Fault Detection in Electric Power Systems Using Kalman Filter

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Streszczenie: Power systems are large dynamic systems which are relevant infrastructure to our society. To keep them operating without long blackouts sufficient and reliable protection is necessary at hardware and software level. It can be accomplished by the implementation of the rapid fault detection algorithms which can be added to the SCADA systems controlling and monitoring power systems. In the following paper the fault detection algorithm for electric power systems is presented. The rudiments of the fault diagnosis concept for model-based methods are introduced with strong emphasis on the state-observer-based and Kalman-filter-based methods. Moreover, the Kalman filter idea is discussed with the application possibility as a fault detection tool to electric power systems. The experiments done on the 9-bus, 3-machine system with Power System Analysis Toolbox in Matlab showed that state estimation methods like Kalman filter can be successfully deployed in the fault detection in dynamic systems in particular in electric power systems.

Słowa kluczowe: Kalman filter, fault, diagnosis, residual, power system

Electric power systems are large dynamic systems which are relevant infrastructure to our society. That is why it is crucial to keep them operating non-stop and prevent them from long power outages similar to The Northeast Blackout of 2003 in the USA and The Southern Brazil blackout of 1999.

It can be accomplished by the implementation of the rapid fault detection algorithms which can be added to SCADA systems controlling and monitoring power systems. The model-based method founded on the Kalman filter proposed e.g. in [1, 2] was applied in this paper in order to detect at which part of the system the fault occurred. Similar but more complex approach based on a bank of so-called unknown input observers was presented in [3]. Moreover, Kalman filters were successfully deployed in dynamic systems fault diagnosis in other areas including flight control systems [4], DC motors [5] or chemical processes [6].

The article is organised as follows: firstly the fault detection in dynamic systems overview is presented with the emphasis on the fault detection via state estimation; in section 2 the Kalman filter idea is discussed; in further parts the results of experiments done on the 9-bus, 3-machine power system model are shown and the brief summary and conclusions are given.

1. Fault Detection

Fault detection in dynamic systems can be considered as diagnostic signals generation based on the process variables. In other words it is a mapping of the state space $\mathbb{X}$ into the diagnostic signals space $\mathbb{S}$ which together with the evaluation of the set $\mathbb{S}$ can provide the information about faults in the system [1]. Fault detection methods can be divided into two major groups based on:

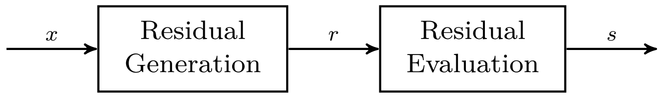
1) the relations between process variables,

2) the analysis and evaluation of one process variable.

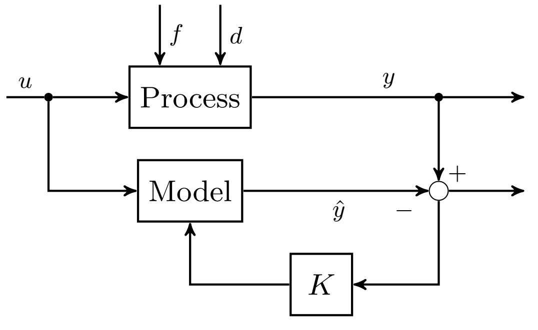
Methods in the former group need the knowledge about the system in the form of analytical, neural or fuzzy quality or quantity model. Additionally, diagnostic signals can be generated by finding simple process variables relations like hardware redundancy of the measurement lines, feedback signal control etc. The latter group comprises of algorithms that usually analyse limits or statistic and spectral parameters (e.g. mean value, expected value etc.) of only one process variable which makes it difficult to distinguish the character of the fault. In this paper we will use fault detection methods based on the analytical model, thus, more detailed description of the first presented group will be provided.

1.1. Analytical Model-Based Fault Detection

Analytical methods that can be applied to fault detection are founded on either on-line identification or state-observers and Kalman filters or input-output linear models or physical models (e.g. balances, movement equations). The general concept of the model-based fault detection algorithm for all above-mentioned methods is presented in Fig. 1. It consists of 2 main steps: the residual generation with the use of the system model and the residual value evaluation which results in the diagnostic signals s generation from residual values r. Residuals can be calculated as either the comparison of the measured value of the state variable with its model-based calculation or difference between left-hand side and right-hand side of the equations describing the system or difference between nominal and estimated model parameters. The residuals evaluation can be addressed by very simple binary methods like step function which assigns 1 to the diagnostic signal once the residual value exceeds the threshold value or by more advanced algorithms based on the mean value of the moving window over residual. Additionally, multi-value or fuzzy logic can be applied as well [1].



Rys. 1. Ogólna idea algorytmu detekcji usterek opartego na modelu systemu.
Fig. 1. The general concept of the model-based fault detection algorithm.



Rys. 2. Schemat obliczania residuów dla metod wykrywania usterek opartych na filtrze Kalmana.
Fig. 2. Residual generation diagram for Kalman-filter-based fault detection methods.

1.2. Fault Detection via State Estimation

For fault detection methods based on the state estimation i.e. state observers and Kalaman filters the residuals generation block from Fig. 1 can be replaced by the one depicted in Fig. 2. The u, f, d vectors denote control, fault and disturbance signals, respectively. In this case, the observer K is used in a different way than in classical approach where it is supposed to provide an estimate of its internal state. The estimated output of the model $\hat{y}$ is compared with the true system's output y. In the fault presence the true output deviates and hence the residual does not equal to zero. After the residual evaluation the diagnostic decision is made.

2. Kalman Filter

The Kalman filter is an optimal stochastic observer that was proposed in the famous paper published by R. E. Kalman in 1960 [7]. Its main goal is the estimation of the state vector $x \in \mathbb{R}^n$ of a discrete-time system that is described by the stochastic linear difference equation:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{1}$$

with a measurement $y \in \mathbb{R}^m$ described as:

$$y_k = Cx_k + v_k,$$

where $u \in \mathbb{R}^p$ and w_k and v_k denote the process and measurement white Gaussian noises with zero mean, respectively. Their covariance matrices are defined as follows:

$$E[w(k)w^T(j)] = Q(k)\delta(k,j), \quad Q = Q^T \geqslant 0 \tag{2}$$

$$E[v(k)v^T(j)] = R(k)\delta(k,j), \quad R = R^T \geqslant 0 \tag{3}$$

$$E[w(k)v^T(j)] = 0, \tag{4}$$

where $\delta(k, j)$ is the Kronecker delta function. The estimated state vector can be calculated with the following Discrete Kalman Filter Algorithm [8]. The Kalman Filter equations are divided into two groups: the time-update (predictor) equations and the measurement-update (corrector) equations:

$$\left.\begin{aligned} \hat{x}_k^- &= A\hat{x}_{k-1} + Bu_{k-1} \\ P_k^- &= AP_{k-1}A^T + Q \end{aligned}\right\} \text{predictor} \tag{5}$$

$$\left.\begin{aligned} K_k &= P_k^- C^T (CP_k^- C^T + R)^{-1} \\ \hat{x}_k &= \hat{x}_k^- + K_k(y_k - C\hat{x}_k^-) \\ P_k &= (I - K_kC)P_k^- \end{aligned}\right\} \text{corrector,} \tag{6}$$

where $\hat{x}_k$ is a state estimate, P_k is an error covariance estimate and K_k is a gain or blending factor which minimizes *a posteriori* error covariance. Variables with and without $^-$ are the *a priori* and *a posteriori* estimates, respectively. In each time-update phase the *a priori* estimates $\hat{x}_k^-$, P_k^- are calculated based on the previous *a posteriori* estimates. In the measurement-update phase a new measurement y_k is used in order to improve the *a posteriori* $\hat{x}_k$ estimate.

3. Experiments

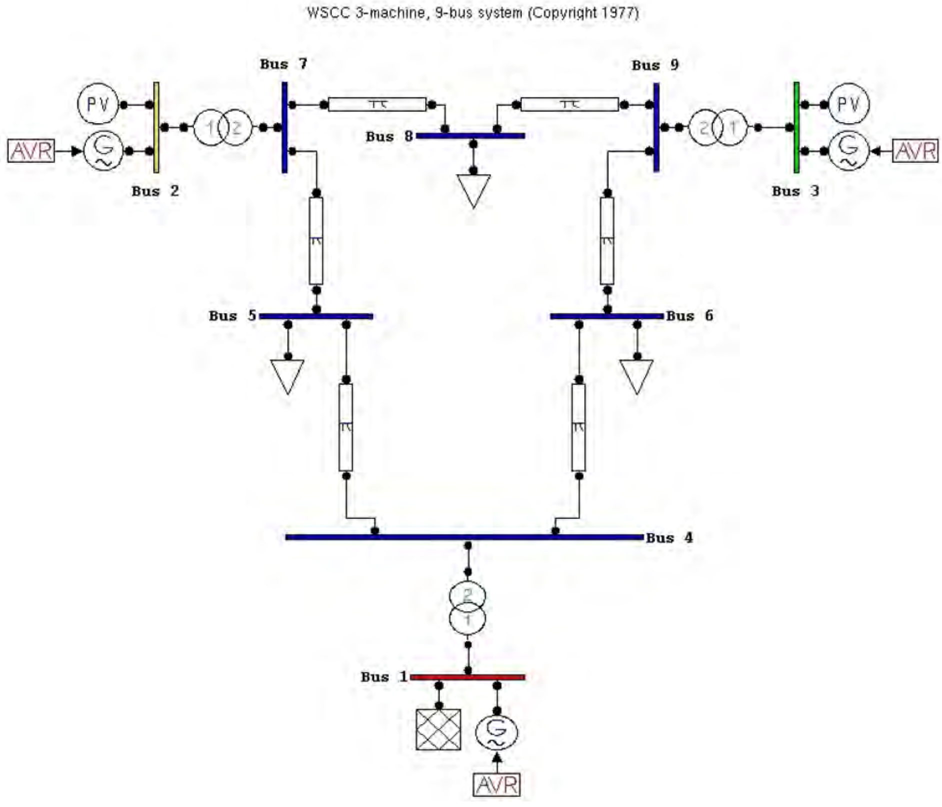
The Kalman filter was designed for the 3-machine, 9-bus power system presented in Fig. 3 which is one of the test models included in the Power System Analysis Toolbox (PSAT) for Matlab developed by Federico Milano [9]. The continuous-time linear model obtained with the use of PSAT was converted to a discrete form (1) with the sampling time $T_0 = 0.001$. Unfortunately due to the matrices dimensions ($A \in \mathbb{R}^{24\times24}$, $B \in \mathbb{R}^{24\times3}$, $C \in \mathbb{R}^{18\times24}$) and the space limitation, system matrices are not given in this paper. During 10 s simulation bus angle and bus voltage residuals were generated to be evaluated. The main objective of the experiments was to detect the fault at the particular bus of the power system. The fault was introduced, in separate tests, to every bus with machine (buses no 1, 2, 3) after 2 seconds from the beginning of the simulation.

Tab. 1. Wartośći kwadratowego wskaźnika jakości dla residuuów kąta i napięcia na magistrali nr 3.
Tab. 1. Integral Square Indexes of voltage and angle residuals of the bus no 3.

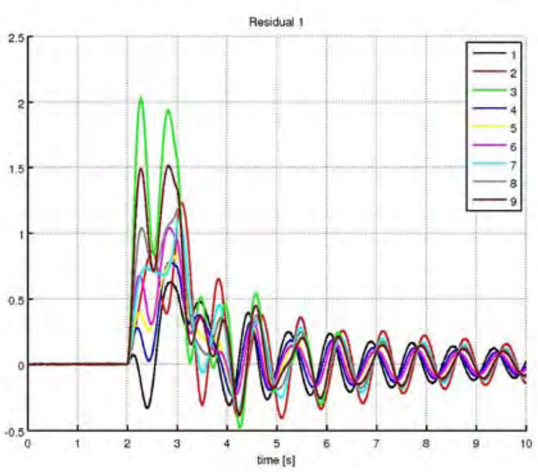
Bus	Bus Angle Residual ISI	Bus Voltage Residual ISI
1	418.75	10.002
2	1059.9	25.886
3	**2653.3**	**101.46**
4	422.42	21.597
5	474.41	32.956
6	676.33	34.531
7	895.69	32.702
8	1133.5	45.682
9	1685.9	67.919

In Figures 4 and 5 bus angle and bus voltage residuals are presented for the case when the fault occurs on the third bus. It can be seen that due to the interconnectivity of the system, the fault is detected on every bus. The influence of the fault on each bus was measured by the integral square indexes (ISI) both of voltage and angle residuals:

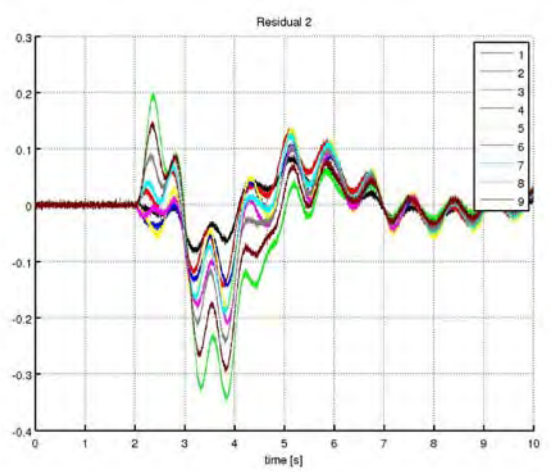
$$J = \int_0^{10} r(t)^2 dt. \tag{7}$$



Rys. 3. Testowy, symulacyjny model 9-cio magistralowego systemu elektroenergetycznego wyposażonego w 3 maszyny synchroniczne.
Fig. 3. 9-bus, 3-machine test power system simulation model [9]



Rys. 4. Residuum kąta.
Fig. 4. Angle residual.



Rys. 5. Residuum napięcia.
Fig. 5. Voltage residual.

The results are collected in Tab. 1. Without complex computation, one can easily notice that residuals of the bus no 3 reach the highest peaks. The same situation took place in the rest of experiments when the fault was present on the buses no 1 and 2. That observation together with ISI results proves that transient state induced by the fault is the most significant on the bus at which the fault occurred.

4. Conclusions

In the following paper it was shown that a basic state estimation method – Kalman filter and simple residuals can be applied to the fault detection in dynamic systems, in particular in electric power systems. Additionally, thanks to higher sampling rate devices like Phasor Meassurement Units, Synchrophasor Vector Processors and fast data protocols (IEEE C37.118, DNP3, OPC) which are being used in electric power systems, the practical real-time implementation of the observer-based fault detection schemes and dynamic state estimation is possible [10]. In further research it would be interesting to extend the system capability of multiple-bus fault diagnosis and to compare the central and distributed fault detection approaches. The type of the fault should be distinguished in future work as well.

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Detekcja usterek w systemie elektroenergetycznym za pomocą filtru Kalmana

Abstract: Systemy elektroenergetyczne należą do klasy dużych systemów dynamicznych odgrywających ogromną rolę we współczesnym świecie. Aby mogły spełniać swoją rolę muszą pracować bez większych zakłóceń. Dlatego konieczne jest zapewnienie im odpowiedniej ochrony na poziomie programowym i sprzętowym. Jednym z rozwiązań jest użycie szybkich algorytmów wykrywania usterek, które mogą być jednym z komponentów systemów SCADA sterujących i monitorujących systemem elektroenergetycznym. W pracy przedstawiono algorytm wykrywania usterek w systemach elektroenergetycznych. Opisano podstawy diagnostyki usterek dla metod stosujących liniowy model systemu, a w szczególności skupiono się na metodach bazujących na obserwatorach stanu i filtrze Kalmana. W rezultacie przedstawiono koncepcję filtru Kalmana i możliwość jego implementacji jako narzędzia do wykrywania usterek w systemach elektroenergetycznych. Eksperymenty wykonano na modelu dziewięcio-magistralowego systemu wyposażonego w trzy maszyny synchroniczne przy użyciu Power System Analysis Toolbox w środowisku Matlab. Pokazały one, że metody estymacji stanu takie jak filtr Kalmana mogą być z powodzeniem stosowane w wykrywaniu usterek w systemach dynamicznych, w szczególności systemach elektroenergetycznych.

Keywords: filtr Kalmana, usterka, diagnostyka, detekcja, system elektroenergetyczny

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