

## Fault diagnosis using particle filter for MEA typical components

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**Abstract:** More electric aircraft (MEA) is a developing trend in modern aerospace engineering aiming for a reduction of the aircraft weight, operation cost and environmental impact through putting more emphasis on the utilisation of electrical power. It has many advantages, but also increases the complexity of the aircraft. Therefore, the requirements of prognostic and health management for MEA are needed. The method that using sequential importance re-sampling (SIR) particle filtering state estimation and smoothed residual to diagnose fault for typical components is discussed. The simulation results show that this method can locate faults accurately and quickly.

### 1 Introduction

More electric aircraft (MEA) including electrical power system (EPS), environment control system, brake and other subsystems, is a highly non-linear and high complex system. Compared to traditional aircraft, its EPS architecture needs to be redesigned [1, 2]. To increase aircraft safety and reduce maintenance cost, advanced diagnostic and prognostic capabilities for EPS are urgent. Many studies have been developed to address the fault diagnosis problem [3–5]. For the complexity of MEA, especially the EPS, fault diagnosis also brings great challenges to the works.

The fault diagnosis uses the information of various state information and existing knowledge to get the comprehensive evaluation of the system operating condition. Thus, it can identify the immediate and potential faults. Fault diagnosis can be divided into knowledge-based methods, methods based analytical models and methods based on signal processing [6]. The model-based filtering method is one of the main methods of fault detection, but this fault detection method requires the system model to be linear and Gaussian distribution. Owing to the environmental impact, the subsystems on the aircraft are strictly non-linear and non-Gaussian systems. Not only the system model is non-linear, but the observation noise also has a complex non-linear and non-Gaussian distribution.

The particle filter is based on Bayesian theory and is a sequential Monte Carlo simulation method used particle probability density. It has been widely used in many fields. This algorithm has great advantages in non-linear dynamic system field. The particle filtering process is shown in Fig. 1. According to the structure and principle of the system, it is necessary to build the nominal model, and then reconstruct the state of the system to get the measurable variables by particle filtering. Compared to the output of the physical system, it is easy to get residual error sequence and analyse the residuals in order to identify the faults.

Gordon proposed the sequential importance of the Monte Carlo method [7]. After that, particle filter has become the research hotspot of non-linear non-Gaussian system state estimation. Kadirkamanathan *et al.* [8] first introduced particle filtering technology to the failure prediction. Alrowaie puts forward an improved likelihood ratio method based on the traditional theory and applies it to the failure prediction of chemical industry [9]. Liang *et al.* [10] proposed a particle filter failure prediction algorithm combining with residual smoothing. The residual smoothing

values of the system state estimation and the actual observed values are used as the fault prediction basis.

The ideal state estimation of particle filter often uses the analytical model of the physical system, but some complex non-linear systems are difficult to establish analytical models. It is easy to build the simulation mode sometimes. In this paper, the faults of auto-transformer unit (ATU) and transformer rectifier unit (TRU) in aircraft EPS using SIR particle filtering state estimation and smoothed residual are conducted. The analytical model of ATU and simulation model of TRU are used to verify the method.

### 2 Fault diagnosis using SIR particle filter

First, the principle of fault diagnosis algorithm based on SIR particle filter and residual smoothing is introduced, and the design steps of the algorithm are given. Then, the models of ATU and TRU power converters commonly used in aviation are built. After injecting faults, they can be diagnosed by using the algorithm.

#### 2.1 Principle of SIR particle filter

For non-linear dynamic systems, the non-linear discrete state-space model can be expressed as

$$x_k = f(x_{k-1}, u_{k-1}) + w_k \quad (1)$$

$$y_k = h(x_k, u_k) + v_k. \quad (2)$$

The first is the state transition equation and the second is the observation equation, where  $x_k$  is the system state variable at the  $k$  moment, the initial probability density is  $p(x_0)$ ;  $y_k$  is the observed values of the state variable  $x_k$  of the system at the  $k$  moment;  $u_{k-1}$  is the input variables of the system;  $w_k$  and  $v_k$  are the state noise and the observation noise, whose covariances are  $Q_k$  and  $R_k$ ;  $f(\cdot)$  and  $h(\cdot)$  represent state transition function and observation function, respectively.

The statistical description of the above state-space equation is as follows.

For system equations, the state transition probability density can be given by

$$p(x_k | x_{k-1}). \quad (3)$$

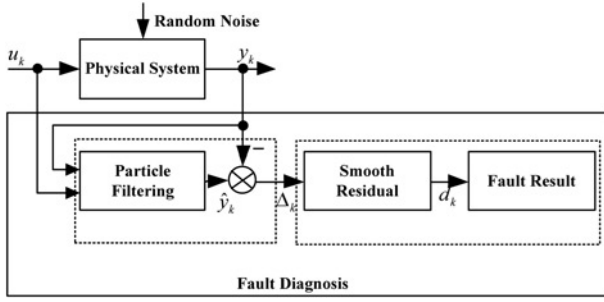


Fig. 1 Particle filtering process

For observational equations, the observation likelihood probability density can be given by

$$p(y_k|x_k). \quad (4)$$

It is assumed that the system state  $x_k$  obeys a first-order Markov process, and the system observation  $y_k$  is independent. The initial prior density of the system state is  $p(x_0)$ . Particle filter uses essentially a posterior probability density function  $p(x_k|y_{1:k})$  which is constructed by measuring the output  $y_k$  of the system.

Particle filter algorithm is applied to fault detection, and the most common method is the SIR particle filtering state estimation and smoothed residual. The core idea is as follows. In the normal operation of the system, the ideal observation value of the system obtained through particle filter should be close to the actual observed value of the system state. When the system fails, the ideal observation value should be kept away from the actual observed value of the system state. The absolute value of the difference between the ideal observation value and the observed value is the residual. Calculate the average value of these residuals in the last  $M$  times. Failure occurs when the value is greater than the threshold.

The algorithm steps are as follows:

(1) Initialisation

A particle set  $\{x_0^i\}_{i=1}^N$  is generated by a priori probability density function  $p(x_0)$  when  $k=1$ . The initial weight of the assignment is  $1/N$ . Then perform the following steps cyclically.

(2) State prediction

$N$  new particles are extracted from the system state transfer probability density, this can be expressed as

$$x_k^i \sim P(x_k|x_{k-1}^i). \quad (5)$$

where  $i=1, 2, \dots, N$ . The particles set  $\{x_k^i\}_{i=1}^N$  are formed at the  $k$  moment.

(3) The solution of likelihood function

After the system state observation  $y_k$  is obtained, the likelihood function of each particle is calculated. The likelihood function can be expressed as

$$P(y_k|x_k^i) = \frac{1}{\sqrt{(2\pi)^m [\det(v_k)]}} \exp \left\{ -\frac{1}{2} (r_k^i)^T v_k^{-1} r_k^i \right\} \quad (6)$$

where  $m$  is the dimension of the state variable and  $r_k^i = y_k - h_k(x_k^i)$  is the prediction error of  $i$  particle.

(4) Update the particle weights and normalise.

The weights can be expressed as

$$\hat{w}_k^i = \frac{w_k^i}{\sum_{j=1}^N w_k^j}. \quad (7)$$

where  $w_k^i = w_{k-1}^i P(y_k|x_k^i)$ .

(5) Resampling of particles based on the degree of degradation. The process can be given by

$$\{x_k^i, \hat{w}_k^i\}_{i=1}^N \rightarrow \{x_k^j, \hat{w}_k^j\}_{j=1}^N. \quad (8)$$

(6) Calculate system state estimation value  $\hat{x}_k$ , which can be expressed as

$$\hat{x}_k = \sum_{i=1}^N x_k^i \hat{w}_k^i \quad (9)$$

(7) Fault detection

Calculate the ideal observation values  $\hat{y}_k$ , which can be expressed as

$$\hat{y}_k = h(\hat{x}_k, 0). \quad (10)$$

The absolute value of the difference between  $\hat{y}_k$  and the actual observed values  $y_k$  can be expressed as

$$\Delta_k = |\hat{y}_k - y_k| \quad (11)$$

Calculate the average value  $d_k$  of the absolute value of the last  $M$  times, which can be expressed as

$$d_k = \frac{1}{M} \sum_{j=k-M+1}^k \Delta_k. \quad (12)$$

If  $d_k$  is smaller than the threshold value  $d_{th}$ , then no fault occurred; otherwise, a fault occurred.

## 2.2 ATU and TRU models

The secondary electric power source of MEA mainly including ATU, TRU, auto-TRU and inverter are used for different voltage grade and AC–DC transformation. ATU carries the energy transmission through the wire, which transfers the same power, but the volume is small. ATU is the aviation common equipment. TRU can convert AC current from AC generator to DC bus, which makes the aircraft system no longer equipped with DC generator. It is widely used in aircraft power supply system. To reduce the waveform distortion and stabilise the output DC voltage, the 12-pulse rectifier with a balanced reactor can be used in the voltage rectifier of the EPS.

Simulation is the important link between programme design and system integration. Especially in the aspect of system failure research, it can be shortened the design cycle and reduced the risk of accidents. A single-channel electrical system for MEA is built, and the related fault diagnosis algorithm can be studied. The EPS model of MEA is shown in Fig. 2.

**Case 1:** ATU converts the 230 AC to 115 V AC. The schematic diagram is shown in Fig. 3.

The turn ratio of the auto-transformer is its transfer function and its observation equation can be set up

$$y_k = u_k/2 + v_k \quad (13)$$

**Case 2:** TRU converts 230 AC to 28 V DC and builds the Simulink simulation model of TRU, which is shown in Fig. 4.

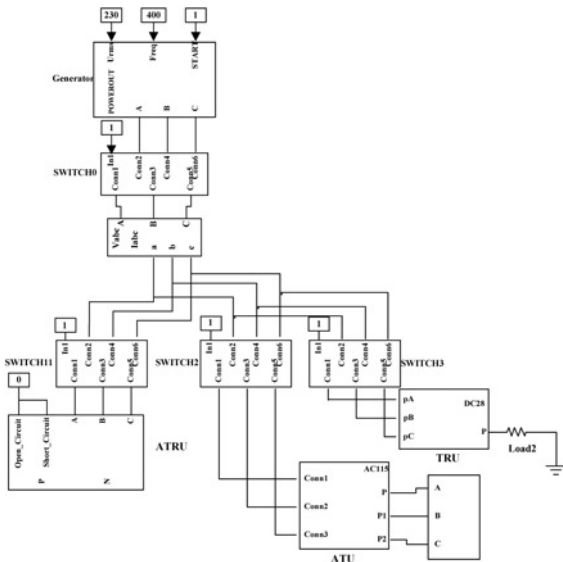


Fig. 2 EPS model

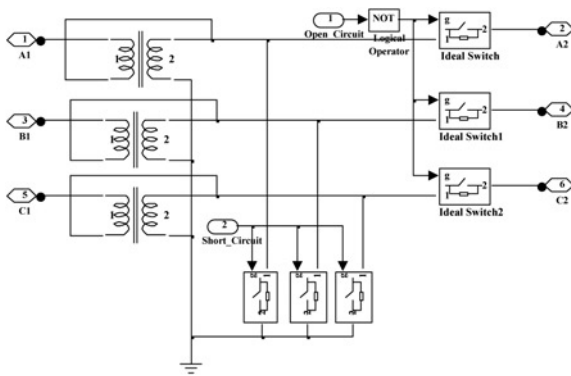


Fig. 3 ATU model

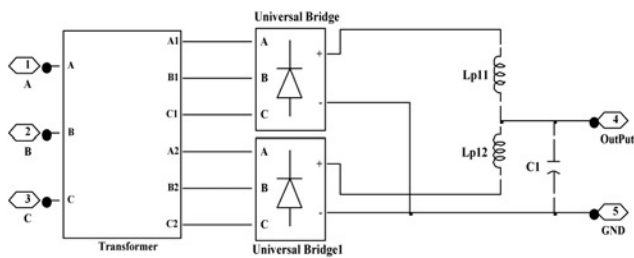


Fig. 4 TRU Simulink model

TRU and ATU as the objects of particle filter fault diagnosis are selected. The ATU is a typical linear link in MEA and its analytic formula is established directly. TRU contains two rectifier bridges, which is a typical non-linear link. The Simulink simulation model can be established for TRU and it can be used as an alternative to analytic model for the normal physical system after validation. The architecture for fault diagnosis using particle filter is shown in Fig. 5.

While the physics-based particle filter is promising, the simulation which can simulate the various fault and noise is more flexible. It is needed to support the design of the algorithm. Thus, the physical system, the noise system and the fault injection system are modelled. Test data are generated from the simulation and used for the

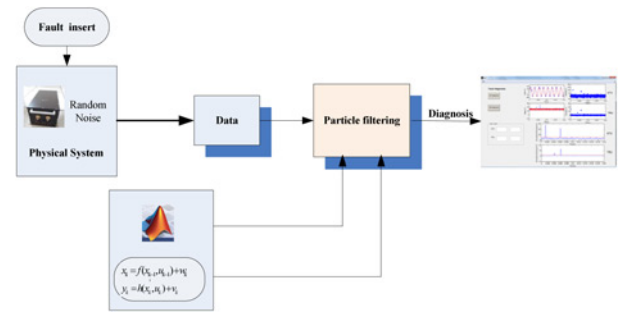


Fig. 5 Proposed architecture for fault diagnosis

particle filter. The graphical user interface is designed for fault injection and displays the simulation results.

### 3 Simulation results

The Gaussian and non-Gaussian noises are added to the system, and then the voltage fault is injected to verify the effect of the particle filter. Set  $Q=1$  and  $R=0.05$ . Set  $N=100$  and  $M=20$ .

*Case 1:* Set the threshold  $d_{th}=15$ . Inject distortion voltage fault of one phase and the simulation results using particle filter can be got. The results of ATU are as follows.

As shown in Fig. 6, the distortion signal produced by ATU sine signal is difficult to give an alarm by sensors (Fig. 7). On the basis of the particle filter algorithm, the distortion signal can be identified and the working state of ATU can be predicted as shown in Fig. 8.

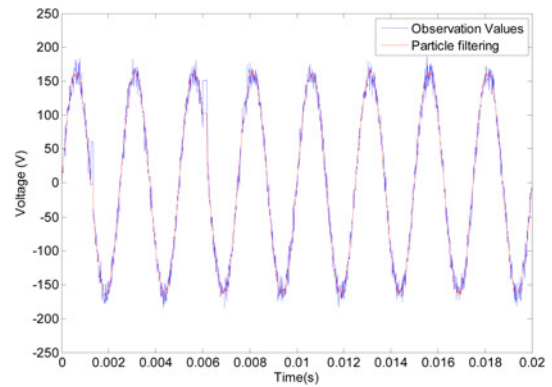


Fig. 6 Observation value using particle filtering

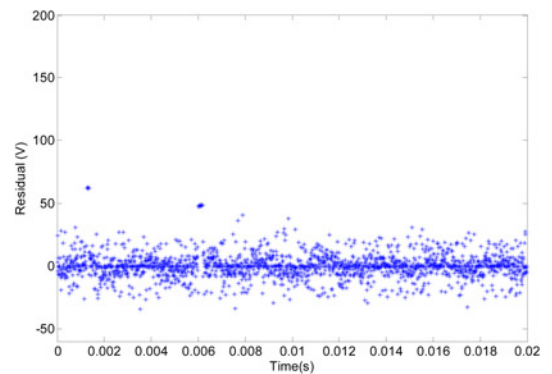


Fig. 7 Residual of ATU

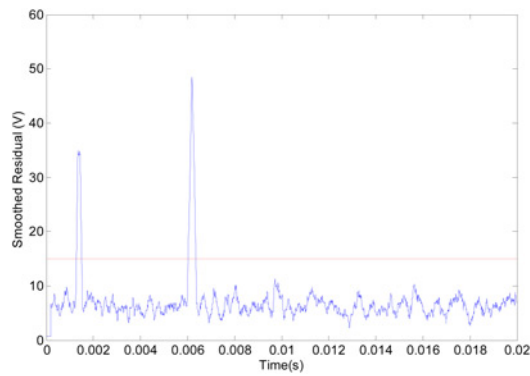


Fig. 8 Fault result of ATU

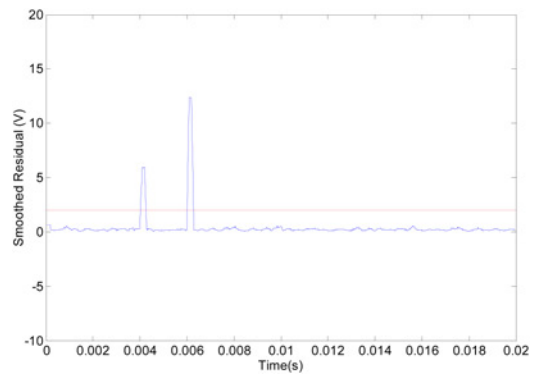


Fig. 11 Fault result of TRU

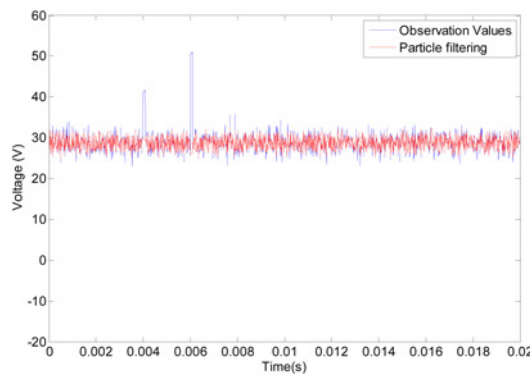


Fig. 9 Observation value using particle filtering

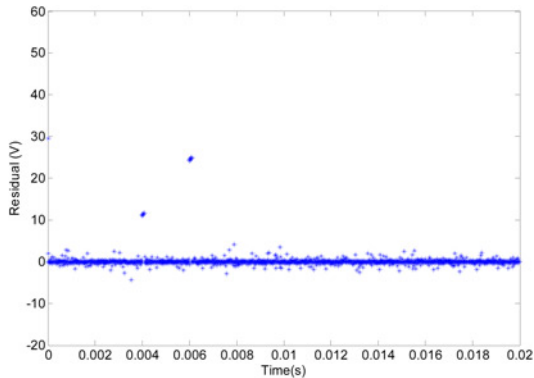


Fig. 10 Residual of TRU

Case 2: Set the threshold  $d_{th}=2$ . Inject the spike pulse voltage fault and the simulation results of the spike pulse fault are provided in Fig. 9.

As shown in Fig. 10, the residuals are more evenly distributed around 0. After smoothing the residuals, the reaction is more sensitive to accidental error as shown in Fig. 11. It explains that particle filter is easy to get the fault point of the system. Particle filter has very strong sensitivity and tracking performance.

## 4 Conclusion

In this paper, ATU distortion fault and TRU spike pulse fault are introduced. We use the analytical model of ATU and the Simulink model of TRU for state estimation. An SIR particle filter with smoothed residual is designed to diagnose the faults. The simulation results show that the algorithm is suitable for the non-linear non-Gaussian system. Particle filter can locate the fault of the system quickly and has higher accuracy of state and parameter estimation. In the future, we will increase the complexity of the model and verify the feasibility of particle filter.

## 5 References

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