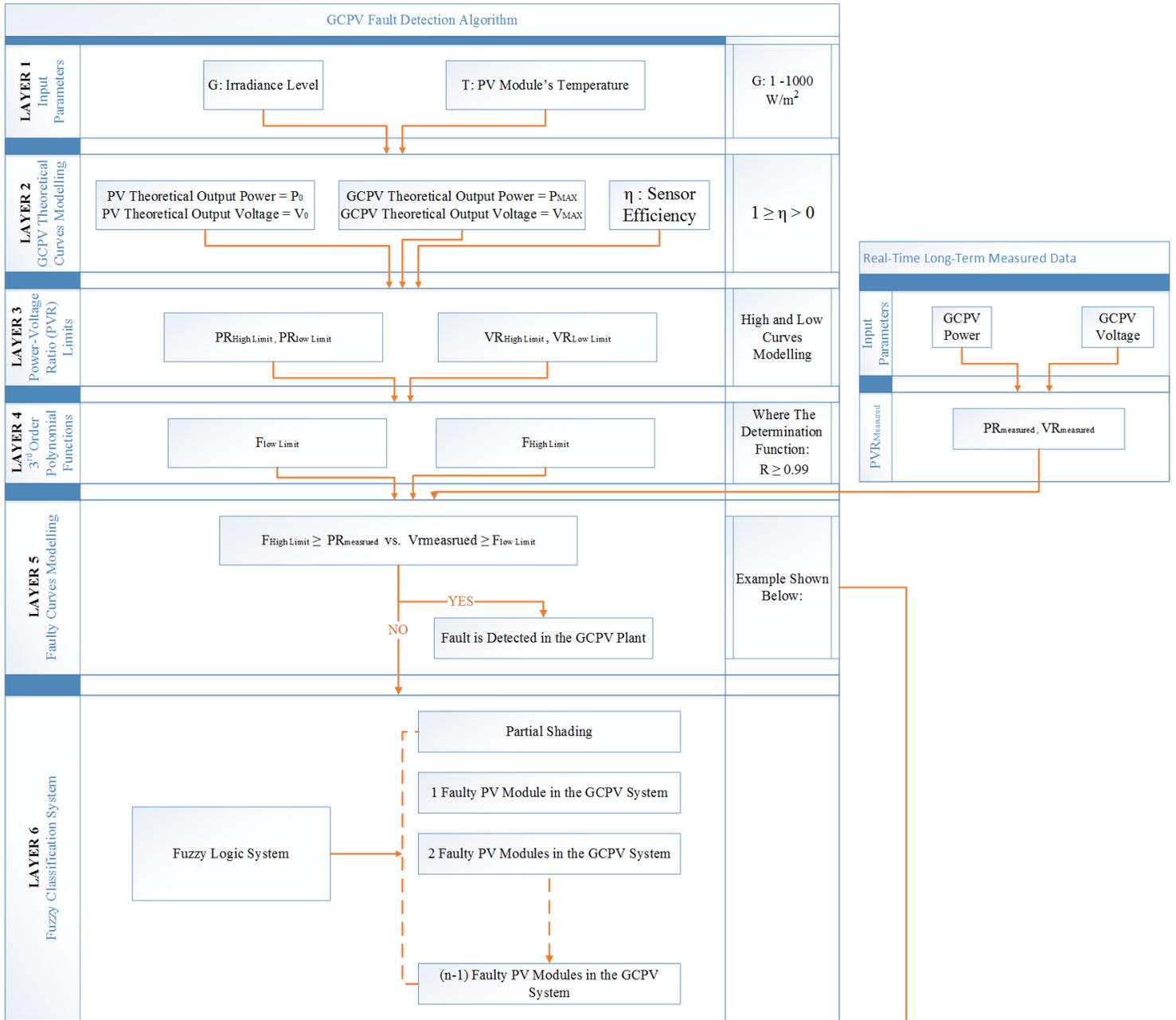


Fig. 3. Detailed flowchart for the proposed fault detection algorithm which contains 5 layers

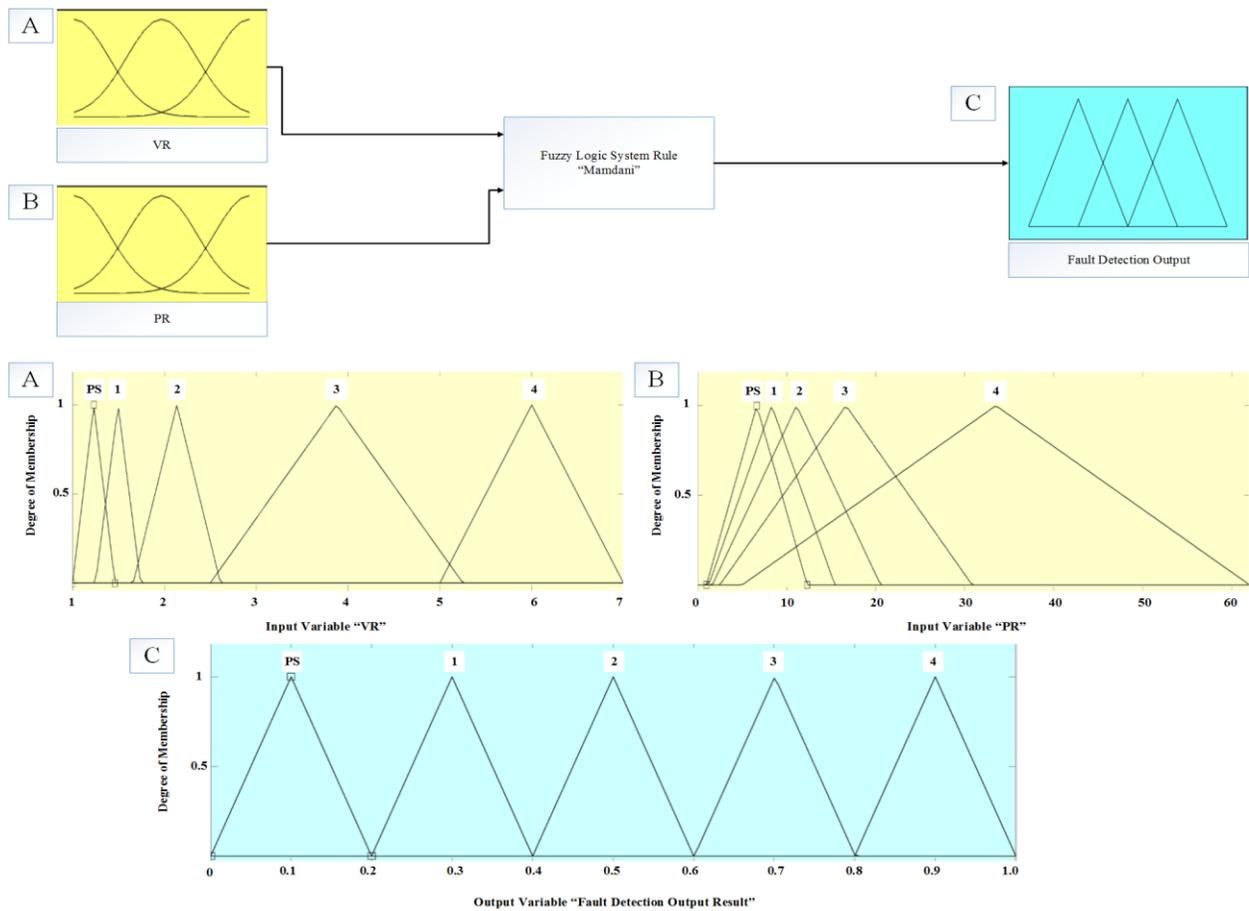


Fig. 4. Fuzzy Logic classifier system design. (A) Voltage ratio input, (B) Power ratio input, (C) Fault detection output

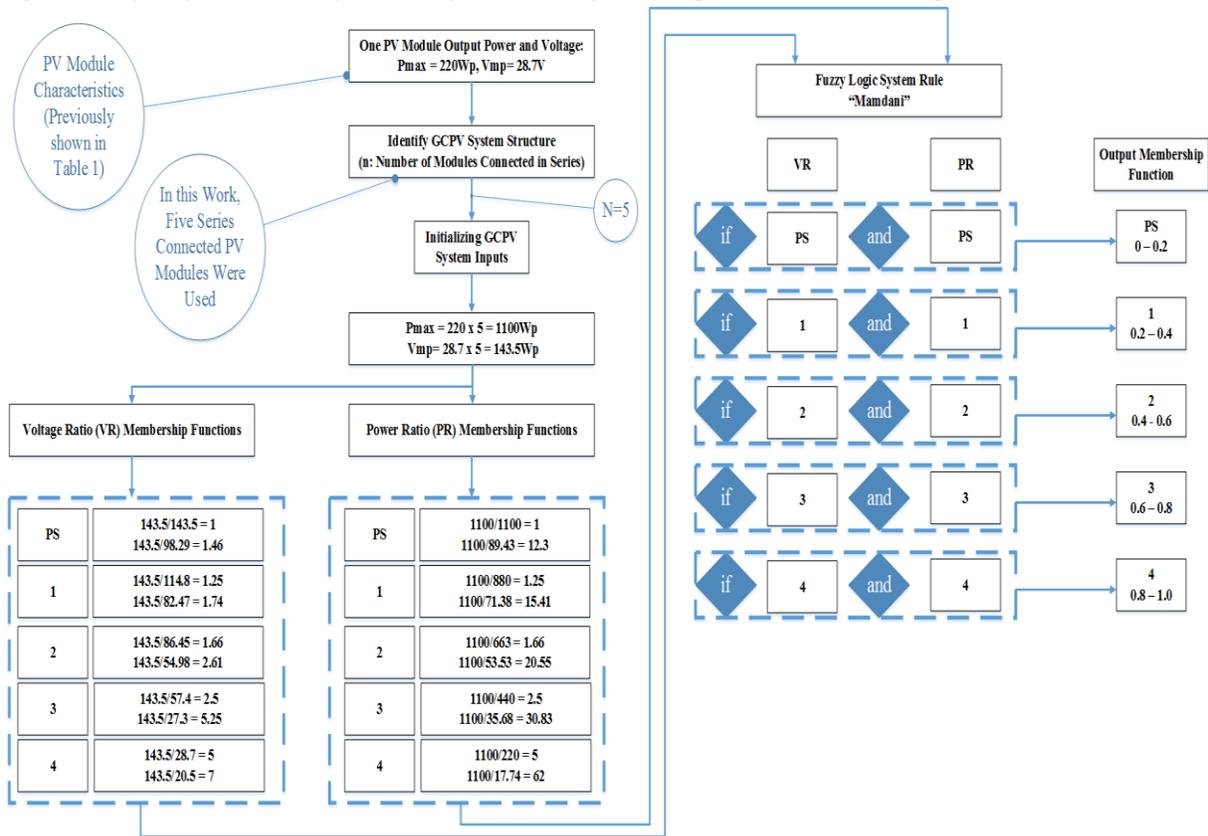


Fig. 5. Mathematical calculations for the fuzzy logic classifier system including VR, PR, Rules and Output Membership Function

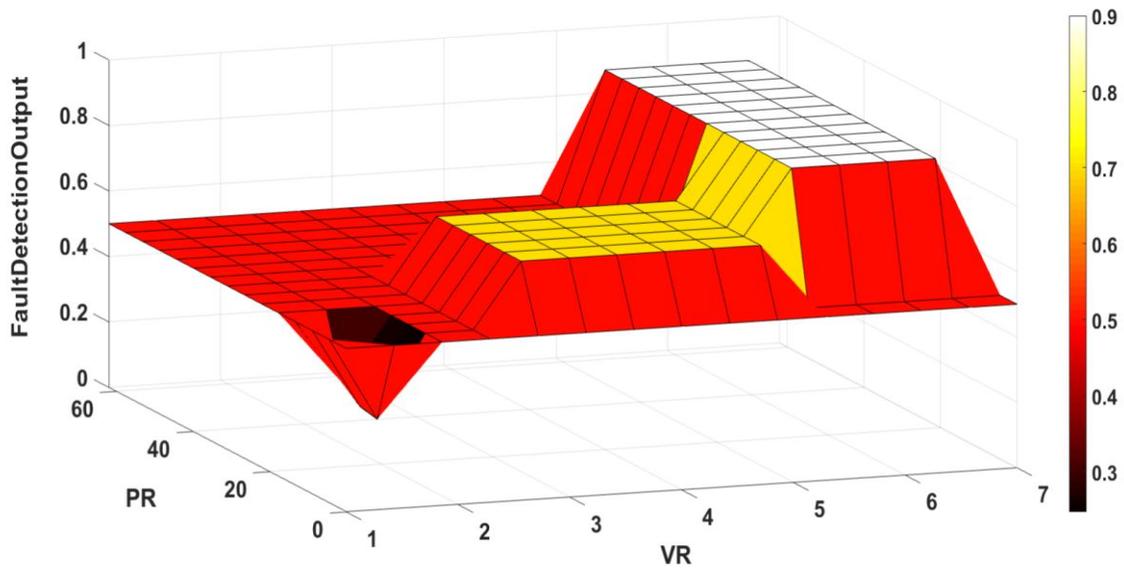


Fig. 6. Fuzzy Logic classifier output surface with VR, PR and the fault detection output membership function

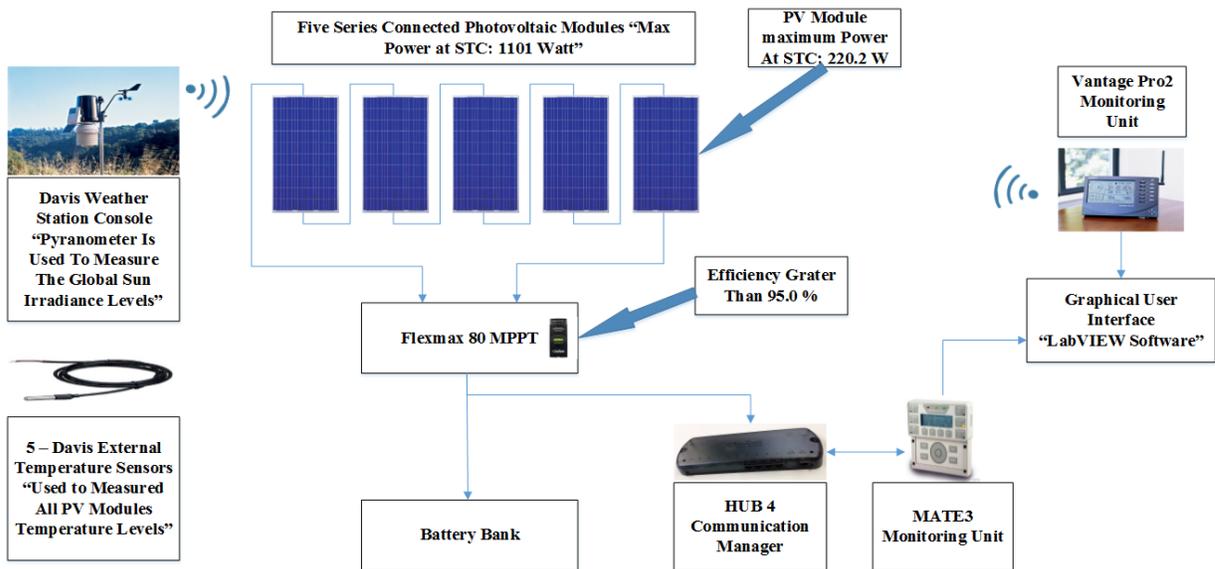


Fig. 7. Examined GCPV Plant Installed at the Huddersfield University, United Kingdom

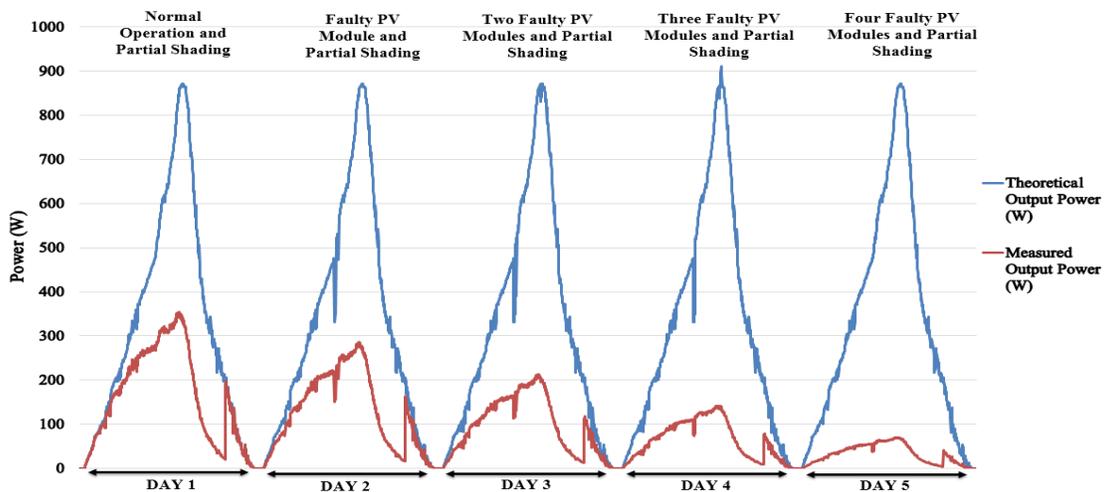


Fig. 8. Theoretical vs. Measured output power during 5 different days

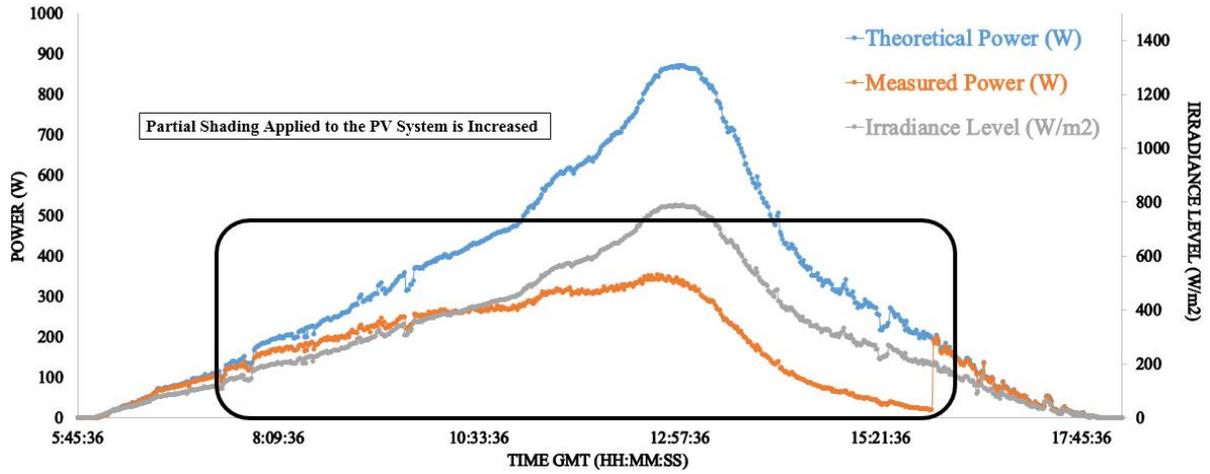


Fig. 9. Theoretical power vs. measured output power for a partial shading effects the GCPV plant

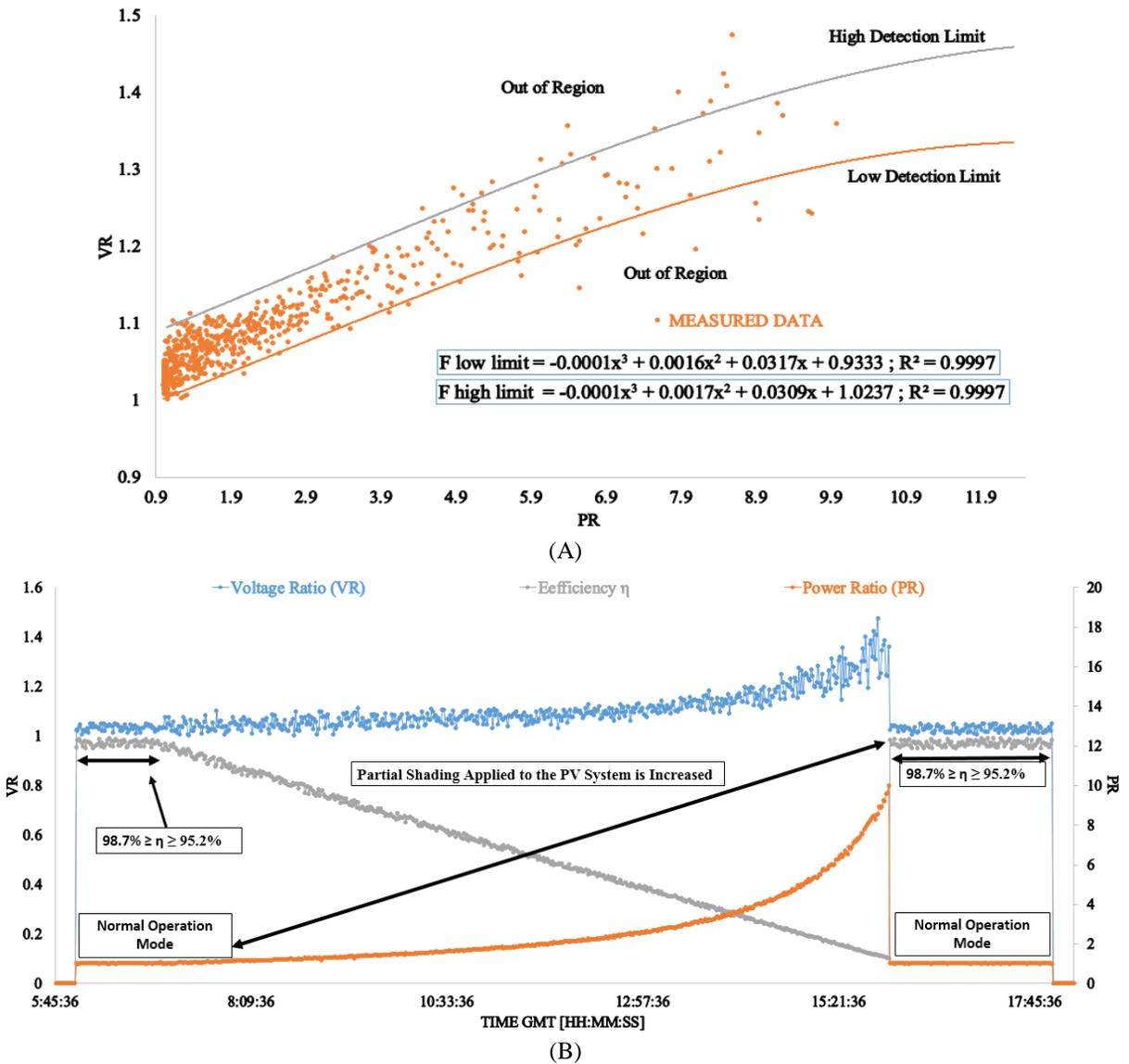


Fig. 10. Theoretical curves vs. real time long term measured data. (A) Theoretical fault curve detection limits for the examined GCPV plant, (B) Voltage ratio, power ratio and the efficiency of the entire GCPV system

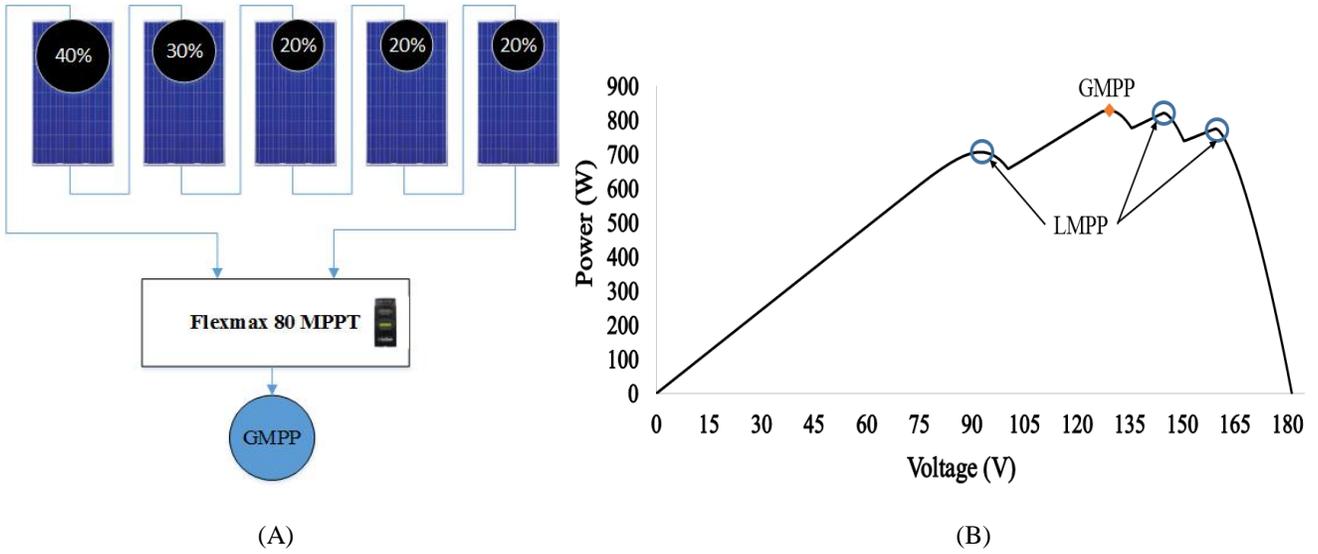


Fig. 11. MPPT unit output power (A) Examined partial shading condition, (B) P-V curve including the output LMPP and GMPP obtained by the MPPT unit

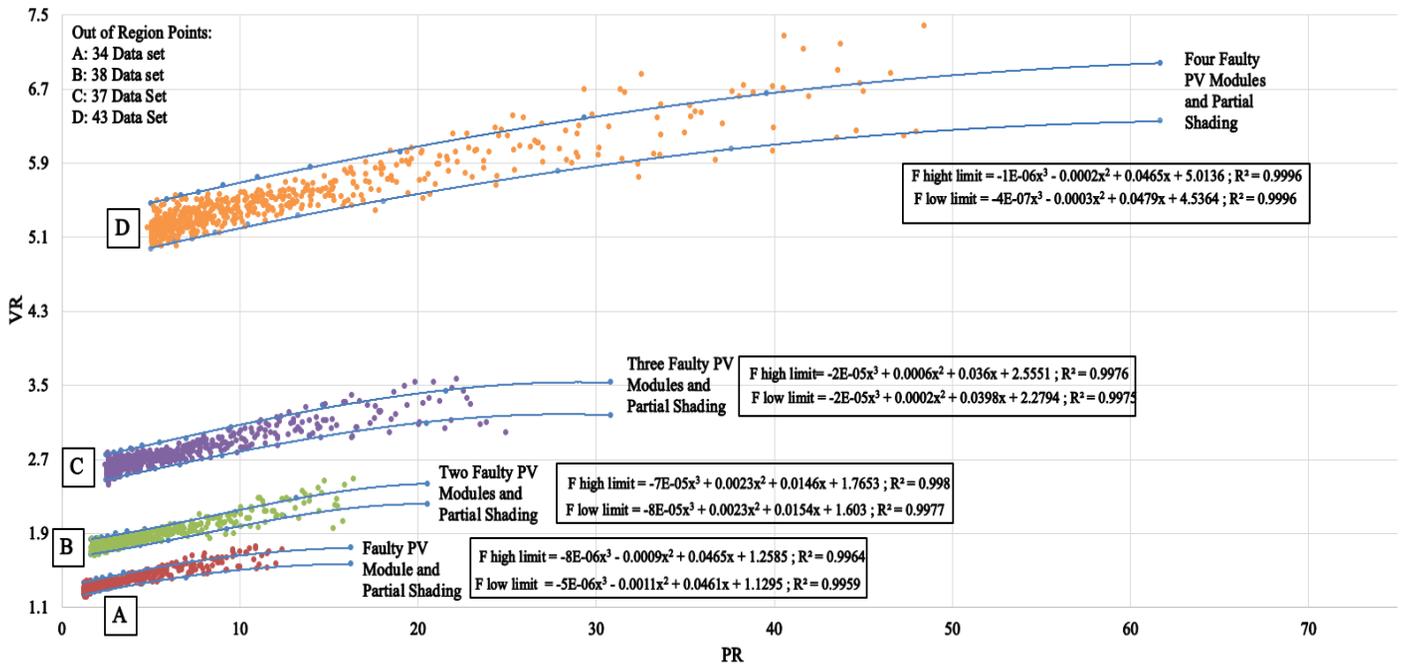


Fig. 12. Theoretical detection limits vs. real-time long-term data measurements for one faulty, two faulty, three faulty and four faulty photovoltaic modules

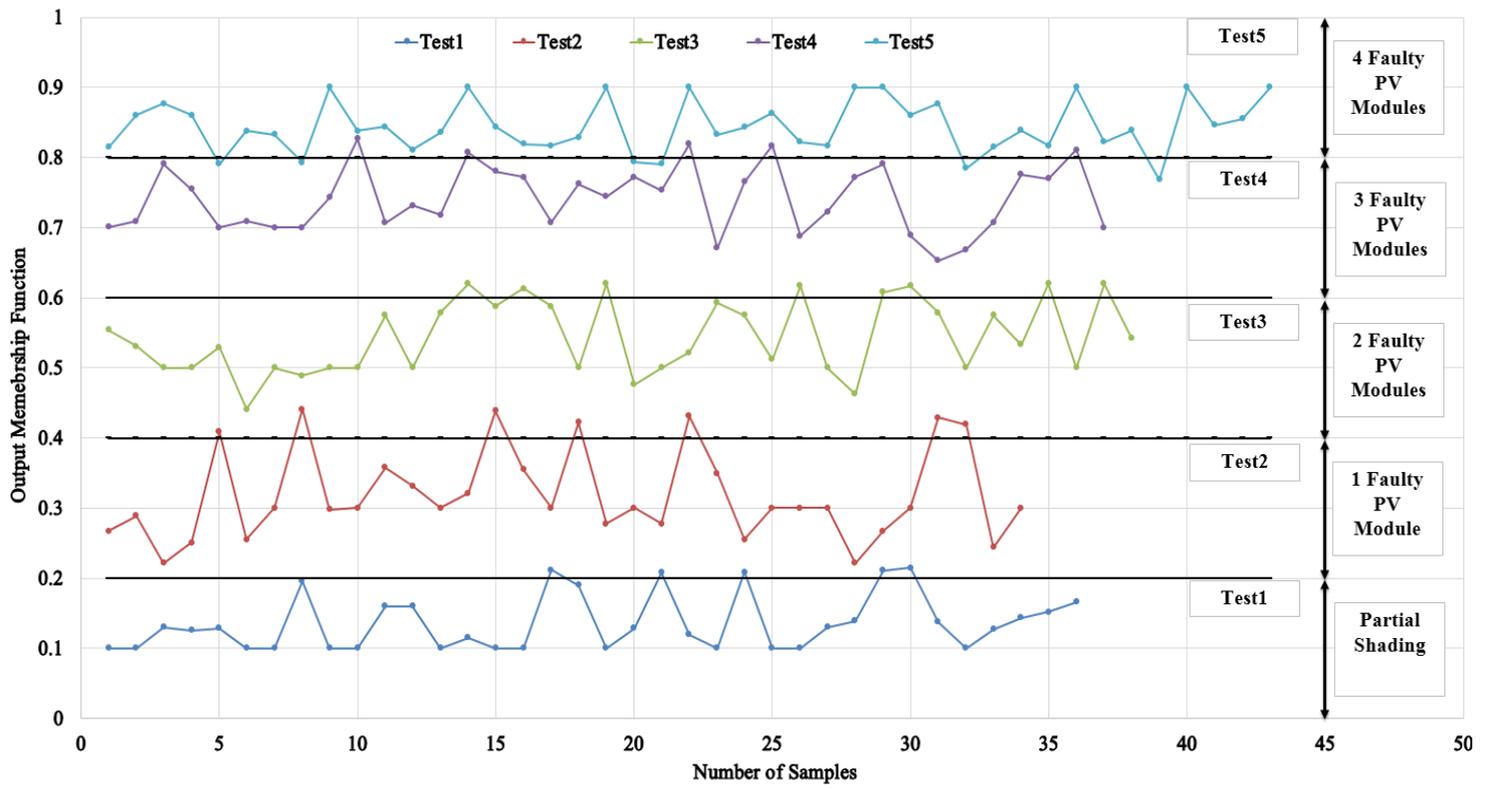
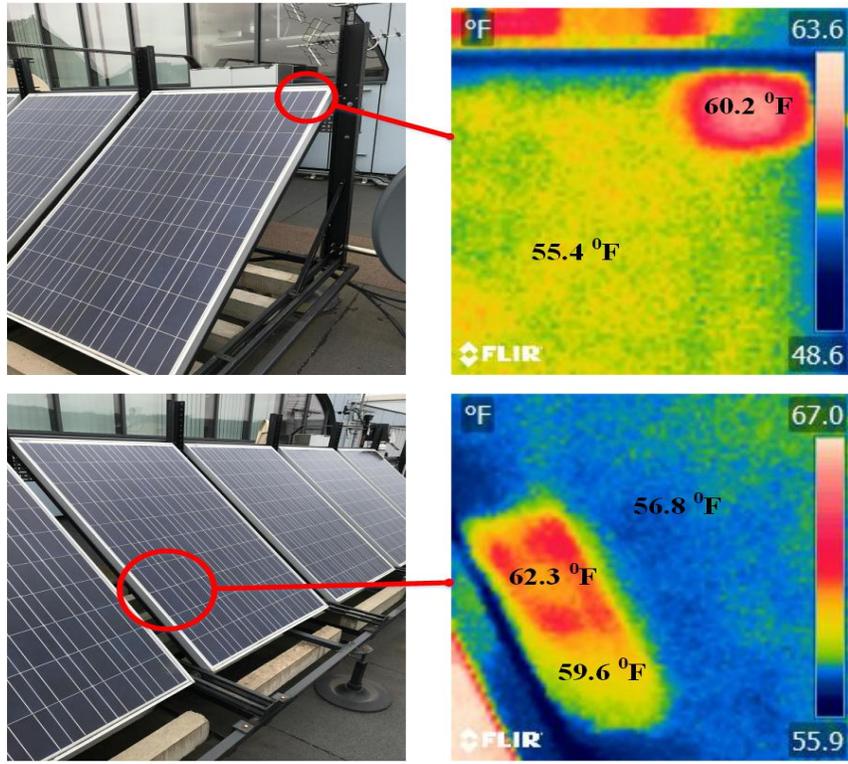
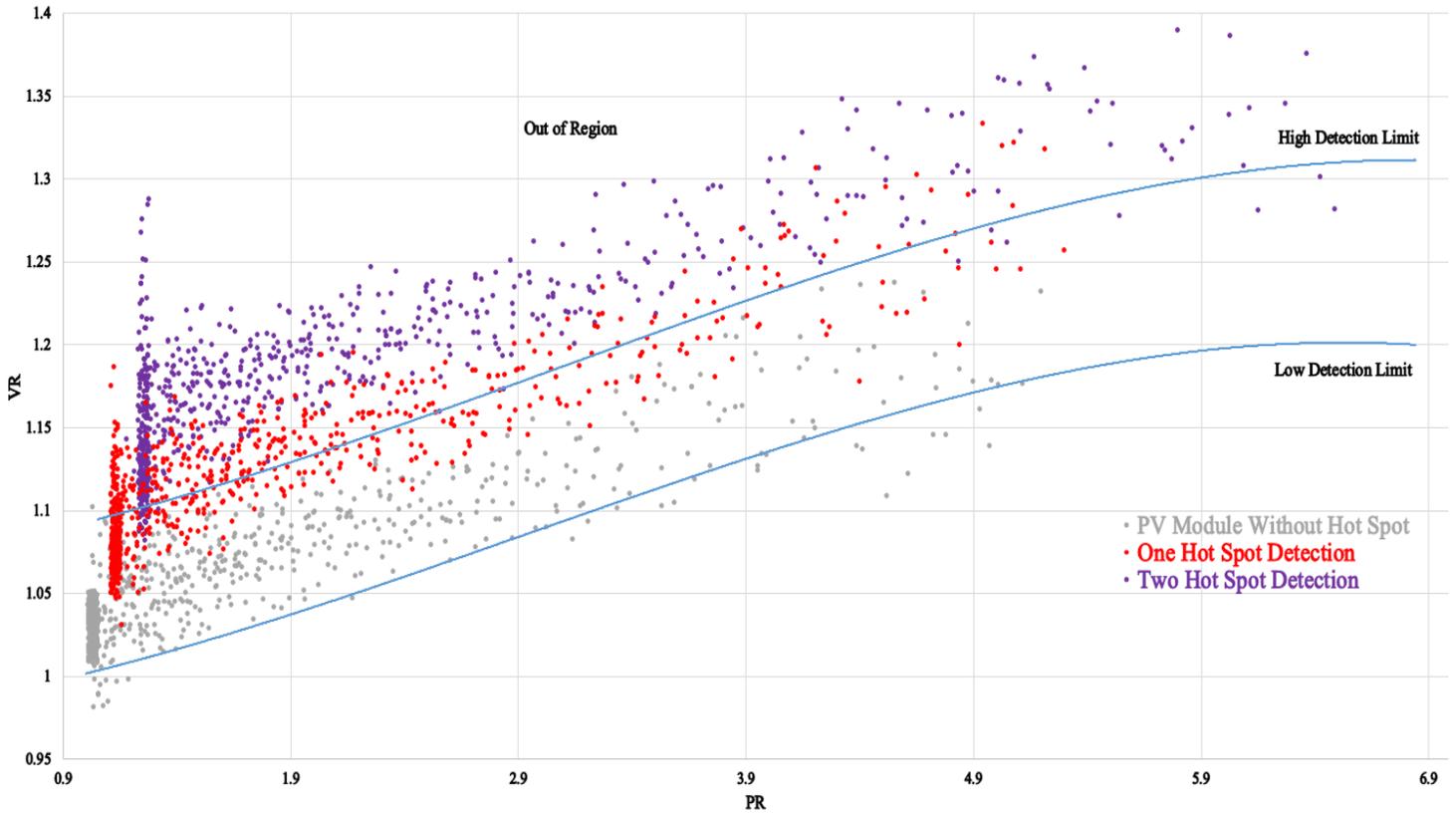


Fig. 13. Out of region samples processed by the fuzzy logic classification system



(A)



(B)

Fig. 14. Theoretical curves vs. real time long term measured data. (A) Hot spot images taken from two different PV modules using FLIR thermal imaging camera, (B) Theoretical fault detection curves vs. measured data obtained from a PV module without hot spots, PV module contains only one hot spot and PV module contains two hot spots

TABLE 1
Electrical Characteristics of SMT6 (60) P PV Module

Solar Panel Electrical Characteristics	Value
Peak Power	220 W
Voltage at maximum power point (V_{mp})	28.7 V
Current at maximum power point (I_{mp})	7.67 A
Open Circuit Voltage (V_{OC})	36.74 V
Short Circuit Current (I_{sc})	8.24 A
Number of cells connected in series	60
Number of cells connected in parallel	1
R_s , R_{sh}	0.48 Ω , 258.7 Ω
dark saturation current (I_o)	2.8×10^{-10} A
Ideal diode factor (A)	0.9117
Boltzmann's constant (K)	1.3806×10^{-23} J.K ⁻¹

TABLE 2
Efficiency Comparison between Four Different Case Scenarios

Test Number	Case Scenario	Without Fuzzy Classifier		Including Fuzzy Classifier	
		Out of Region Samples	Detection Accuracy (DA %)	Out of Region Samples	Detection Accuracy (DA %)
Test 1 (described in section 3.2)	Partial shading effects the GCPV system	37	94.86	5	99.31
Test 2 (presented as A in Fig. 11)	Faulty PV module and partial shading	34	95.27	7	99.03
Test 3 (presented as B in Fig. 11)	Two faulty PV module and partial shading	38	94.72	8	98.80
Test 4 (presented as C in Fig. 11)	Three faulty PV module and partial shading	37	94.86	5	99.31
Test 5 (presented as D in Fig. 11)	Four faulty PV module and partial shading	43	94.03	6	99.16

TABLE 3

Comparative Results between the Proposed Algorithm and the One Presented in Ref. [4], Ref. [7] and Ref. [8]

Case Study		Proposed Algorithm	Ref. [4]	Ref. [7]	Ref. [8]
Year of the Study		2017	2016	2015	2010
Software Used in the Data Analysis		LabVIEW	Not mentioned	Not mentioned	Not mentioned
PV System Capacity		1.1 kWp	Analysis on Single PV modules	1 st : 3 kWp 2 nd : 900 Wp	3.2 kWp
Fault Detection Algorithm Approach	Used Variables	Using power and voltage ratios	Using I-V curve	Current and voltage ratios	Current, voltage and power ratios
	Mathematical Modelling	3 rd order polynomial function	Not used	Not used	Not used
	Statically Analysis Technique	Using T-test method	Not used	Not used	± 2 Standard Deviation
	Machine Learning Technique	Using Fuzzy logic system	Not used	Not used	Not used
Type of the Fault Detected	Partial Shading Conditions	√	√	√	√
	Faulty PV Modules	√	×	√	√
	Hot Spots	√	√	×	×