ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015

Fault Detection and Isolation for ZVS Full Bridge Isolated Buck Converter Based on: Observer Design and Bayesian Network

Abbass H.Zein Eddine[1,2], Iyad Zaarour[1], Francois Guerin[2], Abbas Hijazi[1] , Dimitri Lefebvre[2]

Doctoral School of Science and Technology, Lebanese University, Hadath, Lebanon[1]

GREAH, University Le Havre, Le Havre, France[2]

Abstract: Fault Detection and Isolation (FDI) is an important aspect in designing any electrical power system, particularly those with high power due to the high cost of failure. This paper presents an approach to detect and isolate open circuit faults in Zero Voltage Switching (ZVS) full bridge isolated Buck converters, used in Systems of Multiple Sources of Energy (SMSEs). The estimation of the state variables obtained with an observer are compared to measured state variables in order to generate residuals. The generated residuals are able to detect the faults but unable to isolated them. Consequently, a Bayesian Belief Network (BBN) learned from those residuals is designed in order to isolate the occurring fault. The proposed technique is able to detect the studied faults regardless of disturbance, and isolate the fault type with 99.7 % accuracy.

Keywords: Fault detection and isolation, DC/DC converter, Observer, Bayesian Belief Network.

I. INTRODUCTION

The demand for power electrical energy is increasing. The limited reserves of fuel oil and their unstable prices have significantly increased the interest in green energy (photovoltaic modules, wind turbine, PEMFC, etc). Many topologies of hybrid power systems, or Systems of Multiple Sources of Energy (SMSE) were proposed [1];[2] . Fig.1 shows one of these topologies that connect multi-sources to a DC bus, via identical Zero Voltage Switching (ZVS) full bridge isolated Buck converters in order to supply the load according to a reference voltage. These DC/DC converters are used to manage the coupling and decoupling of the energy sources according to the load demand and available power.

The fragility of power supply systems necessitates the presence of some monitoring systems. As for the studied topology, DC/DC converters used to connect the sources are the most exposed to faults, especially those related to the MOSFET full bridge and in the Buck converter.

Many previous studies have been done to defend several types of DC/DC converters. However none of them have used Bayesian Belief Network (BBN) for isolation and few studies have been conducted for the protection of ZVS full bridge isolated Buck converter.

The author in [3] describes a method to detect faults in a four quadrant chopper based on parallel average model for state estimation. A method for MOSFET faults in a ZVS full bridge isolated Buck converter using the DC link current patterns as the signatures of these faults was proposed in [4].In [5] a FDI method was proposed, following an observer based residual generation applied for a step down Buck converter .In [6] another observer based method was developed for detection in a dual-redundant Buck converter.

Authors in [7] had developed a fault detection method based on wavelet transform for DC/DC Buck converter.

Moreover in [8] a set of residuals were generated using parity space algorithm according to a variable structure state space model in order to detect sensor faults in

ZVS full bridge isolated Buck converter. This work was completed in [9] by using an additional measurement resting on the use of a magnetic near field probe.

FDI methods belong either to model-based or non-model-based approaches. This paper presents a hybrid fault detection and isolation method, based on state estimation by observer (model-based method) for detection and Bayesian belief network (non-model based method) for isolation. Residuals are extracted from the difference between the actual outputs and the estimated ones and are then compared to a calculated threshold for detection.

Those generated residuals are unable to isolate the considered faults. Therefore this task is assigned to the BBN in order to isolate the occurring fault. Note that only open circuit faults are studied. To the best of our knowledge, this paper is the first attempt to create and use BNNs for the fault isolation in power converters. This constitutes the main contribution of the proposed paper.

This paper has 5 sections. Section two presents the of SMSE model and the open circuit faults. Section three describes the fault detection algorithm using observers. Section four details the isolation method by presenting the BBN method for decoupling the faults. Finally, section five sums up the conclusion and perspectives.

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015

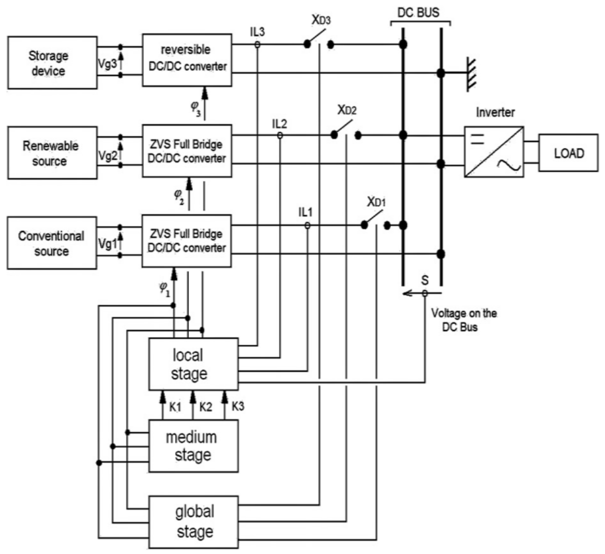


Fig. 1 Topology of the considered SMSEs

II. STUDIED MODEL

A. ZVS Full Bridge Isolated Buck Converters

ZVS full bridge isolated Buck converter (Fig 2) is an essential part in many applications specially those of multisource renewable energy systems. Such DC/DC converters are suitable for managing the energy transfers from the sources to the load through a DC bus [10], by coupling and decoupling several energy sources according to the load needs and source availability. These DC/DC converters are made of high frequency transformer TR1 for isolation , a Buck converter (D5,D6,D7,D8,L,Ce,Re) with a full bridge (Q1,Q2,Q3,Q4) and ZVS . A phase shift controller is used to control the full bridge in order to run in continuous conduction mode alternating between four phases with frequency 100 KHz:

Phase 1: (Q1Q4) closed: from $t=0$ to $t=\varphi T_0$

Phase 2: (Q1d3) closed: from $t=\varphi T_0$ to $t=T_0$

Phase 3: (Q2Q3) closed: from $t=T_0$ to $t=(1+\varphi)T_0$

Phase 4: (Q2d4) closed: from $t=(1+\varphi)T_0$ to $t=2T_0=T$

where $T_0 = T/2$ and T the period (10 µsec)

The authors in [10] and [11] have developed an average state space model that depends on the duty cycle value φ(t) which is modified by the phase shift between V_a and V_b voltages (Fig.2). Let's define the following variables:

Variables	Symbols		
	Instantaneous	average	measured average
Magnetizing current of the HF transformer	i_m	I_M	I_{mM}
Inductance current	i_L	I_L	I_{mL}
Source current	i_g	I_g	I_{mg}
Output voltage	s	S	S_m
Source voltage	-	-	V_G
Threshold diode voltage	V_d		
DC bus capacity	C_{dc}		

Let $X_M = (I_M, I_L, S)^T$ be the state vector,$U_M = (V_G, V_d)^T$ be the input vector and $Y_M = (I_{mg}, I_{mL}, S_m)^T$ be the output vector. The average model is represented with the equations (1) and (2). This model will be used as a reference model in the next section in order to design the observer used for fault detection and diagnosis.

$$\dot{X}_M = A_M(\varphi(t)).X_M(t) + B_M(\varphi(t)).U_M$$
$$Y_M(t) = C_M(\varphi(t)).X_M + d(t) \qquad (1)$$

where d(t) represents the measurement error vector. A_M , B_M and C_M are given by equation (2):

$$A_M(\varphi) = \begin{pmatrix} \frac{R_{mos}\varphi + R_{mos} + r_p}{L_M} & 0 & 0 \\ \begin{matrix} n \\ -\frac{n(2R_{mos}+r_p)}{L} \end{matrix} & -\frac{r_L + \varphi r_s + n^2\varphi(2R_{mos}+r_p)}{L} & -\frac{1}{L} \\ 0 & \frac{1}{C_{eq}} & -\frac{1}{R_{eq}C_{eq}} \end{pmatrix}$$

$$B_M(\varphi) = \begin{pmatrix} 0 & 0 \\ \frac{n.\varphi}{L} & -\frac{2}{L} \\ 0 & 0 \end{pmatrix}, \qquad C_M(\varphi) = \begin{pmatrix} \varphi & n.\varphi & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$R_{eq} = \frac{R_e R_{ch}}{R_e + R_{ch}} \;;\; C_{eq} = C_e + C_{dc} \qquad (2)$$

r_p, r_s, L_M and $R_{mos}$are respectively the primary resistance, the secondary resistance, the magnetizing inductance of the HF transformer (TR1) and the MOSFET transistors (Q1,Q2,Q3,Q4) channel resistance. L, r_L , C_e and $R_e$are respectively the coil inductance, the coil resistance, the capacity and the resistance of the Buck converter. n is the ratio of the HF transformer. R_{ch} is the load.

B. Open Circuit Faults

SMSEs coupled on a DC bus are fragile particularly the DC/DC converters that couple those sources. Power electronics system faults can be decomposed into three categories: open circuit faults, short circuit faults and leakage related to the building blocks in electronics components (coils, transistors, diodes,...). In this work open circuit faults that may affect the ZVS full bridge isolated Buck converter are modelled and studied.

Three main frequent faults are taken into consideration. In MOSFET (Q1) open circuit fault (fault1), phases 1 and 2 are affected such that i_g=0 and I_M=0, because in normal case Q1 is open in phases 3 and 4.In this faulty case no current can flow in the primary circuit during the first two phases. In diode (D8) open circuit fault (fault2), only the first phase is affected and I_L is the only affected parameter. Finally coil (L) open circuit (fault3) influences the four phases. The secondary circuit is open and I_L=0 thus I_g= I_M. In addition the primary circuit variables (I_g, V_G, I_M) are no longer related with the secondary circuit variables (I_L, S). Table II represent the average state space model corresponding to each fault.

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015

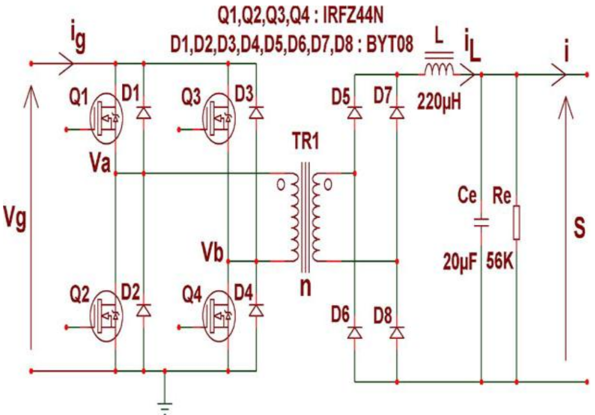


Fig. 2 Structural diagram of the ZVS full bridge isolated Buck converter

III.FAULT DETECTION

A. Observer Method And Residual Generation

Luenberger's observer model based method is used for detection. Based on the state space model (1) the observer equations are designed. These equations are equivalent to the fault-free system equations except an additional term comparing the actual measured output y to the estimated output $\hat{y}$. The equations of the observer are given by (3):

$$\dot{\hat{X}} = A_{obs}.\hat{X}_M(t) + B_{obs}.[\,U_M Y_M] \qquad \widehat{Y_M} = C_M.\hat{X}_M \quad (3)$$

where $A_{obs} = (A_M - L_{obs}C_M)$, $B_{obs} = [B_M L_{obs}]$ and L_{obs} is the observer gain.

An important task in the design of observers is the selection of its gain L_{obs} . Let us define the estimation error e(t) $=X_M(t) - \hat{X}_M(t)$, L_{obs} should be selected such that the eigenvalues of A_{obs} are larger than those of A_M, and lies in the left-hand side of the complex plane, thus the dynamics of the estimation error $(\dot{e(t)} = (A_M - L_{obs}C_M)\, e(t))$ converges to zero and the estimated state $\hat{X}_M(t)$ will rapidly and asymptotically approach $X_M(t)$. This designed observer will be used to generate residuals. Our method depends on residual analysis, these residuals represent the difference between the system measured variables (I_{mg}, I_{mL}, S_m) with the estimated ones (4):

$$r(t) = y(t) - \hat{y}(t) \qquad (4)$$

At each sampling time the measured values are compared to the estimated one to get a vector r(t) of residuals. This vector will be used to detect the occurrence of the considered faults.

B. Threshold And Detection

In fault free case the residuals are equal to zero in the average, the occurrence of any fault will be reflected as a deviation in the r(t) vector. Fault detection in the proposed method is based on monitoring the residual vector and capturing any deviation that may arise with a value greater than a calculated threshold. Since the standard deviation represents how much the values of each variable are far from its mean, it was chosen to be the base of the threshold, by computing the k^{th} standard deviation.

Three residuals are considered: r(t) = $(r_{I_{mg}}, r_{I_{mL}}, r_{S_m})$, therefore there should be three thresholds one for each residual. Threshold are calculated according to equation (5) where k is chosen according to several tests in order to capture the ideal one to avoid false alarms:

$$Threshold = k.\sigma = k.\sqrt{\frac{\sum_{i=1}^{N}(r_i - \mu)}{N}} \qquad (5)$$

where µ is the mean of the calculated residual r_i in no fault case and N is the number of measured points.

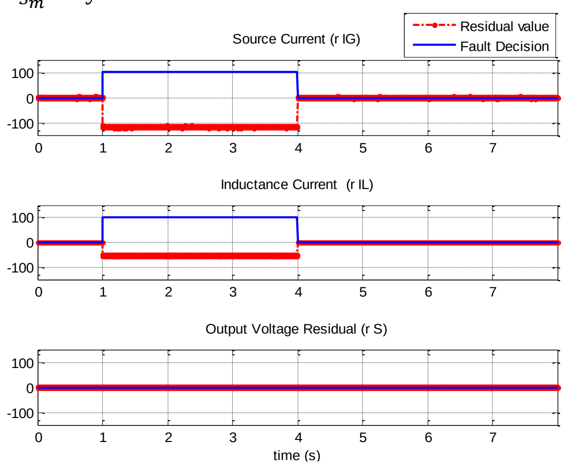
C. Detection Results

The proposed detection method was validated using several Matlab/Simulink simulations. Table 1 shows the values of the case study variables. In addition, equations (1) to (5) plus the modelled fault equations, are considered in sampled time with the sampling period Te =1ms according to a first order method. A uniform random signal (+/-0.001 V, seed : 0) is considered to represent the noise. The faults are simulated from t=1s until t=4s. The residuals are sensitive to the considered faults and robust to the disturbances as shown in Fig 3 (red lines).

TABLE I: CASE STUDY PARAMETERS

R_{mos}	r_l	r_s
0.005 Ω	0.2 Ω	0.05 Ω
r_p	L_M	L
0.05 Ω	$20\ \mu H$	$120\ \mu H$
Φ	R_e	C_e
0.5	$56\ K\Omega$	$330\ \mu F$
C_{dc}	R_{ch}	n
$10\ \mu F$	25 Ω	5
V_d		
0.3 V		

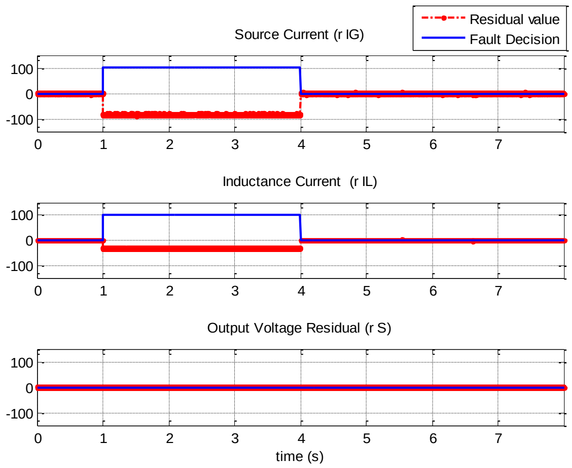
The generated residuals are compared each with its calculated threshold and the and the fault decision is shown (blue line) in Fig.3. The detection of faults arises when at least one of the three residuals becomes above its calculated threshold. Fig.3 demonstrates that faults are detected with negligible latency. Even though r_{S_m}(r S in Fig.3) is not important in the three selected faults. But it is introduced since this study is a part of a project to build a DFI system that deals with additional faults in which r_{S_m} may be effected.



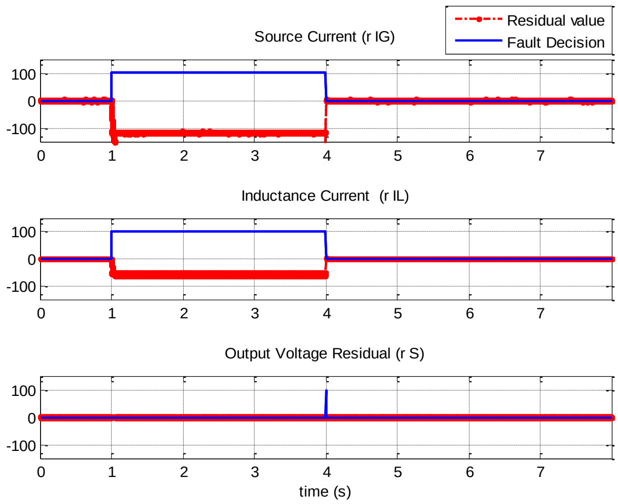
(a)

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015



(b)



(c)

	$\boldsymbol{A_M(\varphi)}$	$\boldsymbol{B_M(\varphi)}$	$\boldsymbol{C_M(\varphi)}$
Fault1	$\begin{pmatrix} -\frac{\varphi Rmos + Rmos + r_p}{2L_M} & \frac{nL_M(r_s + r_L) + n\varphi L(2Rmos + r_p)}{2L_M L} & \frac{n}{2L} \\ -\frac{n\varphi(2Rmos + r_p)}{2L} & -\frac{\varphi n^2(2Rmos + r_p) + \varphi . rs + 2r_L + r_s}{2L} & -\frac{1}{L} \\ 0 & \frac{1}{C_{eq}} & -\frac{1}{R_{eq}C_{eq}} \end{pmatrix}$	$\begin{pmatrix} -\frac{\varphi}{2L_M} & \frac{(1-\varphi)L + 2nL_M}{2L_M L} \\ \frac{n\varphi}{2L} & -1/L \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} \frac{\varphi}{2} & \frac{n\varphi}{2} & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \frac{1}{2} \end{pmatrix}$
Fault2	$\begin{pmatrix} -\frac{(\varphi R_{mos} + Rmos + r_p)}{L_M} & 0 & 0 \\ -\frac{n(2R_{mos} + r_p)}{L} & -\frac{\varphi r_S + r_L + 2\varphi n^2(R_{mos} + r_p)}{L} & -\frac{1}{L} \\ 0 & \frac{1}{C_{eq}} & -\frac{1}{R_{eq}C_{eq}} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 \\ \frac{n\varphi}{2L} & -2/L \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} \varphi & n.\varphi & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$
Fault3	$\begin{pmatrix} -\frac{\varphi Rmos + r_p + Rmos}{L_M} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{1}{C_e R_e} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} \varphi & n.\varphi & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

IV. FAULT ISOLATION

Beyond detecting the fault, knowing its magnitude, duration, location and type is beneficial to prevent its effects on the system. Fault isolation stands for specifying the type of the detected fault. This task is assigned to a Bayesian belief network model, since the generated residuals are not able to isolate the detected fault.

A. Bayesian Belief Network Model

Bayesian Belief Network (BBN) [12];[13] is a probabilistic directed acyclic graphical model, which is a brand of statistical models. These networks are defined by specifying their qualitative and quantitative components. The BBN structure (qualitative), which is made of nodes that represent the random variables and arcs for the dependency between the nodes. The BBN parameters (quantitative), i.e. the Conditional Probability Tables (CPT's) are filled with conditional probabilities for each node giving its parents.

1) Structure

BBN structure can be identified by an expert [14], by a structure learning algorithms [15];[16] or by a combination of both [17]. In this work, after well understanding the system, a Naive Belief Classifier (BNC) structure was selected and used as a first attempt to use BNNs for power converter fault isolation.

The BNC classifier was the subject of a particular attention [18] in the context of the supervised classification. Its performance was compared to other well-known classification statistical method [19]; [20]. In addition to its simplicity, BNCs have low sensitivity to noise. In BNC the observed variables $(r_{I_{mg}}, r_{I_{mL}}, r_{S_m})$ are assumed to be independent, the presence of correlations between those variables reduces the efficiency of the BNC [21]. However, [15] shows that even with the existence of correlated variables, BNC classifier gives good results compared to other more complicated classifiers. The structure is shown in Fig.4.

2) Parameters

The advantage of BNC lies in the possibility of decoupling the faults based on learning from the previously generated residuals related to the coupled faults. The conditional probability tables of the BNC are learned according to the generated residual data after adaptation using maximal likelihood algorithm [22]; [23]. Some works are done offline to categorize the data. For each fault simulation (3 sec) we have about 3000 sampled point r(t),

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015

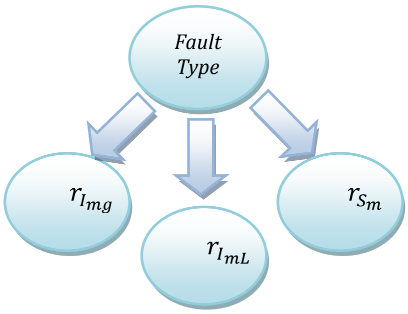


Fig. 4 Proposed BNC structure

where r(t) belongs to R^3 (Fig.3) . Fault1, Fault2 and fault3 residuals were considered and only the points related to the faulty case (from t=1s to t=4s) were discredited [24], while those related to the fault-free case were ignored. From this step we got three datasets R_{f_1}, R_{f_2} and R_{f_3} of 3000 descretized point each, the first related to the residuals generated during the occurrence of fault1, the second for the residuals generated during the occurrence of fault2 and the latter for the residuals generated during the occurrence of fault3 . Next for each data set a column was added to represent the class of each dataset points (labeling) . In the first dataset each point was labeled as f1 (for fault1), in the second data set as f2 (for fault2) while the points in the third dataset were labeled as f3 (for fault3).
After labeling, 50% of each dataset were used for BNC learning, and Maximum Likelihood Estimation algorithm was used [25]. While the other 50% were used for testing.
In order to evaluate the learning process and to insure that the system was well learned, the 50% that were used for learning were reused for learning validation. Let $L_{f_1}, L_{f_2} and\ L_{f_3}$ be the data used for learning from $R_{f_1}, R_{f_2} and\ R_{f_3}$ respectively. The BNC will estimate the class (f1, f2 or f3) for each record of $L_{f_1}, L_{f_2} and\ L_{f_3}$. Fig.5 (a) shows the BNC classification of the records of data that belongs to L_{f_1} , Fig.5 (b) presents those that belongs to L_{f_2} and Fig.5 (c) presents those that belongs to L_{f_3} compared to their actual classes. With the x-axis for the observation r(t) and the y-axis for the fault type (f1 for fault1, f2 for fault2 and f3 for fault3). One can recognize that the classifications of the BNC are compatible with the actual classes in most of the data points since in three graphs the green line which stands for the BNC classifications coincides with the dotted blue line which represents the actual fault type. The confusion matrix in Table IV (a) details the results. Only 6 data point were misclassified, 1 of them belongs to L_{f_1} , 2 belongs to L_{f_2} and 3 belongs to L_{f_3}. Thus the system has learned by 99.8 %.
After the structure identification and parameter estimation, the BNC will be used as an inference tool.

3) Inference

This network relies on inference algorithms to compute beliefs in the context of observed evidence [26]. Inference is the process of updating probabilities of outcomes (CPTs) based upon the relationships in the model and the evidence known about the situation at hand. Inference algorithms can be exact or approximated inference [27]. In our proposed BNC, the junction tree algorithm was used. It's one of the most popular exact inference algorithms [28]; [29]; [30].

B. Isolation

The isolation is based on inference. that is to calculate the probability of any combination of variables values given any observation ($P(X/O)$ where X is a set of random unknown variables represented by the nodes in the BBN and O is the set of observed variables usually equal to $\bar{X}$). The collected residuals which were recorded after fault detection, they are used to fed the BNC. Those records are passed through the BNC which will give the probability of the responsibility of each fault to this observation.

Let A be the set of recorded residual observations.

$$A = \{\, r(t) = (r_{I_{mg}}, r_{I_{mL}}, r_{S_m}) \,/ t \in [0, \ldots, n] \,\} \quad (6)$$

where 0 is the time where fault is detected and n is the final time.
Let B be the probability of occurrence of each fault given an observation of residuals at time t.

$$B = \{P(t) = \left(P_{f_1}, P_{f_2}, P_{f_3}\right) \ such\ that\ P_{f_i} = P(f_i/r(t))\ with\ r(t) \in A\ and\ i \in [1,2,3]\,\}. \quad (7)$$

Let C be the set of values that represent the most probable fault responsible for each observation defined as follow:

$$C = \left\{f_i \,/\, P_{f_i} = max(P(t))\ and\ \ P(t) \in B\right\} \quad (8)$$

The fault that is isolated will be the most frequent one in set C.

C. Isolation Results

Our test was applied to isolate faults 1, 2 and 3. To verify the efficiency of the proposed BBN method. The performance of the isolation process was validated using the remaining 50% from each dataset $R_{f_1}, R_{f_2} and\ R_{f_3}$. Let $A_{f_1}, A_{f_2}\ and\ A_{f_3}$ represents the remaining 50% of R_{f_1}, $R_{f_2} and\ R_{f_3}$ for testing respectively. Consequently the cardinality Card (A_{f_1})= Card (A_{f_2}) = Card (A_{f_3}) = 1500 discretized point. For each point r(t) in $A_{f_1}, A_{f_2}\ or\ A_{f_3}$, r(t) is fed to the BNC. The BNC will returns a value p(t) = { $P_{f_1}(t) = P\,(f_1/r(t)), P_{f_2}(t) = P\,(f_2/r(t))$, $P_{f_3}(t) = P(f_3/r(t))$}. Let $B_{f_1}, B_{f_2}\ and\ B_{f_3}$ be the set of p(t)'s for the points r(t) that belongs to $A_{f_1}, A_{f_2}\ and\ A_{f_3}$ respectively. Those sets are viewed in Fig.5 (d), (e) and (f). Interestingly, the two figures show high probabilities for the actual fault type in each set. That is in Fig.5 (d) the probabilities correspondent to fault 1 (green triangles) are very high compared to those of fault2 (red plus) and fault3 (blue dots) and the same for Fig.5 (e) and (f) it’s quite clear that the probabilities related to fault 2 and fault 3 are the greatest respectively.
Moreover, this figure (Fig.5 (d), (e) and (f)) hides in a valuable measurement known as belief index that indicate the confidence of the classification decision. This index can be calculated as the mean of the probabilities $P_{f_1}(t)$, $P_{f_2}(t)$ and $P_{f_3}(t)$ in each of the three sets B_{f_1}, B_{f_2} and B_{f_3}. Following equation 8, we have for B_{f_1}, $P\_Avg_{f_1}$= 0.99 versus $P\_Avg_{f_2}$= $9.4{\times}10^{-4}$ and $P\_Avg_{f_3}$ =0.001. The same for B_{f_2} and B_{f_3} see Table III. These calculated indices strongly support the BNC classifications.

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015

$$P\_Avg_{f_i} = \frac{\sum_{j=1}^{N}(P_{f_i}(t))_j}{N} \qquad (9)$$

where $P_{f_i}(t) \in B_f$ and $N=|B_f|$.

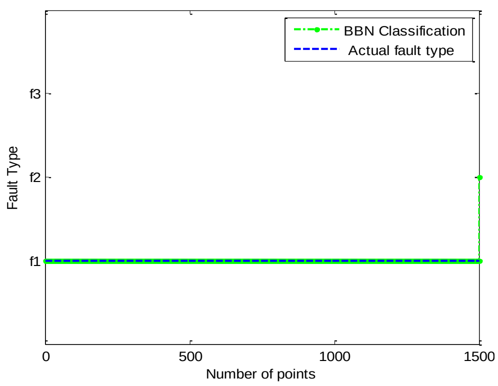
For the sake of isolation, for each P(t) let $c(t) = f_1$ if max(P(t))= $P_{f_1}(t)$, $c(t) = f_2$ if max(P(t))= $P_{f_2}(t)$ and $c(t) = f_3$ if max(P(t))= $P_{f_3}(t)$. And let C_{f_1}, C_{f_2} and C_{f_3} be the set of c(t)'s for the elements P(t)'s that belongs to B_{f_1} , B_{f_2} and B_{f_3} respectively.

The green lines in Fig.5 (g), (h) and (i) visualizes the sets C_{f_1}, C_{f_2} and C_{f_3} respectively, the x-axis for the observation number and the y-axis for the fault type. The doted blue lines represents the class actual value of each point r(t) in the A sets. It is very clear that in the faulty cases the BNC was able to classify the correct fault type. The confusion matrix in Table.4 (b) explains the graph (Fig. 5 (g), (h) and (i)). 8 point from $A_{f_3}$are misclassified, however, only 1 point of $A_{f_1}$and 2 points of A_{f_2} are misclassified. This test shows a very good accuracy 99.7% for our proposed BNC.

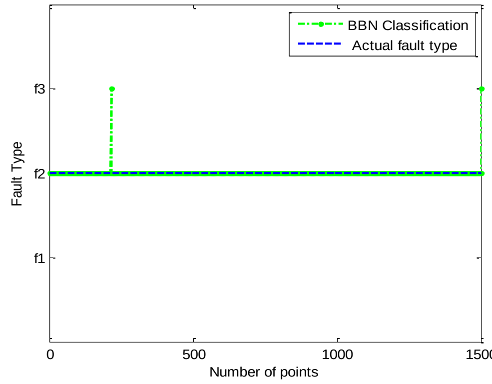
Moreover, to improve the credibility of the isolation decision, the frequency of f_1, f_2 and f_3 are calculated and the one with higher frequency (most frequent) is isolated. For instance consider C_{f_3}, $freq(f_3) = 1492$ which is greater than $freq(f_1) = 6$ and $freq(f_2) = 2$. That leads to isolate f_3 which is the correct actual fault in this case (the same can be done for C_{f_1} and C_{f_2}).

V. CONCLUSION

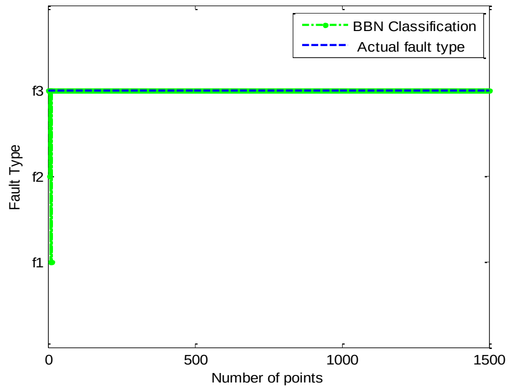
In this paper, a detection and isolation strategy for open circuit faults in ZVS full bridge isolated Buck converters was proposed. The approach is based on residual generation, using observers, by a comparison between estimated outputs and actual ones for detection, and Bayesian belief network for isolation. The proposed technique is able to detect the studied faults regardless of disturbance with negligible latency, and isolate the fault type with 99.7% accuracy. Moreover, this proposed BNC had recorded high and supportive confidence indexes for the three faults classification decision i.e. about 99% for the three faults. In the future this work can be extended to cover more faults such as close circuit faults by taken into account parameters due to thermal effects. And benefit from BBN capabilities in FDI domain. In addition the work will be developed to cover a system of multi DC/DC converters to detect the faulty converter and isolate the occurring fault. Finally, the method will be implemented and validated on ZVS full bridge isolated Buck converters.



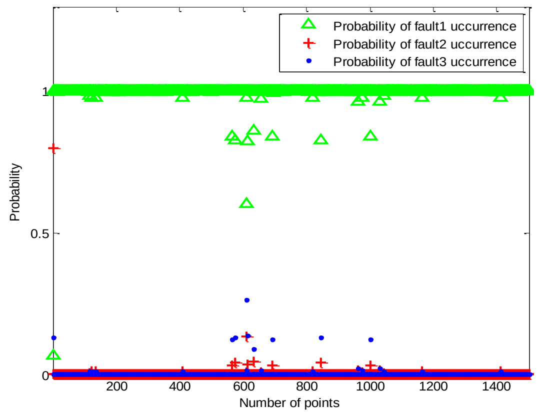
(a)



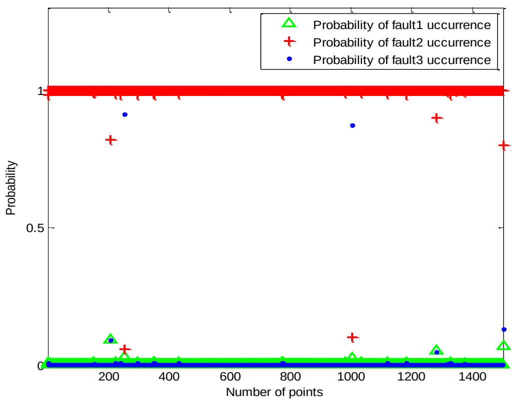
(b)



(c)



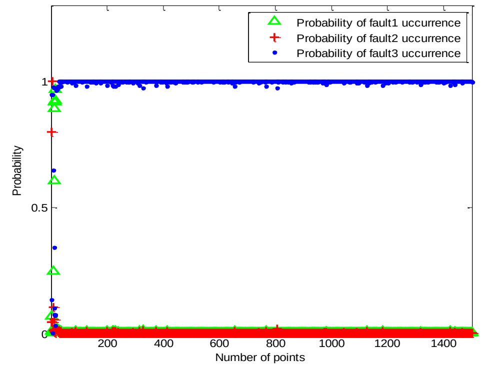
(d)



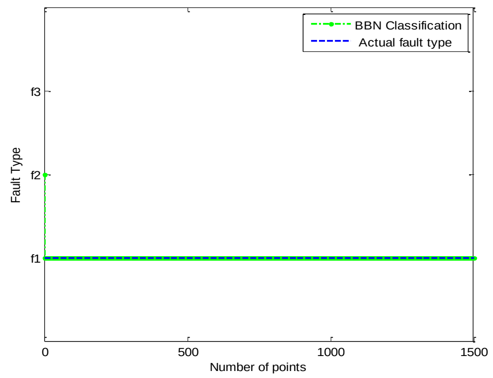
(e)

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

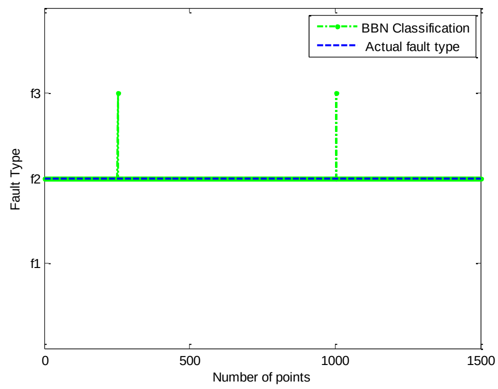
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015



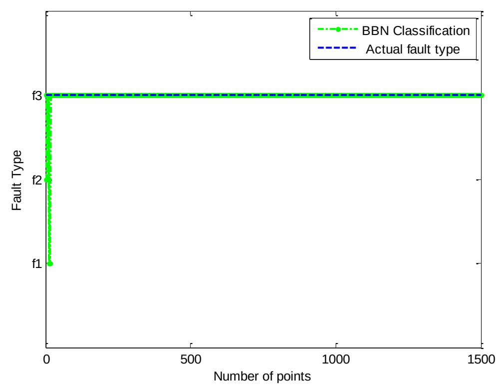
(f)



(g)



(h)



(i)

Figure.5. BBN Classifications: (a), (b) and (c) for learning evaluation; (d),(e) and (f) for probabilities and confidence; (g), (h) and (i) for validation.

TABLE III THE BELIEF INDEX (MEAN OF PROBABILITIES).

Faults	B_{f_1}	B_{f_2}	B_{f_3}
Fault 1	0.998	9.4×10^{-4}	0.001
Fault 2	3.1×10^{-4}	0.998	0.0015
Fault 3	0.004	0.0018	0.994

TABLE IV. THE BELIEF INDEX (MEAN OF PROBABILITIES)

Actual Class / Classification	Fault 1	Fault 2	Fault 3
Fault 1	1499	0	2
Fault 2	1	1498	1
Fault 3	0	2	1497

(a)

Actual Class / Classification	Fault 1	Fault 2	Fault 3
Fault 1	1499	0	6
Fault 2	1	1498	2
Fault 3	0	2	1492

(b)

REFERENCES

[1] Guerin, F., Lefebvre, D., and Loisel, V. 2012. "Supervisory control design for systems of multiple sources of energy". Control Engineering Practice, 20(12), 1310-1324.

[2] Hui, J., Bakhshai, A., and Jain, P. K. 2010. "A hybrid wind-solar energy system: A new rectifier stage topology". In Applied Power Electronics Conference and Exposition (APEC), 2010 Twenty-Fifth Annual IEEE (pp. 155-161). IEEE. Austin, TX,USA (Feb)

[3] Berendsen, C. S., Champenois, G., Davoine, J., and Rostaing, G. 1992. "How to detect and to localize a fault in a DC/DC converter?". InIndustrial Electronics, Control, Instrumentation, and Automation, 1992. Power Electronics and Motion Control., Proceedings of the 1992 International Conference on (pp. 536-541). IEEE.San Diego, CA,USA (Nov)

[4] Kim, S. Y., Nam, K., Song, H. S., and Kim, H. G. 2008. "Fault diagnosis of a ZVS DC–DC converter based on DC-link current pulse shapes" . Industrial Electronics, IEEE Transactions on, 55(3), 1491-1494.

[5] Alavi, S. M., Saif, M., and Fekriasl, S. "Multiple Fault Detection and Isolation in DC-DC Converters".

[6] Levin, K. T., Hope, E. M., and Domínguez-García, A. D. 2010. "Observer-based fault diagnosis of power electronics systems". In Energy Conversion Congress and Exposition (ECCE), 2010 IEEE (pp. 4434-4440). IEEE. Atlanta, GA, USA (Sep)

[7] Gao, J., Ji, Y., Bals, J., Kennel, R., and Center, G. A. "Fault Detection of Power Electronic Circuit using Wavelet Analysis in Modelica". In Proceedings of the 9th International MODELICA Conference (pp. 513-522). Munich, Germany

[8] Guerin, F., and Lefebvre, D. 2009. "Residual analysis for the diagnosis of hybrid electrical energy systems". IFAC Safeprocess 2009, Invited Session on "Diagnosis and Environmental Issues. Sants Hotel, Spain

[9] Guerin, F., Labarre, C., and Lefebvre, D. 2011a. "Magnetic near-field measurement for FDI of ZVS full bridge isolated buck converter". In Diagnostics for Electric Machines, Power Electronics and Drives (SDEMPED), 2011 IEEE International Symposium on (pp. 344-349). IEEE. Bologna, Italy (Sep)

[10] Guérin, F., Lefebvre, D., Mboup, A. B., Parede, J., Lemains, E., and Ndiaye, P. A. S. 2011b. "Hybrid modeling for performance evaluation of multisource renewable energy systems". Automation Science and Engineering, IEEE Transactions on, 8(3), 570-580.

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 7, July 2015

[11] Mboup, A. B., Guerin, F., Ndiaye, P. A., and Lefebvre, D. (2008, June). "Multimodel for the coupling of several dc/dc power converters on a dc bus". InIndustrial Electronics, 2008. ISIE 2008. IEEE International Symposium on (pp. 1507-1512). IEEE.
[12] Jensen, F. V. (1996). "An introduction to Bayesian networks" (Vol. 210). London: UCL
[13] J.Pearl. "Probabilistic Reasoning inIntelligent Systems : Networks of Plausible Inference ".MorganKaufmann,SanMateo,1988.
[14] Wiegerinck, W. 2005. "Modeling Bayesian Networks by Learning from Experts". In BNAIC (pp. 305-312).
[15] Friedman, N., Geiger, D., and Goldszmidt, M. 1997. "Bayesian network classifiers". Machine learning, 29(2-3), 131-163.
[16] Pearl, J. Causality: Models, Reasoning, and Inference. Cambridge. 2000.
[17] Flores, M. J., Nicholson, A. E., Brunskill, A., Korb, K. B., and Mascaro, S. 2011. "Incorporating expert knowledge when learning Bayesian network structure: a medical case study". Artificial intelligence in medicine, 53(3), 181-204.
[18] Tiplica, T., Verron, S., Kobi, A., and Nastac, I. 2006. "FDI in multivariate process with naive bayesian network in the space of discriminant factors". In Computational Intelligence for Modelling, Control and Automation, 2006 and International Conference on Intelligent Agents, Web Technologies and Internet Commerce, International Conference on (pp. 216-216). IEEE.(Nov)
[19] Langley, P., Iba, W., and Thompson, K. 1992. "An analysis of Bayesian classifiers". In AAAI (Vol. 90, pp. 223-228).(July)
[20] Madden, M. 2003. "The performance of Bayesian network classifiers constructed using different techniques". In Proceedings of European conference on machine learning, workshop on probabilistic graphical models for classification (pp. 59-70).(July)
[21] Langley, P., and Sage, S. 1994. "Induction of selective Bayesian classifiers". In Proceedings of the Tenth international conference on Uncertainty in artificial intelligence (pp. 399-406). Morgan Kaufmann Publishers Inc.(July).
[22] Grossman, D., and Domingos, P. 2004. "Learning Bayesian network classifiers by maximizing conditional likelihood". In Proceedings of the twenty-first international conference on Machine learning (p. 46). ACM.(July).
[23] Redner, R. A., and Walker, H. F. 1984. "Mixture densities, maximum likelihood and the EM algorithm". SIAM review, 26(2), 195-239.
[24] Colot O F, Olivier PC, El Matouat A. 1994, "Information Criteria and Abrupt Changes in Probability Laws" , Signal Processing VII: Theory and Applications. pp.1855-18858.(Sep)
[25] King, G. 1989. Unifying political methodology: "The likelihood theory of statistical inference". University of Michigan Press
[26] Huang, C., and Darwiche, A. 1996. "Inference in belief networks: A procedural guide". International Journal of Approximate Reasoning, 15(3), 225-263
[27] Guo, H., and Hsu, W. 2002. "A survey of algorithms for real-time Bayesian network inference". In AAAI/KDD/UAI02 Joint Workshop on Real-Time Decision Support and Diagnosis Systems. Edmonton, Canada.(July)
[28] Jensen F.V., Lauritzen S.L., and Olesen K.G. 1990: "Bayesian updating in causal probabilistic networks by local computations". Computational Statistics Quarterly 4:269-292.
[29] Cowell, R. 1998. "Introduction to inference for Bayesian networks". In Learning in graphical models (pp. 9-26). Springer Netherlands.
[30] Pan, H., McMichael, D., and Lendjel, M. 1998. "Inference algorithms in bayesian networks and the probanet system ". Digital signal processing, 8(4), 231-243.