ICIC Express Letters
Volume **10**, Number **8**, August **2016**

ICIC International ©2016 ISSN 1881-803X
pp. **2037–2044**

ROBUST STOCHASTIC FAULT DETECTION OF PHOTOVOLTAIC POWER GENERATOR SYSTEMS: REAL-TIME IMPLEMENTATION

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Received February 2016; accepted May 2016

Abstract. *Fault detection technique is considerably significant to timely prevent economic loss on industrial dynamic systems. We propose a novel robust stochastic fault detection approach for photovoltaic (PV) power generators using Bayesian networks (BN) theory as well as the general likelihood ratio test (GLRT) approach. We statistically represent a BN model against PV power systems in terms of a relationship from its input and output variables. Conditional probability distribution for statistical variables in a constructed BN model is defined as the Weibull function and we derive a parameter estimation rule for a BN model based on the maximum likelihood (ML) theory. Next, we propose a decision making scheme in realizing our fault detection mechanism with the GLRT method against PV power generator systems. We demonstrate reliability and practicability of the proposed fault detection methodology through real-time experiments with a test-bed of PV power systems.*

Keywords: PV generator, Fault detection, Bayesian network, GLRT, Maximum likelihood

1. **Introduction.** Photovoltaic (PV) power generators have been widely employed over the world because it is significantly regarded as the best alternative energy system. Until now, there are many research issues for developing PV generator systems in the fields of engineering and scientific applications [1,2].

Mellit and Kalogirou developed dynamic model of PV battery systems by using neural-fuzzy inference techniques in terms of its voltage and current characteristic analysis with respect to solar irradiation, temperature, and humidity [3]. Chin et al. proposed a novel maximum power point tracking (MPPT) method for stand-alone PV systems through numerical modeling of it with a well-known Matlab© software [4]. Duan et al. developed wireless communication based monitoring systems to supervise quality of power from distribution typed PV generators via global positioning systems (GPS) equipment [5]. Singh et al. addressed an integrated monitoring technique for PV power systems through Internet communications [6] and Tina and Grasso developed Web based monitoring and control methodologies for stand-alone PV power systems and applied particularly in computing effectiveness of energy [7]. More recently, advanced remote monitoring systems for distributed PV power systems have been addressed for hierarchical managements mainly including clients of PV systems, users, and operating terminals in the proposed software framework [8].

Nowadays, PV systems obviously incline to be employed in small-scaled appliances or specific embedded systems since considerably effective solar cells have been widely addressed. For such particular purpose, an electric performance of them should be accordingly enhanced. Much attention for realizing advanced PV system techniques requires developing of fault detection approach to timely find abnormality of it out due to unexpected fault.

We propose a novel fault detection method for PV power systems by using stochastic modeling and general likelihood ratio test (GLRT) theory. It is well known that the GLRT based detection scheme is useful for stochastic dynamic systems in which probability distribution estimation is employed to define the likelihood function in classifying specific signals sequentially [9]. Firstly, we statistically represent a Bayesian networks (BN) model from an input-output relationship of PV power systems. Conditional probability distribution given as its BN parameters is mathematically defined as the Weibull probability function in which non-negative input variables from PV systems are involved obviously. Secondly, we derive a parameter learning algorithm for a constructed BN model to seek its optimal parameter vectors via a maximum likelihood (ML) strategy. Next, a fault detection algorithm is proposed in which two Weibull probability distributions against normal and abnormal PV system variables are mathematically represented to derive a decision making algorithm. We test reliability and practicability of the proposed fault detection algorithm through real-time experiment for PV power generator systems.

This paper is organized as follows. We present a mathematical representation for PV modules in Section 2. A BN model for dynamics of PV generators and its parameter estimation are derived in Section 3. We propose our fault detection algorithm for PV power systems in Section 4 and describe real-time experiments and its results to test its reliability in Section 5. Lastly, conclusions and future work are respectively provided in Section 6.

2. **Mathematical Model of PV Generators.** Basically, PV generators include multiple solar modules which are electrically connected in series and parallel. We illustrate an electric circuit model for a PV module in Figure 1 and mathematically express the output current I_{pv} [2] as

$$I_{pv} = I_{ph} - I_o \left[\exp \frac{q\left(V_{pv} + I_{pv}R_s\right)}{d\delta T} - 1 \right] - \left(\frac{V_{pv} + I_{pv}R_s}{R_p} \right) \tag{1}$$

where V_{pv}[V] is the output voltage, d is the diode factor, I_o[A] is the saturation current of the diode, I_{ph}[A] is the photocurrent of the solar cells, $R_s[\Omega]$ is the series resistance, $R_p[\Omega]$ is the bypass resistance, δ[J/K] is the Boltzmann constant, q[C] is the elementary charge, and T[K] is ambient temperature of a solar cell. A photocurrent I_{ph} is analytically defined as a function of solar irradiance $G[\mathrm{W/m^2}]$ and temperature T[K] is mathematically given by

$$I_{ph} = I_{ph-stc} \frac{G}{G_{stc}} \left[1 + a_0(T - T_{stc})\right] \tag{2}$$

where I_{ph-stc}[A] is the short-circuit current measured at reference conditions, coefficients T_{stc}[K] and $G_{stc}[\mathrm{W/m^2}]$ are solar irradiance and ambient temperature respectively at

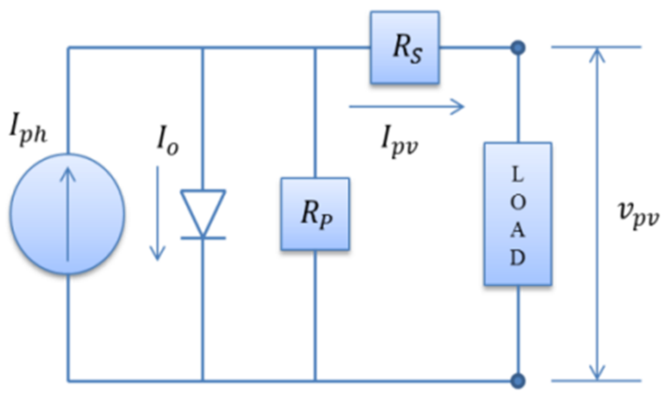

FIGURE 1. An electric circuit model of PV cells

reference conditions, and a_0 is a short-circuit temperature coefficient. The saturation current I_0 in (1) is expressed as a nonlinear function of temperature given by

$$I_0 = C_0 T^3 \exp\left(-\frac{E_{gap}}{\delta T}\right) \tag{3}$$

where C_0 $\left[\mathrm{AK}^{-3}\right]$ is a temperature coefficient from PV parameter fitting and E_{gap}[eV] is a band gap. We recognize from the electric dynamic model of the PV power generators that solar radiation and ambient temperature directly influence its electric power quantity. Moreover, the two variables are obviously stochastic and correspondingly the electric power is regarded as a random variable.

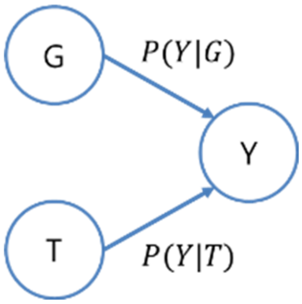

Figure 2. The Bayesian network model

3. **Bayesian Networks Model for PV Dynamics.** The BN model is a graphical representation for stochastic casual systems based on probability and statistics theory [10]. For constructing generic BN models, nodes and arrows are employed to graphically indicate random variables against stochastic dynamic systems and their dependencies to express causality with conditional probability. We depict a specific BN model in Figure 2 to describe such dynamic relationship for PV power system. Here, random variables G, T, and Y stand for respectively solar radiation, ambient temperature, and output power from PV system. In Figure 2, from the statistic point of view, a constructed BN model includes two conditional probabilities $P(Y|G)$ and $P(Y|T)$, and consequentially leads the joint conditional probability $P(Y|G,T)$. Because of non-negative continuous random variable Y, it is reasonable that the conditional probability $P(Y|G,T)$ involves the Weibull distribution expressed mathematically as [11]

$$f_Y(Y|G,T) = \begin{cases} \alpha y^{\beta-1} \exp\left(-\frac{\alpha y^{\beta}}{\beta}\right), & \text{if } y > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where parameters α and β are given to determine shape of the distribution. These two parameters are optimally estimated with data sequences obtained from established PV power systems through parameter learning algorithm. Next, we present the maximum likelihood (ML) scheme based parameter estimation procedure for the BN model. First, we define a likelihood function by applying the logarithms to N observations of a sampled output value $y(n)$ measured from a given PV system as

$$L = \sum_{n=1}^{N} \ln\left(f_Y(y(n)|G,T,\alpha,\beta)\right) = N\ln(\alpha) + (\beta-1)\sum_{n=1}^{N}\ln(y(n)) - \frac{\alpha}{\beta}\sum_{n=1}^{N} y^{\beta}(n) \tag{5}$$

Based on a well-known ML estimation theory, we obtain two estimating equations in terms of α and β from the likelihood function in (5) by equaling to zero as

$$\frac{\partial \ln L}{\partial \alpha} = \frac{N}{\alpha} - \frac{1}{\beta}\sum_{n=1}^{N} y^{\beta}(n) = 0 \tag{6}$$

$$\frac{\partial \ln N}{\partial \beta} = \sum_{n=1}^{N} \ln(y(n)) + \frac{\alpha}{\beta^2} \sum_{n=1}^{N} y^{\beta}(n) - \frac{\alpha}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \ln(y(n)) = 0 \tag{7}$$

Solving these two equations with respect to the parameters α and β yields its estimation rules in which both are mutually correlated and become a function of the output $y(n)$. However, it is rarely straightforward to solve directly these equations in (6) and (7) from analytical calculation methods. Alternatively, we need to seek its solutions through a numerical optimization approach such as a gradient descent algorithm for our estimation task. In order for applying this optimization method, we first define an objective function including the two estimating equations in (6) and (7) as

$$J = \min_{\alpha,\beta} \frac{1}{2} \left(J_1^2 + J_2^2 \right) \tag{8}$$

where

$$J_1 = \frac{N}{\alpha} - \frac{1}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \tag{9}$$

$$J_2 = \sum_{n=1}^{N} \ln(y(n)) + \frac{\alpha}{\beta^2} \sum_{n=1}^{N} y^{\beta}(n) - \frac{\alpha}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \ln(y(n)) \tag{10}$$

We apply a gradient descent based optimization method to derive adjustment rules of the two parameters α and β as

$$\alpha(k+1) = \alpha(k) - \eta \frac{\partial (J_1 + J_2)}{\partial \alpha} \tag{11}$$

$$\beta(k+1) = \beta(k) - \eta \frac{\partial (J_1 + J_2)}{\partial \beta} \tag{12}$$

where $\eta \in (0,1)$ is a learning parameter. We calculate the partial differential terms in (11) and (12) as

$$\frac{\partial J_1}{\partial \alpha} = -\frac{N}{\alpha^2} \tag{13}$$

$$\frac{\partial J_2}{\partial \alpha} = \frac{\partial J_1}{\partial \beta} = \frac{1}{\beta^2} \sum_{n=1}^{N} y^{\beta}(n) - \frac{1}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \ln(y(n)) \tag{14}$$

$$\frac{\partial J_2}{\partial \beta} = -\frac{\alpha}{\beta^3} \sum_{n=1}^{N} y^{\beta}(n) + 2\frac{\alpha}{\beta^2} \sum_{n=1}^{N} y^{\beta}(n) \ln(y(n)) - \frac{\alpha}{\beta} \sum_{n=1}^{N} y^{\beta}(n) (\ln(y(n)))^2 \tag{15}$$

These results are simply substituted to (11) and (12) and we finally obtain adjustment rules of the two parameters as

$$\begin{aligned} \alpha(k+1) = \alpha(k) - \eta \Bigg\{ & \left(-\frac{N}{\alpha} + \frac{1}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \right) \frac{N}{\alpha^2} + \left(\sum_{n=1}^{N} \ln(y(n)) + \frac{\alpha}{\beta^2} \sum_{n=1}^{N} y^{\beta}(n) \right. \\ & \left. - \frac{\alpha}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \ln(y(n)) \right) \left(\frac{1}{\beta^2} \sum_{n=1}^{N} y^{\beta}(n) - \frac{1}{\beta} \sum_{n=1}^{N} y^{\beta}(n) \ln(y(n)) \right) \Bigg\} \end{aligned} \tag{16}$$

$$\begin{aligned}\beta(k+1) = \beta(k) - \eta \Bigg\{ & \left(\frac{N}{\alpha} - \frac{1}{\beta}\sum_{n=1}^{N} y^{\beta}(n)\right)\left(\frac{1}{\beta^2}\sum_{n=1}^{N} y^{\beta}(n)\right. \\ & \left. - \frac{1}{\beta}\sum_{n=1}^{N} y^{\beta}(n)\ln(y(n))\right) + \left(\sum_{n=1}^{N}\ln(y(n)) + \frac{\alpha}{\beta^2}\sum_{n=1}^{N} y^{\beta}(n)\right. \\ & \left. - \frac{\alpha}{\beta}\sum_{n=1}^{N} y^{\beta}(n)\ln(y(n))\right)\left(- \frac{\alpha}{\beta^3}\sum_{n=1}^{N} y^{\beta}(n) + 2\frac{\alpha}{\beta^2}\sum_{n=1}^{N} y^{\beta}(n)\ln(y(n))\right. \\ & \left. - \frac{\alpha}{\beta}\sum_{n=1}^{N} y^{\beta}(n)(\ln(y(n)))^2\right)\Bigg\}\end{aligned} \tag{17}$$

These two estimation rules appear somewhat complicated for computational procedure, but simple mathematical operations are applied recursively to update the parameters. As well, this computational configuration leads easy real-time implementation in terms of calculation burden. This estimation is iteratively carried out until a satisfactory performance reaches through a suitable parameter testing.

4. **Fault Detection Algorithm.** We propose our fault detection algorithm by using a GLRT methodology in which two hypotheses are predefined to determine whether fault occurs or not in the PV systems. We begin with a definition of the binary hypothesis [12] as

$$\begin{cases} H_0 : y(t) = y_0(t);\ \text{No fault} \\ H_1 : y(t) = y_0(t) + \tilde{y}(t);\ \text{Fault} \end{cases} \tag{18}$$

where the hypothesis H_0 involves normality of PV systems, but for the hypothesis H_1 we consider that PV system abnormally works with fault. In (18), a nominal output variable $y_0(t)$ is given as a random variable with the Weibull probability distribution and an auxiliary variable $\tilde{y}(t)$ stands for a deterministic perturbation feasibly occurring in abnormal PV systems. Namely, the hypotheses in (18) indicate that under H_0 the output variable $y(t)$ in PV power systems involves the Weibull distribution with nominal parameters α_0 and β_0. While the Weibull distribution for the output $y(t)$ under H_1 is configured with parameters α_1 and β_1. The former is determined from normal PV systems and the latter is continuously estimated in actual real-time implementation. We utilize the proposed estimation algorithm in (16) and (17) for this task in constructing the decision making mechanism in (18). Next, a GLRT method is applied to the decision making rules in (18) for devising our fault detection algorithm. We observe N independently and identically distributed (IID) samples $y(n) = y_0(n)$, $n = 0, \ldots, N-1$ under H_0 and $y(n) = y_0(n) + \tilde{y}(n)$ under H_1 from the Weibull distribution. Thus, under H_0 the probability distribution function is expressed as

$$f_Y(Y|G,T;H_0) = \prod_{n=0}^{N-1}\left(\alpha_0 y^{\beta_0 - 1}(n)\exp\left(-\frac{\alpha_0 y^{\beta_0}(n)}{\beta_0}\right)\right) \tag{19}$$

and under H_1 we similarly have

$$f_Y(Y|G,T;H_1) = \prod_{n=0}^{N-1}\left(\hat{\alpha}_1\left(y(n) - \tilde{y}(n)\right)^{\hat{\beta}_1 - 1}\exp\left(-\frac{\hat{\alpha}_1\left(y(n) - \tilde{y}(n)\right)^{\hat{\beta}_1}}{\hat{\beta}_1}\right)\right) \tag{20}$$

where $\hat{\alpha}_1$ and $\hat{\beta}_1$ are estimates of parameters α_1 and β_1. We apply the GLRT scheme to constructing a decision making in our fault detection algorithm from the hypothesis in (18). Based on the GLRT, we select H_1 if

$$L(Y) = \frac{f_Y(Y|G,T;\hat{\alpha}_1,\hat{\beta}_1,H_1)}{f_Y(Y|G,T;\alpha_0,\beta_0,H_0)} > \gamma \tag{21}$$

where γ is a predefined threshold which is properly chosen from iterative real-time experiments. Otherwise, in case of satisfying $L(Y) \leq \gamma$, the hypothesis H_0 is chosen. Applying the logarithm to (21) we have

$$\ln L(Y) = \ln\left(f_Y(Y|G,T;\hat{\alpha}_1,\hat{\beta}_1,H_1)\right) - \ln\left(f_Y(Y|G,T;\alpha_0,\beta_0,H_0)\right) > \gamma' \tag{22}$$

where $\gamma' = \ln\gamma$. We substitute (19) and (20) to the right term of (22) respectively and expand as

$$\begin{aligned}\ln\left(f_Y(Y|G,T;\alpha_0,\beta_0,H_0)\right) &= \ln\left(\prod_{n=0}^{N-1}\left(\alpha_0 y^{\beta_0-1}(n)\exp\left(-\frac{\alpha_0 y^{\beta_0}(n)}{\beta_0}\right)\right)\right)\\ &= N\ln\alpha_0 + (\beta_0-1)\sum_{n=0}^{N-1}\ln y(n) - \frac{\alpha_0}{\beta_0}\sum_{n=0}^{N-1} y^{\beta_0}(n)\end{aligned} \tag{23}$$

and

$$\begin{aligned}&\ln\left(f_Y(Y|G,T;\hat{\alpha}_1,\hat{\beta}_1,H_1)\right)\\ &= \ln\left(\prod_{n=0}^{N-1}\left(\hat{\alpha}_1\left(y(n)-\tilde{y}(n)\right)^{\hat{\beta}_1-1}\exp\left(-\frac{\hat{\alpha}_1(y(n)-\tilde{y}(n))^{\hat{\beta}_1}}{\hat{\beta}_1}\right)\right)\right)\\ &= N\ln\hat{\alpha}_1 + \left(\hat{\beta}_1-1\right)\sum_{n=0}^{N-1}\ln(y(n)-\tilde{y}(n)) - \frac{\hat{\alpha}_1}{\hat{\beta}_1}\sum_{n=0}^{N-1}(y(n)-\tilde{y}(n))^{\hat{\beta}_1}\end{aligned} \tag{24}$$

These results in (23) and (24) finally lead a likelihood function in (22) as

$$\begin{aligned}\tilde{L}(Y) = {}& N\left(\ln\alpha_0 - \ln\hat{\alpha}_1\right) + \left(\hat{\beta}_1-1\right)\sum_{n=0}^{N-1}\ln\left(y(n)-\tilde{y}(n)\right) - (\beta_0-1)\sum_{n=0}^{N-1}\ln y(n)\\ &- \frac{\hat{\alpha}_1}{\hat{\beta}_1}\sum_{n=0}^{N-1}(y(n)-\tilde{y}(n))^{\hat{\beta}_1} + \frac{\alpha_0}{\beta_0}\sum_{n=0}^{N-1} y^{\beta_0}(n) > \gamma'\end{aligned} \tag{25}$$

To compute a likelihood function in (25), a series of observation data of the output $y(n)$, $n = 0, \ldots, N-1$ and estimate of the parameters α_i and β_i, $i = 0, 1$ in the Weibull probability density function are required to establish our fault detection algorithm. We first estimate these two Weibull parameters based on the adjustment rules in (16) and (17), and then compute a likelihood value in (25) including sequential observation of the output power $y(n)$ from PV power systems. This computational procedure for our fault detection algorithm is illustrated in Figure 3.

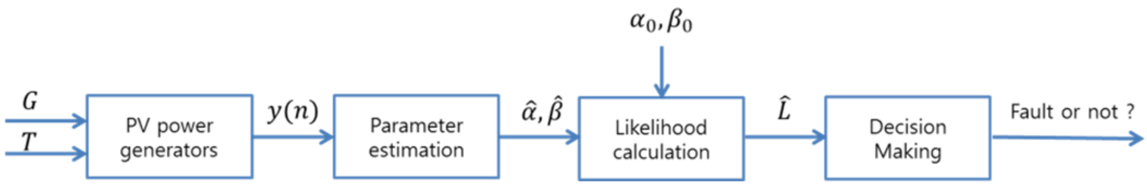

FIGURE 3. Computational procedure for the proposed fault detection approach

5. **Real-Time Experiments.** We accomplish real-time experiments for demonstrating reliability of the proposed fault detection approach using a test-bed of PV generator systems. We construct a PV power generator composed of six PV modules with individually same electric specification as follows: Maximum output power 20.0[W], maximum voltage 19.5[V], maximum current 1.3[A], open-circuit voltage 23.5[V], and short-circuit current 1.34[A]. We acquire output voltages of the PV generator under different irradiation and

ambient temperature with the halogen lamps as lighting sources. Figure 4 illustrates individual voltages against different irradiations from 150[W/m^2] to 950[W/m^2] under three different ambient temperature conditions of 15[°C], 25[°C] and 35[°C]. We utilize these measured voltages in Figure 4 to construct the Weibull distribution function through the proposed estimation method in Section 3. For testing the proposed fault detection algorithm, we measure the output voltage from PV generator during 500[sec] and apply an electric fault to it around 250[sec]. Figure 5 shows time-histories of the output voltage of PV system with fault. Here, we observe that the output voltage abruptly declines to about 17.5[V] around 250[sec] due to fault. Finally we calculate the likelihood expressed in Section 4 against the output voltage in Figure 5 and illustrate time-histories of the normalized values for same time period in Figure 6. We recognize from Figure 6 that the likelihood is similarly reduced to averagely 0.25 around 260[sec]. Moreover, it is obvious that a shape of the curve in Figure 6 is similar to that of the output voltage in Figure 5. Here, there is an abrupt change in the likelihood around 260[sec] since the fault occurs in the PV system. This result indicates that it takes about 10 seconds to detect the abnormal behavior of the PV system after an occurrence of the fault. Therefore, we assure that our proposed fault detection works effectively to timely abnormality of the PV system and its performance is very reliable in the real-time implementations.

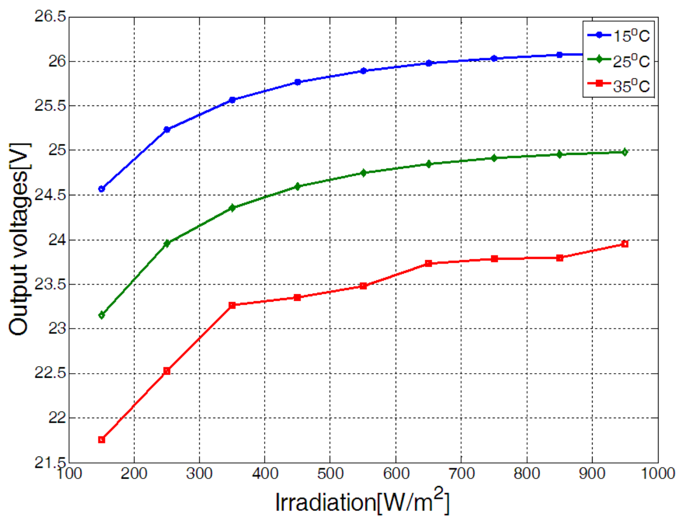

Figure 4. Voltages under different radiations and temperatures

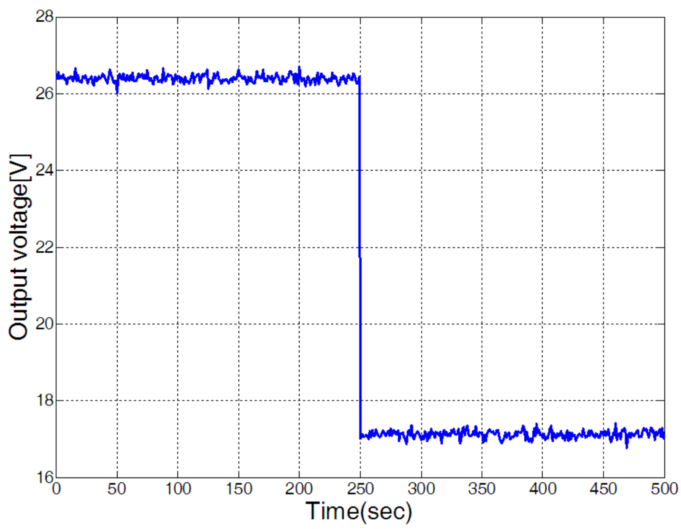

Figure 5. Time-histories of the output voltage under fault

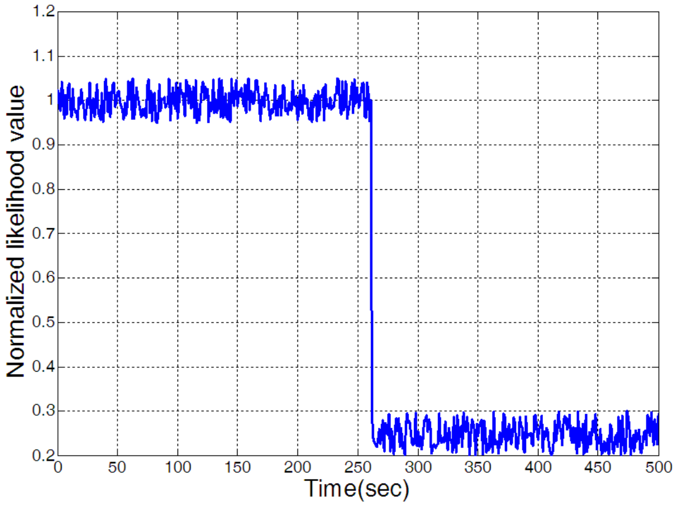

FIGURE 6. Time-histories of the normalized likelihood values

6. **Conclusions.** This paper presents a novel fault detection approach for PV power generator systems to timely recognize abnormality of it for minimizing electrical damages. We employ the Bayesian network theory to represent stochastic dynamics of PV systems and the GLRT approach to establish decision making in our fault detection framework. We conduct real-time experiment to test the proposed fault detection methodology through a test-bed of PV systems. We demonstrate from this task that it effectively works in that fault is timely detected by checking the likelihood value. Future work will include practical applications in which we apply the proposed fault detection technique to PV power systems established in industrial fields.

Acknowledgment. This work was supported by the 2010 Research Fund of Ulsan College.

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