Online Fault Diagnosis Method for Grid-Connected Inverters Based on Finite-Set Mixed Logical Dynamical Model Prediction

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Online Fault Diagnosis Method for Grid-Connected Inverters Based on Finite-Set Mixed Logical Dynamical Model Prediction

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Abstract—The grid-connected inverter is a key device in the renewable energy power generation system and large-scale energy storage system, which the operational stability and reliability are the basis for the efficient and safe application of electrical energy. A real-time fault diagnosis method of a three-phase for grid-connected application combining a mixed logic dynamic (MLD) model and finite control set model predictive control (PCS-MPC) is proposed. This paper not only realizes the open circuit fault diagnosis and location of the switching devices in the main power circuit, but also discusses the threshold issues and post-fault operations. The advantage of the proposed method is that it directly uses the control data and measurement signals of the controller without extra sensors and calculation, which will shorten the fault diagnosis time and occupy less calculation resource of the main processor. Simulation results illustrate the quickness of the fault identification and accurate position with robustness to the interference of the diagnosis method. Finally, the effectiveness of the diagnosis method was verified by a 1500W experimental prototype in a laboratory.

Index Terms—fault diagnosis, finite control set model predictive control, grid-connected inverter, mixed logical dynamic model

I. INTRODUCTION

REGARDLESS of the promotion and application of renewable power generation technology, or the future requirements of smart grids for improving the quality of the grids and reducing fault loss, inverter fault diagnosis technology has a crucial influence. Grid-connected inverters often face the threat of failures due to the complexity of their working environment and structures. How to improve the reliability of the grid-connected inverters and minimize the impact of the fault is an urgent problem to be solved [1]–[3]. The structural faults of the main power circuit are usually divided into two categories, such as open-circuit and short-circuit fault, which has an enormous impact on the grid and could cause the system break down [4], [5].

Many researchers have been tried to obtain a reliable diagnostic method to detect and diagnose the faults of the circuit automatically. For example, a zero-vectors-based method with primary inductance energy analysis is introduced to the fault diagnosis in [6]. The use of Parks vector approach as an effective fault diagnostic tool for voltage source inverter (VSI) faults was firstly proposed in [7]. Li et al. [8] used the mutation of the instantaneous frequency of the current vector when the inverter has an open circuit fault to realize the rapid diagnosis of the open circuit fault of the power switching device. However, the position of the faulty switch tube cannot be located, so it is impossible to perform fault tolerance and post-fault maintenance. Yong et al. [9] locate the fault phase of the inverter through the analysis of the current vector angle, and then use the current average diagnostic variable to locate the specific position of the fault switch, which can complete the fault diagnosis within 60% of the fundamental cycle. This current vector feature analysis method overcomes the shortcomings of the instantaneous frequency method, but it needs to select more thresholds. Some other current based approaches are performed in [10]–[13]. The average current Park vector method, which calculates period average current of the three-phase outputs [10], [11]. Because a non-zero component appears when an open-circuit fault occurs, and the current variable exhibits a specific amplitude and phase characteristic. As a supplementary improvement, the normalized DC current method is presented in [11]. The normalized value is calculated for each phase to identify the faulty power device. However, this approach requires very complex pattern recognition algorithms that are not suitable for integration into the microcontroller of converters.

With the development of signal processing technology, the method of decomposing the current signal by means of wavelet analysis and fast Fourier transform (FFT) is also adapted to the related technology of fault diagnosis. Lin et al. use FFT to transform the output current of the dual-buck DC-AC converter to extract the parameter fault features as the input of fuzzy cerebellar model neural network (FCMNN) classifier and obtained excellent diagnosis results [14]. However, the Fourier transform is difficult to effectively extract the characteristic information of the mutation signal. Wavelet analysis is used in [15] in order to extract the energy of fundamental component over different scales from stator current. Mellit et al. combines fast Fourier transform and wavelet transform, and selects the optimal wavelet function suitable for fault detection according to the frequency component of the fault signal after FFT to extract fault characteristics [16]. However, this type of method generally requires a large number of mathematical calculations, which result in a big computing burden, and it is not conducive to online diagnosis.

In recent years, data-driven fault diagnosis methods have
been widely used in the field of power electronic converter. Moosavi et al. using an artificial neural network (ANN) structure and extraction of pattern method to effectively distinguish faults [17]. Cai et al. proposed a data-driven diagnosis method for three-phase inverter combining FFT and Bayesian networks, and the fault diagnosis of the inverter was realized by measuring the output voltage of different fault modes [18]. Sun et al. [19] proposed a deep belief network (DBN) for the structural and parametric faults of closed-loop single-ended primary inductance converter, and crow search algorithm (CSA) was introduced to select the optimal number of neurons in the hidden layer of DBN. The methods in [17]–[19] all need to combine the signal processing technology mentioned above to extract effective fault features from the original sampling signal, which makes the feature extraction process more complex and increases the time of fault diagnosis.

Model-based methods like parity space method or observer based methods have been attractive during recent years due to their fast response and simple implementation [20]. Model-based method can define and identify fault behaviors based on system principles [21], [22], which means a more convenient online diagnosis, compared with data-based and knowledge-based methods. In respect of advantages mentioned above, a fault diagnosis method based on model prediction is proposed. The open-circuit fault diagnosis and location for the grid-connected inverter could be obtained by the combination of finite control set-model predictive control (FCS-MPC) and a mixed logical dynamical (MLD) model. The strategy has the online, simple, quick characteristics so as to be easily embedded in the microcontroller. Moreover, the threshold issues and post-fault operations have been discussed as well in this paper. The proposed method is verified by a 1500W experiment and it can achieve optimal resource utilization and online processing based on the fault diagnosis function with scarcely additional costs. The main contributions and highlights of this paper are demonstrated below:

1) The FCS-MPC combined with MLD is applied to control three-phase grid-connected inverter. As a closed-loop control strategy, FCS-MPC performs well in terms of dynamic response and steady state of the grid-connected inverter. Decentralized systems model only is considered only instead of the modulation algorithm with linear approximation, so the control strategy requires little computing resource.

2) To improve the parameter robustness of the control method, we propose a universal and simple online parameter identification technique based on the recursive least squares (RLS) method to estimate the parameters. Since the grid-side currents and the grid voltage are already required for FCS-MPC, the algorithm is independent of the control process without any additional sensors.

3) All operation principles of open circuit fault are demonstrated in detail via MLD, and the system model of the open circuit fault is established. A fault diagnosis algorithm based on FCS-MPC is designed to detect faults by means of the residuals between the trend prediction and actual output, and the finite set method is used to identify and locate the states of the faulty switches. When the grid-connected current is discontinuous, the faulty switch can be located within a shorter period of time accomplished by the residuals between analyzing the prediction and real-time measurement. In addition, the definition and selection of the threshold is limited.

The rest of this paper is structured as follows: fault modeling and analysis are studied in section II. Section III presents the scheme of control and diagnosis. The effectiveness of the proposed method is verified through simulation and hardware experiments in section IV. Finally, the conclusion is drawn in section V.

II. FAULT MODELING BASED ON MIXED LOGIC DYNAMIC MODEL

A. Mixed Logical Dynamic Model for A Three-phase Inverter

The inverter is widely applied in the interfaces of grid-connected power systems such as distributed generation, micro-grids, and energy storage systems. The overview structure of grid-connected inverter system is depicted in Fig. 1. The power emitted by the distributed energy source is connected to the input of the inverter. The converter and the filter network convert the DC power into AC power for the grid corresponding to the action of the controller. As shown in Fig. 1, the grid-connected inverter consists of the converter filter network and the controller part.

![Grid-connected inverter system diagram](image)

Fig. 1. Grid-connected inverter system diagram.

![Three-phase grid-connected inverter topology](image)

Fig. 2. Three-phase grid-connected inverter topology

It is necessary to analysis the fault behaviors by grasping the structural composition of the entire grid-connected system. Taking into account the focus of this paper, the part of the grid-connected inverter is simplified and, equivalent the distributed power supply to a DC bus as shown in Fig. 2. The LCL filter network is simplified as a single inductance, since the unit power factor to the grid connection is obtained in this paper, and the frequency of the output grid-connected current is consistent with the grid frequency. Furthermore, these six switching devices are fully controlled switching devices with
anti-parallel diodes, and the main research focus of this paper is how to find the open-circuit faults of the switching devices as illustrated in Fig. 2. The three-phase voltage variables are illustrated as (1).

\[
\begin{align*}
    u_{an} &= L_0 i_{an}/dt + R_0 i_{an} + e_a \\
    u_{bn} &= L_0 i_{bn}/dt + R_0 i_{bn} + e_b \\
    u_{cn} &= L_0 i_{cn}/dt + R_0 i_{cn} + e_c
\end{align*}
\]  

(1)

According to the traditional state space model (1), the output voltages are relevant to the switching states and the current state. However, traditional modeling does not meet the nonlinearity of switching operation for power electronics. The inverter is a typical hybrid system. The mixed logical dynamic model can simultaneously represent the continuous state change and discrete state change of the inverter. It is more convincing to analyze the nonlinear characteristic with fault behaviors of switching devices and to reduce modeling errors through mixed logical dynamical methods. However, a mathematical model that accurately describes the characteristics of a circuit is the key to accurate control and diagnosis. Logic variables delta is defined to demonstrate the direction of output currents, shown as the following expression in (2).

\[
\begin{align*}
    \delta_t &= 1 \leftrightarrow i_a > 0 \\
    \delta_n &= 0 \leftrightarrow i_a < 0 \\
    \delta_b &= 1 \leftrightarrow i_b > 0 \\
    \delta_n &= 0 \leftrightarrow i_b < 0 \\
    \delta_c &= 1 \leftrightarrow i_c > 0 \\
    \delta_n &= 0 \leftrightarrow i_c < 0
\end{align*}
\]  

(2)

The paper summarizes the logical relationships in these circuits and expresses them mathematically. The output terminal voltages expressed as follows, which are related to the switching signal and current status.

\[
\begin{align*}
    u_{ao} &= V_{dc} s_1 \bar{s}_2 (s_1 + \bar{s}_1 \delta_t) \\
    u_{bo} &= V_{dc} s_3 \bar{s}_2 (s_3 + \bar{s}_3 \delta_b) \\
    u_{co} &= V_{dc} s_2 \bar{s}_3 (s_2 + \bar{s}_2 \delta_c)
\end{align*}
\]  

(3)

Defined the three discrete auxiliary variables \(\delta_1, \delta_2,\) and \(\delta_3\) are shown in (4).

\[
\begin{align*}
    \delta_1 &= \bar{s}_1 (s_1 + \bar{s}_1 \delta_t) \\
    \delta_2 &= s_3 \bar{s}_2 (s_3 + \bar{s}_3 \delta_b) \\
    \delta_3 &= s_2 \bar{s}_3 (s_2 + \bar{s}_2 \delta_c)
\end{align*}
\]  

(4)

Then the output voltages can be rewritten as (5).

\[
\begin{bmatrix}
    u_{an} \\
    u_{bn} \\
    u_{cn}
\end{bmatrix} = \frac{V_{dc}}{3} \begin{bmatrix}
    2 & -1 & -1 \\
    -1 & 2 & -1 \\
    -1 & -1 & 2
\end{bmatrix} \begin{bmatrix}
    \delta_1 \\
    \delta_2 \\
    \delta_3
\end{bmatrix}
\]  

(5)

Combining the equations above mentioned, the MLD model of a three phase grid-connected inverter is constructed as follow in (6).

\[
\begin{bmatrix}
    \frac{\partial \delta_1}{\partial t} \\
    \frac{\partial \delta_2}{\partial t} \\
    \frac{\partial \delta_3}{\partial t}
\end{bmatrix} = \begin{bmatrix}
    L_0 & 0 & 0 \\
    0 & L_0 & 0 \\
    0 & 0 & L_0
\end{bmatrix} \begin{bmatrix}
    i_a \\
    i_b \\
    i_c
\end{bmatrix} + \begin{bmatrix}
    e_a \\
    e_b \\
    e_c
\end{bmatrix}
\]  

(6)

The MLD model based on output current could describe accurately the variety of discrete states and continuous states. When an open circuit fault occurs in a three-phase grid-connected inverter, discrete input variables are different from the actual switching signals. Considering the low probability of multiple open-circuit in actual situations, only the open circuit fault of a single switching device is discussed in this paper. Each open-circuit fault situation could be described accurately with the aid of MLD method. The final output current and voltage show the corresponding fault characteristics, and the function of fault diagnosis could be obtained through the analysis of these fault characteristics.

B. Model Parameter Estimation

A parameter identification technique based on RLS is used for estimating and update the established model parameters. By step-wise process of the algorithm, the inductance \(L\) and resistance \(R\) are converged quickly to alleviate the error between physical model and ideal model.

The model of grid-connected converter can be expressed by matrix terms:

\[
\begin{align*}
    y(k) &= \Phi^T(k-1) \theta(k-1) + \xi(k-1) \\
    \Phi^T(k-1) &= \begin{bmatrix} i(k-1) & u(k-1) & e(k-1) \\ 1 - \frac{R(k-1)}{L(k-1)} & \frac{R(k-1)}{L(k-1)} \end{bmatrix} \\
    \theta(k-1) &= \begin{bmatrix} R(k-1) \end{bmatrix}
\end{align*}
\]  

(7)

Where \(\xi(k-1)\) denotes the model residual at time \(t-1\).

The parameter vector is estimated and updated by the following equations as:

\[
\begin{align*}
    \hat{\theta}(k) &= \hat{\theta}(k-1) + K(k) \left[ y(k) - \Phi^T(k-1) \hat{\theta}(k-1) \right] \\
    K(k) &= \frac{P(k-1) \Phi(k-1)}{\lambda + \Phi^T(k-1) P(k-1) \Phi(k-1)} \\
    P(k) &= \frac{1}{\lambda} \left[ I - K(k) \Phi^T(k-1) \right] P(k-1)
\end{align*}
\]  

(9)

Where \(K\) is the gain matrix, \(P\) is the covariance matrix, \(\alpha\) is the smaller positive integer, and \(\lambda\) is the forgetting factor. Suitable forgetting factor can balance disturbances suppression and the time of tracking parameter variations. The smaller choice may lead to weaken the capability of anti-disturbances. By contrast, the bigger choice makes the algorithm tend to reduce the sensitivity to system changes. Generally, \(\lambda\) can be set between 0.95 and 0.995 [23]–[25].

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C. Open-Circuit Fault Model

The open-circuit fault modeling could follow the normal situation, which is depending on the switching signal, faulty switches, and current status. The paper establishes a system model for each open-circuit fault of a switching device, since the discrete input variables correspond to each fault situation, respectively. The paper evaluates faults based on the built fault model. Take open-circuit in A phase for an instance, the switching signal is. Especially, the logical variable δ is redefined in order to prevent interference caused by disordered fault current and by using the characteristic of voltage and current. They have the same frequency and phase in unit power factor when there is a grid connection. The faulty model of the discrete input variables is as follows.

\[
\begin{align*}
\delta_1' &= \delta_4 + \delta_3 \\
\delta_2 &= \delta_4 (s_3 + s_3 \delta_3) \\
\delta_3 &= \delta_2 (s_3 + s_3 \delta_3)
\end{align*}
\]

Therefore, the three-phase output voltage \([u_{an} \ u_{bn} \ u_{cn}]\) can be expressed in formula (14).

\[
\begin{bmatrix}
u'_{an} \\
u_{bn} \\
u_{cn}
\end{bmatrix} = \frac{V_{dc}}{3} \begin{bmatrix}
2 & -1 & -1 \\
-1 & 2 & -1 \\
-1 & 1 & -2
\end{bmatrix} \begin{bmatrix}
\delta_4 \\
\delta_2 (s_3 + s_3 \delta_3) \\
\delta_2 (s_3 + s_3 \delta_3)
\end{bmatrix}
\]

From fault model actions in front of open-circuit fault is analyzed, when open-circuit fault occurs on the power device \(T_1\) as shown in Fig. 2, at the moment the current of phase A is positive, then the output voltage of phase A is keeping non-positive. When an open-circuit fault occurs in the power device \(T_2\) of the same bridge arm, if the phase A current is negative, then the output voltage of phase A remains non-negative. The principle of other open-circuit faults could be deduced in the same way. When the fault phase opens, the current is intermittent. It can be observed that not only the currents change, but also there is an abnormal change in voltages. When the circuit is running in the open circuit failure mode, the three-phase voltage, and the current exhibit different distortions. Online diagnostic algorithms and fault handling schemes can be designed based on such features.

III. CONTROL STRATEGY AND DIAGNOSIS APPROACH

A. Finite-set MLD Model Predictive Control for Three-phase Inverter

FCS-MPC is widely applied in the control of power converters with excellent dynamic response and abundant conditional constraints. However, the research on fault diagnosis of FCS-MPC is relatively scarce. The general idea is to predict future sample values based on present information such as switching states, currents and voltages in the circuit, and comparison with references by a defined cost function. The algorithm evaluates and implements the best switching states for the next sample period. The structure of a control system is shown in Fig. 3. A finite set model predictive control based on the discrete state mainly consists of four parts, namely, finite control set, predictive model, evaluation function and delay compensation. The prediction model is obtained by discrete processing based on the inverter model, the evaluation function acts as a constraint to implement a current tracking reference, and the delay compensation is to consider the time when the model predictive control calculation is executed, leaving an entire sampling period for the operation and execution of the algorithm.

The differential term could be discretized with Euler front formula, where \(T_s\) represents sampling period, \(i(k+1)\) and \(i(k)\) are predictive and sampling values, respectively.

\[
\frac{di}{dt} = \frac{i(k+1) - i(k)}{T_s}
\]

Combining with MLD model of the three-phase inverter system, there is the predictive model in the a-b-c coordinate.

\[
\begin{bmatrix}
i_a(k+1) \\
i_b(k+1) \\
i_c(k+1)
\end{bmatrix} = \left(1 - R \frac{T_s}{L}\right) I_{3 \times 3} \begin{bmatrix}
i_a(k) \\
i_b(k) \\
i_c(k)
\end{bmatrix}
\]

\[
\begin{bmatrix}
u_{an}(k) - \epsilon_a(k) \\
u_{bn}(k) - \epsilon_b(k) \\
u_{cn}(k) - \epsilon_c(k)
\end{bmatrix}
\]

Clark transform is used to convert the three-phase static coordinate to the two-phase stationary coordinate, and the result is as (17) shown. Then Park transform can be used to expressed the predictive model of the grid-connected inverter in the rotated coordinate.

\[
\begin{bmatrix}
i_a(k+1) \\
i_b(k+1)
\end{bmatrix} = \left(1 - R \frac{T_s}{L}\right) I_{2 \times 2} \begin{bmatrix}
i_a(k) \\
i_b(k)
\end{bmatrix}
\]

\[
+ T_s / L \begin{bmatrix}
u_a(k) - \epsilon_a(k) \\
u_b(k) - \epsilon_b(k)
\end{bmatrix}
\]

\[
i_d(k+1) = i_a(k+1) \cos \theta + i_b(k+1) \sin \theta \\
i_q(k+1) = -i_a(k+1) \sin \theta - i_b(k+1) \cos \theta
\]

where \(\theta\) is the rotation angle of the coordinate. Targeting the reference current and considering the constraints, the cost function for MPC is defined as:

\[
g_{can} = \left[\tilde{i}_d^2(k+1) - i_d(k+1)\right]^2 + \left[i_q^2(k+1) - i_q(k+1)\right]^2
\]

where \(i_d(k+1)\) and \(i_q(k+1)\) represent current prediction components, respectively. In this way, the active and reactive components of the input grid power can be controlled.

Three-phase grid-connected inverters have only a limited number of switch sets or control sets, based on MLD foundation, all of the FCS-MPC discrete models can be fully
expanded to represent each control set, including control sets under fault behavior. Not only makes predictive control simple and straightforward, but also makes open-circuit fault diagnosis more traceable. Moreover, it can also make full use of existing sampling and switching status information to embed fault diagnosis algorithms into the existing control programs.

B. Online Fault Diagnosis Approach Based on MLD Model Prediction

In this paper, the diagnosis strategy is divided into three procedures, which include detection, location, and post fault measures. The fault detection is in the first place, assuming that open-circuit occurs in the k instant, the algorithm predicts the current \( i_a(k+1) \) and \( i_p(k+2) \) for the next sampling period based on mentioned predictive model, and compares it to the corresponding sampling values after stack latch processing, synchronous scrolling with FCS-MPC control. The detection scheme is depicted in Fig. 4.

![Figure 4: Fault detection scheme diagram.](image)

A residual vector is expressed in (20), where \( r(k+2) \) represents a residual function of output vectors, \( i_a(k+2) \) and \( i_p(k+2) \) are predictive currents with their real sampling values in the same instant.

\[
r(k+2)^2 = [r_a(k+2) - i_a(k+2)]^2 + [r_p(k+2) - i_p(k+2)]^2
\]  
(20)

The residual vector, as the most important variable for the fault distinguishes in the fault detection process, should meet the characteristics, such as keeping relative lower than a threshold in faultless situation and increasing significantly when the faults occur. Compared with the traditional fixed value which often determined by experience, expression (21) could effectively solve the frequent adjustment of thresholds due to system operation changes.

\[
r(k) = \frac{r(k)}{I_a(k)} = \frac{r(k)}{\sqrt{r_a^2(k) + r_p^2(k)}}
\]  
(21)

C. Fault Location Principle

The switching states of the controller are divided into seven categories according to FCS-MPC, including a normal switch status \( S_f \) and six open circuit faults \( S_{f1} \) to \( S_{f6} \), the predictive model calculates seven different current variables by estimating the predicted values of the seven statuses separately, as shown in Fig. 5. The solid line indicates the finite sets expansion applied to the algorithm, the controller traverses each of the switching states and predicts the current value of the fault output based on the kth sample value and open fault model. There are six kinds of vectors corresponding to the case where six switching devices are open-circuit, and the seventh vector corresponds to the control vector in the normal state.

![Figure 5: Fault diagnosis principle.](image)

The system obtains new samples at the \((k+1)\) instant, and it compares seven predictive currents with the sampling. If the seventh current vector is closest to the real sample value, which means there is no fault in the circuit; while if one of the other six current vectors is not closest to the real sample value, the corresponding fault model and fault switch device are determined. A fault cost function as expression (22) is defined to scale the proximity of each faulty prediction to the actual sampling value.

\[
f_{\text{cost}}[j] = \left[ i_a(k+1) - i_a^{(p)}(k+1) \right]^2 + \left[ i_p(k+1) - i_p^{(p)}(k+1) \right]^2 
\]  
(22)

Due to modeling deviation and sampling signal interference in practice, a moving average window is added to improve the accuracy and reliability of the diagnosis scheme, where \( f_j(k) \) represents each selected orientation function. The function is equal to one if the corresponding vector is chosen, and equal to zero if not. \( N \) represents the width of the moving average window.

\[
F_j(k) = \frac{1}{N} \sum_{j=k-N}^{k} f_j(k)
\]  
(23)

In Fig. 6, if there is no open circuit fault, the algorithm may have some false alarms due to factors such as sampling interference, but after moving window filtering, the output of the function does not exceed the threshold. When an open circuit fault occurs, the positioning function is concentrated in the vicinity of 1 in large numbers. Although there is a missed diagnosis, the output after window filtering exceeds the threshold, and the corresponding output can correctly respond to the faulty device.

The cumulative sum of the fault function \( \sum f_j(k) \) is shown in Fig. 7. When there is no open fault switch during time 0 to \( t_1 \), the faultless situation \( f_7 \) was selected each time and the sum of \( f_j \) increases linearly. At the same time, the fault function \( f_i \) of \( T_i \) is always zero. If there is an open fault in switch \( T_i \) after time \( t_1 \), the sum of fault function \( f_1 \) will increase very quickly, but it does not increase linearly with the time for there is no
difference between the faultless situation $f_2$ and fault situation $f_1$ when switch $T_1$ is not used.

![Fig. 6. Principle of positioning of fault function.](image)

![Fig. 7. Fault positioning function.](image)

In the two-level three-phase inverter, the antiparallel diode of the bridge arm will be cutoff when the open circuit fault occurs mainly because the voltage of DC bus is always higher than the voltage of the grid, causing the discontinuousness of the fault phase current. The current will be closed to 0 when the polarity of the current in the non-fault phase changes. Thus, the divergence between $\lambda_1$ and $\lambda_2$ is too small to determine the threshold if subtraction is used. Too small selection of the threshold can give rise to misdagnosis and too large selection of the threshold can lead to the increase of the diagnostic time. The original fault predictive model is not conducive to the development of fault diagnosis research, so an intermittent flag variable $\lambda$ is introduced, which is defined as (24).

$$\lambda = \left| \frac{\lambda_1}{\lambda_2} \right|$$  \hspace{1cm} (24)

where $\lambda_1$ defined as the theoretical value of output current increment, and $\lambda_2$ defined as the actual value of output current increment. Where $m$ represents the phase number, $a$, $b$, and $c$.

$$\lambda_1 = T_5 \frac{u_m - i(k)}{R} - e_m$$  \hspace{1cm} (25)

$$\lambda_2 = i_{\text{sample}}(k) - i_{\text{sample}}(k - 1)$$  \hspace{1cm} (26)

The moving average window method mentioned above is also used to reduce the influence on modeling deviation and sampling signal interference in practice. In addition, the ratio form avoids the influences on the diagnosis, which caused by the deviation between actual and rated parameters of the device.

In this paper, the residual vector between healthy predictive model and actual fault output is introduced, since the residual vector is independent of the system operating state, but indicates the abnormal status information, especially on the open-circuit occasion, where the residual vector has a significant increase. The diagram of the diagnosis system is depicted in Fig. 8.

![Fig. 8. Fault diagnosis and control system.](image)

Taking the open fault of the A phase upper leg $T_1$ as an example, the switch signal $s_1$ is zero constantly, causing the actual discrete output $\delta'(k)(\delta'(k) \neq \delta(k))$ to become as expression (27).

$$\delta(k) = \begin{bmatrix} \delta_4 \delta_5(k) \\ \delta_6(s_1 + s_5 \delta_5(k)) \\ \delta_5(s_1 + s_5 \delta_5(k)) \end{bmatrix}$$  \hspace{1cm} (27)

And the three-phase current residual vector can also be expressed in (28).

$$\epsilon(k + 1) = \Lambda \epsilon(k) + B_\Sigma \{ \delta(k) - \delta'(k) \} = \Lambda \epsilon(k) + \frac{v_{dc} L}{3} s_5 \frac{T_5}{2} \left[ \begin{array}{cc} 1 & 1 \end{array} \right]^T$$  \hspace{1cm} (28)

When the A phase upper leg $T_1$ is open, phase A has a negative residual, and positive residuals in B phase and C phase are produced. It will result in different DC biases, integrate the residuals of the three phases separately. The residual integration will increase in a specific direction after fault occurs, and the change rules are shown in Table I. The algorithm identifies the faulty switch when the variable exceeds the limiting.

**D. Evaluation of Diagnosis and Post-fault Reconfiguration**

Obviously, there is still no perfect solution for open circuit faults. The following are the main points for the evaluation of the diagnostic strategy and the direction of optimization. Firstly, minimize diagnosis time, which ensure effective implementation of diagnostic measure. Secondly, as few extra sensors as possible, the extra device will increase the complexity of the system that may cause more risks. Thirdly, the influence
of control strategy, there are various strategies for one system, the closed-loop, for example, has a strong correction ability which will interfere the diagnosis. Finally, robustness and sensitivity need a compromise and balance.

Fig. 9. Fault tolerant topology of inverter with bidirectional switches.

A modified hardware topology with four bridge arms and bidirectional switching devices is shown in Fig. 9, which plus a predictive model reconstruction strategy can be used for fault tolerant control after one of the switch opened. And the whole process work-flow can be illustrated in Fig. 10. Firstly, the MLD-based FS-MPC is introduced to control the inverter in normal situation and detect the fault at the same time. In the meantime, the parameter identification algorithm is initiated to enhance the performance of the converter control. Secondly, when an open-switch fault was detected, the MLD-based fault model is used to position the open arm. Finally, post-fault reconfiguration action is activated after fault position.

![Diagram](image.png)

**TABLE I**

<table>
<thead>
<tr>
<th>Faulty Switch</th>
<th>Three-phase positioning variable</th>
<th>$e_a(k+1)$</th>
<th>$e_b(k+1)$</th>
<th>$e_c(k+1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_1$</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>$T_2$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>$T_3$</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>$T_4$</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>$T_5$</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>-</td>
</tr>
</tbody>
</table>

**E. Multiple Open-Circuit Fault**

The above diagnosis method for single open-circuit faults is also applicable to the multiple open-circuit faults. As for the multiple faults (not the faults in the same bridge arm), the intermittency of the current lasts shorter than the same when the single fault occurs and the residual integration of the three-phase currents scarcely reaches saturation simultaneously, leading to increase the diagnostic time when all the residual integration is utilized to locate the faults. Therefore, the two residual integration which reach saturation firstly are selected to judge the faulty mode, and the diagnostic rules are shown in Table II. In particular, the two residual integration which reach saturation firstly are ambiguous at the scenario of the faulty switches on the upper or lower bridge simultaneously (e.g. $T_1$ and $T_3$) because the different time when faults occur may result in the different time that the saturation of the residual integration is detected. In respect of the faulty switches on the different side of the bridge (e.g. $T_1$ and $T_5$), only two residual integration can be stable in the following of faults occurrence because the normal phase does not intermit. The cost function of possible faulty mode based on the polarity of the residual integration will be calculated as soon as two residual integration reach saturation. The fault mode with smallest cost function (i.e. the faulty mode which the predicted fault current

![Diagram](image.png)

**TABLE II**

<table>
<thead>
<tr>
<th>$e_a(k+1)$</th>
<th>$e_b(k+1)$</th>
<th>$e_c(k+1)$</th>
<th>Faulty switches</th>
</tr>
</thead>
<tbody>
<tr>
<td>$+$</td>
<td>$X$</td>
<td>$-$</td>
<td>$T_1, T_5$</td>
</tr>
<tr>
<td>$+$</td>
<td>$-$</td>
<td>$X$</td>
<td>$T_1, T_2$</td>
</tr>
<tr>
<td>$-$</td>
<td>$+$</td>
<td>$X$</td>
<td>$T_1, T_4$</td>
</tr>
<tr>
<td>$-$</td>
<td>$X$</td>
<td>$+$</td>
<td>$T_5, T_{15}$</td>
</tr>
<tr>
<td>$X$</td>
<td>$+$</td>
<td>$-$</td>
<td>$T_1, T_3$</td>
</tr>
<tr>
<td>$-$</td>
<td>$X$</td>
<td>$+$</td>
<td>$T_5, T_{15}$</td>
</tr>
</tbody>
</table>

**Start**

- **Output measurement**
- **Parameter estimation and update**
- **MLD model based control-set prediction**
  - Minimize cost function to select the output
  - Calculate the residual vector $r(k)$
  - $r(k) > R_{th}$
  - FCS-MPC

- **Fault position**
  - Cut off grid connection unit
  - Reconstruction the system using backup switch bridge arm
  - Restart up the system

- **Fault function moving average $F_j(k)$**
  - $F_j(k) > F_{th}$

- **Grid reconected**
  - Phase locked loop (PLL) control
  - PLL ok ?
  - Y

- **Fault identification**
  - $F_j(k) > F_{th}$
  - Post-Fault reconfiguration

**Fault output of three-phase residual vector**
is closest to the actual fault current) is regarded as the faults in practice. In addition, the faults in the same bridge arm are detected and located only when the intermittent flag variables $\lambda_d$, $\lambda_h$, $\lambda_c$ exceed the threshold continuously more than half an electrical cycle. It should be noted that the fault tolerant topology mentioned in the previous section can only isolate the single fault or the multiple faults in the same bridge arm. Generally, the inverter tends to halt and generate the alarm signal when other multiple faults occur.

IV. SIMULATION AND EXPERIMENTAL RESULTS

A. Simulation Results

A simulation platform in PSIM environment was built to verify the MLD based FCS-MPC control strategy and the diagnostic algorithm presented in this paper. The main parameters of the system are listed in Table III.

The dynamic waveform of the grid connection is shown in Fig. 11. The total harmonic distortion (THD) is 3.18% in the steady state, and power factor is 0.988 in the full load condition. The performance is satisfied with a high quality grid connection.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{dc}$</td>
<td>DC350V</td>
<td>Voltage of DC bus</td>
</tr>
<tr>
<td>$V_{ac}$</td>
<td>AC110V</td>
<td>Voltage of Grid</td>
</tr>
<tr>
<td>$f_s$</td>
<td>20kHz</td>
<td>Inverter switching frequency</td>
</tr>
<tr>
<td>$f_{grid}$</td>
<td>50Hz</td>
<td>Grid frequency</td>
</tr>
<tr>
<td>$P_e$</td>
<td>1500VA</td>
<td>Inverter output power</td>
</tr>
<tr>
<td>$L$</td>
<td>10mH</td>
<td>Inverter filter inductor</td>
</tr>
<tr>
<td>$C$</td>
<td>1000uF</td>
<td>DC bus capacitor</td>
</tr>
</tbody>
</table>

**Fig. 11.** Dynamic grid-connected waveform.

The open-circuit diagnosis waveform is shown in Fig. 12, which indicates the switch $T_1$ open in the instant $t_0$, and identify variable of three-phase with the current of A phase. The identified variable $e_6$ is increasing rapidly, while $e_b$ and $e_c$ are decreasing, which means that fault position will be quickly and robust to interference. The integral threshold value of the identified variable is selected as 10A, and then the algorithm completes the positioning of the $T_1$ open-circuit fault at instant $t_2$. The entire fault identification process from $t_0$ to $t_2$ only takes 5ms. The diagnosis waveform in the case of inductive reactive power output is shown in the Fig. 14, it can be seen that the entire fault location process takes 11ms, which is approximately one quarter of the output current cycle.

Since the grid-connected inverter has the operating characteristics of a large load variation range, the parameter robustness experiment was carried out in Fig. 15. It can be seen that the load change without a fault did not cause the fault identification signal to change, which shows that the proposed method cannot be affected by the disturbance of the load change and cause a false alarm, and it has certain robustness to the load change.

**Fig. 12.** Simulation diagnosis waveform of $T_1$ open-circuit fault.

**Fig. 13.** Simulation diagnosis waveform of $T_2$ and $T_4$ open-circuit fault.

The proposed method can also diagnose the multiple faults. Fig. 13 shows the currents of three-phase when $T_2$ and $T_4$ fails at the instant $t_0$. $i_a$ and $i_c$ tend to be zero during their negative-half cycle because $T_3$ and $T_4$ are upper switches of the bridges. $e_b$ increases rapidly and $e_c$ decreases rapidly and fault diagnosis completes at the instant $t_3$ after the failure of $T_2$ and $T_4$, which obey the diagnostic rules in Table II. That is to say, the proposed method meets the more complicated diagnostic requirements.

The simulation waveform of the fault-tolerant control scheme is shown in Fig. 16. It can be observed that the A phase current is merged into the grid again at the zero-crossing point and maintains synchronous phase with the grid phase voltage, which verifies the effectiveness of the proposed fault-tolerant operation scheme.
B. Experimental Results

Physical experiment on a 1500W prototype is tested in laboratory as Fig. 17 shown. The experimental platform is used to verify proposed scheme by means of a DSP processor TMS320F28069 as the core controller. The effect of the grid connection of experimental prototype is consistent with the simulation result, and a good dynamic and steady state output is obtained as shown in Fig. 18.

The experimental results of fault diagnosis are shown in Fig. 19 and Fig. 20. The scenario in Fig. 19 was supposed that external departure $T_1$ open circuit fault at instant $t_0$. Then detection is achieved at instant $t_1$, and positioning is done at instant $t_2$. Since the first quarter of the current cycle of open circuit fault occurs is within the negative half of $i_x$ and the total time is about 12ms, the fault location time is consistent with the simulation analysis, which verifies the effectiveness of the proposed diagnosis method. Compared with other mainstream

<table>
<thead>
<tr>
<th>Fault diagnosis method</th>
<th>Detection time (% of the current fundamental period)</th>
<th>Additional cost</th>
<th>Robustness</th>
<th>Computation burden</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency-based method [26]</td>
<td>$&gt;100%$</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Neutral point voltage-based method [27]</td>
<td>$25%$</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Observer-based method [13]</td>
<td>$5%-58%$</td>
<td>Low</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Proposed method</td>
<td>$20%-55%$</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
</tbody>
</table>
litteratures using current methods, which requires a fundamental period to complete, the proposed method requires only half a cycle of output current from fault occurrence to fault identification, which shortens the fault location time by more than half. In addition, there is no wrong fault identification during output load changing as shown in Fig. 20, which means that the proposed fault diagnosis method has robustness to external interference.

C. Analysis Of Comparison between The Proposed Method And Previous Methods

Table IV set out to demonstrate that the proposed method has better performance compared with other methods in terms of some indexes including detection time, additional cost, robustness and computation burden. As can be seen in this table, some of methods present shorter diagnostics time, but more complicated calculation and additional cost is necessary. In contrast, the proposed method uses the results of MPC directly, which can be easily embedded into DSP controller.

V. CONCLUSION

An online diagnosis method for the most common power device open-circuit faults in grid-connected inverters is proposed in this paper, which is significant with application of renewable energy in smart grid. The presented method is based on model prediction, combing with MLD model, the simulation and experimental results verified the effectiveness of the proposed scheme. The techniques of threshold evaluation and a sliding window are adopted in the software algorithm, which can satisfy the certain robustness to quickly and accurately diagnose the open fault of the switching device. It can not only reduce the diagnostic time, but also can eliminate the need for additional sensors based on the completion of the diagnostics function. Therefore, it is easy to integrate into the micro-controller of grid-connected inverters.

REFERENCES


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