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# FAULT DETECTION AND ISOLATION FOR POWER ELECTRONIC SYSTEMS FEATURING PARAMETER UNCERTAINTY

**ABSTRACT** *An assumption was made in this paper that monitoring both the converter and its control means actually continuous formulation (i.e. repeatedly) of diagnoses of their states automatically via a suitable computer diagnostic system. In other words it is diagnosing on-line carried out in real time. The authors assume that mainly the operating signals are used for diagnostic purposes since it is not recommendable to disturb the process with any additional test signals. This paper presents a fault detection and isolation scheme for systems with modeling uncertainties where not all the state variables are measurable. The proposed fault diagnosis architecture consists of a fault detection estimator and a set of isolation estimators. Each estimator corresponds to a specific fault type. Employing orthogonal transforms made it possible to depict the power electronics state variable in terms of appropriate linear combination of base functions, so far approximated by a time set. There were families of binary orthogonal Walsh and Haar functions used in the investigation. The presented approach may be considered a numeric-analytical method. The investigation of power electronic converter signals was carried out using fast processing algorithms.*

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# 1. INTRODUCTION

Diagnostics of dynamic systems operating in uncertain conditions has been a subject of intensive research for more than a decade. This research resulted in various techniques based on models in which residuals sensitized to faults were generated and evaluated. Simultaneously they revealed the problems that are encountered in improving the developed diagnostic algorithms' robustness for disturbances. As may be concluded from the relevant literature the effects of the emerging faults may be hardly, if at all, separated completely from the disturbances influencing the system's dynamics.

It is assumed in this paper by the authors that the nonlinearity bound with the fault function of the converter is known at least partially, and that at the same time there exists some uncertainty over the definition of some of the converter's parameters. Detection and localization estimators were used to monitor the drive operation. The essence of the diagnostics may be reduced to a procedure, in which a set of localization estimators activated after a fault is detected by the detection estimator. The operation of each of the fault localization estimators is based on linear filtration technique using a set of appropriate adaptive thresholds.

Making use of the results presented in [6, 8] it was assumed, that the fault detection and isolation block may be implemented as a set of $N$+1 nonlinear adaptive estimators, where $N$ is the number of nonlinear faults $F$ as defined in [6]. One of those nonlinear adaptive estimators was used in this paper for fault detection. The others were performing as fault isolation (localization) estimators and were activated only in the case when a fault was detected. The authors presumed that every single estimator of $N$ corresponded to a particular fault of the defined fault class. The block diagram of the complete architecture is shown in [8].

Considering these assumptions under normal operating conditions (i.e. when no faults occur) a single detection estimator was the only estimator to monitor the system. Once a fault was detected the set of localization estimators was activated, and the single detection estimator switched into the fault function approximation mode. The task of the set of estimators was just to accomplish the identification and isolation of the fault that had just appeared.

A case when none of the isolation estimators found match of its parameters to the detected fault (up to a certain reasonable level) corresponded to the occurrence of a new fault type. The approximated fault model could then be used to update the class of faults and for updating the content of the isolation estimators.

The investigation carried out by the authors has shown that a fault model generated either by the appropriate isolation estimator (when a match with the pattern was found) or approximation/detection estimator may be used later to diagnose a probable fault, or may be used in the process of the system self-adjusting to a new, pre-fault situation.

## 2. THE MATHEMATICAL MODEL

The authors assumed that all the continuous signals flowing within the investigated system are quantifiable both in time domain and in their values as well. However, the discrete signals are applied directly. Having in mind this assumption a class of dynamic systems described by the following relationship was considered:

$$\left.\begin{aligned} x &= Ax + \rho(y,u) + \xi(x,u,\mathrm{t}) + B(t - \mathrm{T}_0)\nu(y,u) \\ y &= Cx + d(x,u,\mathrm{t}) \end{aligned}\right\} \qquad (1)$$

where:
$x \in \Re^n$ is the state vector of the system, $u \in \Re^m$ is the input signals vector $y \in \Re^l$ is a measurable system's output signal, while:
$\xi(x,u,\mathrm{t}) : \Re^n \times \Re^m \times \Re^+ \mapsto \Re^n$, $\rho(y,u) : \Re^l \times \Re^m \mapsto \Re^n$, $\nu(y,u) : \Re^l \times \Re^m \mapsto \Re^n$, and $d(x,u,\mathrm{t}) : \Re^n \times \Re^m \times \Re^+ \mapsto \Re^l$ are smooth discrete vector functions, and the pair of matrices (***A***, ***C***) is an observable pair. Appearing in the relationship (1) vector functions $\xi(x,u,\mathrm{t})$ and $d(x,u,\mathrm{t})$ represent the modeling uncertainty (which means uncertainty in stating the values of the selected system parameters) in the state and output equations, respectively. The vector function $\rho(y,u)$ represents the dynamics of the base model. The term expressed by the product $B(\mathrm{t}-\mathrm{T}_0)\cdot v(y, u)$ is responsible for changes in the system dynamics caused by the occurring fault. Matrix function $B(\mathrm{t}-\mathrm{T}_0)$ reflects the time profile of the fault, and $\mathrm{T}_0$ is the unknown instant of the fault occurrence. Vector function $v(y, u)$ represents the nonlinear fault function. However, only a case of step by step evolving faults is considered in this work. Basing on the math model of the system as introduced by the relation (1) a single detection estimator's task is to accomplish the following relationship [8]:

$$\dot{\hat{x}}^0 = -\Psi^0(\hat{x}^0 - x) + \rho(x,u) + \hat{\phi}(x,u,\hat{\mu}^0) \tag{2}$$

where $\hat{x}^0 \in \Re^n$ is the estimated state vector, $\hat{\phi} : \Re^n \times \Re^m \times \Re^p \mapsto \Re^n$ is an on-line approximation model, $\hat{\mu}^0 \in \Re^p$ represents the vector of adjustable weights of the on-line approximator, and $\Psi^0 = \mathrm{diag}(\psi_1^0, ..., \psi_n^0)$, where $\psi_i^0 < 0$ is the *i*-th pole of the estimator. The initial value of the weight vector $\hat{\mu}^0(0)$ should be chosen so to meet the condition:

$$\hat{\phi}\big(x,u,\hat{\mu}^0(0)\big) = 0, \quad \forall(x,u) \in D \tag{3}$$

which corresponds to the case when the system is operated appropriately and no faults occur.

The key element of a nonlinear estimator as described by the relation (2) is *an on-line approximator*, denoted as $\hat{\phi}$. When a fault is present, $\hat{\phi}$ is providing adaptive structure for the on-line approximation of an unknown fault function. This is attained by adapting the weight vector $\hat{\mu}^0(\mathrm{t})$, which results in appropriate changes of the approximator's output and input signals. The term "on-line approximator" is used throughout this paper to denote nonlinear multivariable approximation models with adjustable parameters or weights, similarly to those encountered in other approaches, like neural networks, fuzzy logic networks, systems described by spline functions, or by using variety of transforms (e.g. wavelet transforms).

Various results of the investigations of the approximation on-line models have been reported within several recent years in the context of intelligent control systems [9]. Some properties of the on-line approximators, like linear parameterization and "curse of dimensionality" play key role, when such structures are used as fault function estimators in diagnostic systems. Special attention is due to the comparison of different models of the on-line approximation presented in literature.

There are three main approaches to represent modeling uncertainty appearing in the literature [3, 4]. In the first of them, called a decoupling method, it is assumed that modeling uncertainty has structure feature. Taking the uncertainty into consideration makes it possible to decouple the faults from the modeling uncertainty by using linear or nonlinear state transforms [6]. In cases when such a decoupling is feasible attempts can be made to employ very effective methods of setting up fault detection and isolation algorithms [8]. If the model, however, is not structurized, decoupling faults from uncertainty in reckoning the values of parameters is not possible, which then justifies another approach, which in the literature is called “a limiting (or restricting) approach”. Here the modeling uncertainty has to be limited explicitly by a constant or a function. This restriction may be used for introducing thresholds to distinguish the results of the fault from the modeling uncertainty [6]. Another important approach that has been extensively used in the literature to present modeling uncertainty is formulation of the problem on stochastic (random) base.

The modeling uncertainty considered in this paper is based on the limiting approach with limiting functions $\bar{\xi}(y,u,\mathrm{t})$ and $\bar{d}(y,u,\mathrm{t})$, adopted as limiting functions of measurable quantities $y$, $u$ and $\mathrm{t}$. This formulation includes heterogeneous limits $\bar{\xi}$ and $\bar{d}$, therefore extending the attainable detection and isolation capabilities as a robust fault diagnostics system. In case when the heterogeneous limits $\bar{\xi}(y,u,\mathrm{t})$ and $\bar{d}(y,u,\mathrm{t})$ are not known, then this may be considered a special case with constant limits $\bar{\xi}$ and $\bar{d}$, however such an assumption may lead to some errors.

## 3. A CONCEPT OF DIAGNOSTIC BLOCK ARCHITECTURE

The assumption here is that the state variables are restricted prior the fault occurrence and just after that as well, and that available are the results of the measurements $\boldsymbol{y}(\mathrm{t})$ and $\boldsymbol{u}(\mathrm{t})$. Another assumption was made that the feedback controller is designed so that physical states of the system stay limited for all $t \geq 0$ (i.e. prior and after the fault occurrence). This way the investigation was constrained to gradually evolving faults.

Shown in Fig.1 architecture of a fault diagnostics consists of a fault detection estimator and a set of their isolation estimators. Each isolation estimator should correspond to a specific fault, belonging to a class of faults.

Under normal operating conditions, when no faults occur, the fault detection estimator is the only one to monitor the system. After a fault is detected, the set of isolation estimators becomes active, and the fault detection estimator signal is transmitted to the fault function approximation model. A case when no isolation estimator accounts for the appearing fault (up to a certain, reasonable degree) corresponds to the occurrence of a new, unknown type fault, and this fault approximation model may then be used for updating the class of faults.

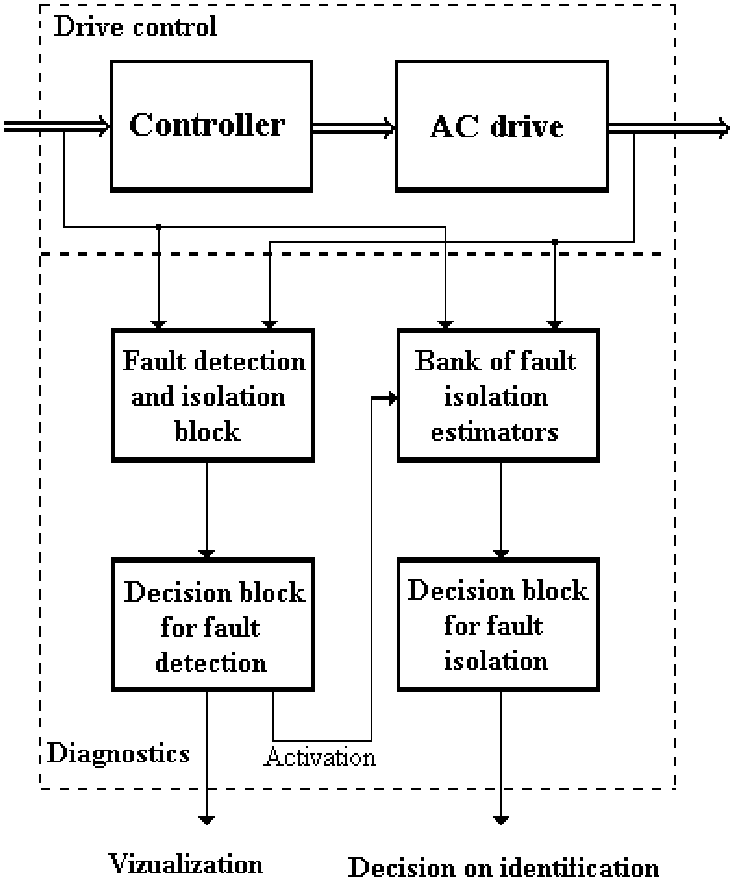


**Fig.1. Block diagram of fault diagnostics architecture.**

The fault model as generated by the estimators (when a match is the case) may be used to diagnose the fault and to carry on later handling. The most important part of each estimator is the on-line approximator, expressed by the *i*-th element $\hat{\phi}_i$ of the function $\hat{\phi}$ that describes the fault model:

$$\hat{\phi}_i(x,u,\hat{\mu}_0)=\sum_{j=1}^{v}c_{ij}\varphi_j(x,u,\sigma_j)\,;\quad c_{ij}\in\Re\,;\ \sigma_j\in\Re^k \tag{4}$$

where: $\varphi_j(x,u,\sigma_j)$ are given parameterized base functions, and $c_{ij}$ and the elements $\sigma_j$ are the parameters that are to be defined, i.e. $\hat{\mu}^0 \underline{\underline{\Delta}}(c_{ij},\sigma_j : i=1,...,n,\quad j=1,...,v)$.

When a fault occurred then employing relation (4) and computing the parameters of the approximator $\hat{\phi}$ made possible the adaptation of the on-line approximation process of the unknown fault function. This was attained by adaptation of the elements of the appropriate weights vector $\hat{\mu}^0(\mathrm{t})$, which resulted in a changed behaviour of the approximator's input/output. Another problem, beyond the scope of this work, is to design an effective learning algorithm for updating the weight vector $\hat{\mu}^0$. The solution employed here is similar to the one quoted in the literature to describe nonlinear multivariable approximation models with adjustable parameters or weights, like neural networks, fuzzy logic networks, polynomials, spline functions, wavelet transforms, etc.

A fault is detected when at least one component of the output estimation error $\in^0_{y_j}(\mathrm{t})$ exceeds its corresponding threshold $\overline{\in}^0_{y_j}(\mathrm{t})$. More precisely the instant of a fault detection $\mathrm{T_d}$ is defined as the first time instant for which $\in^0_{y_j}(\mathrm{t}) > \overline{\in}_{y_j}(\mathrm{t})$ for some $\mathrm{t} \geq 0$ and some $j = \{1,...,l\}$, or

$$\mathrm{T_d} \;\underline{\Delta}\; \inf \bigcup_{j=1}^{l} \left\{\mathrm{t} \geq 0 : \in^0_{y_j}(\mathrm{t}) > \overline{\in}^0_{y_j}(\mathrm{t})\right\} \tag{5}$$

The problem of robustness of a system that works following similar principles was investigated by the authors of [8] for the single input case, on the assumption of no measurement errors, with fixed constraints $\overline{\xi}$ and uncertainty $\xi(x,u,\mathrm{t})$, and additionally assuming known initial states of the system. Considering these assumptions the dead zone limitation in reckoning the estimator's threshold may be simplified to a constant $\overline{\in}^0_{y_j} = k_j \overline{\xi}/\lambda_j$ by adopting the upper constraint in time, where $k_j$ and $\lambda_j$ are positive constants defined in [9]. Stability of the proposed fault detection system including the aforesaid additional assumptions was acknowledged in the same work. Those results may be extended on the nonlinear model of the converter, as discussed in this paper.

The residuum of each fault isolation estimator is associated with an adaptive threshold, which may be accomplished on-line by using linear filtering methods [2, 4]. The occurrence of a particular fault is excluded when at least one of the residuum components corresponding to the isolation estimator exceeds its corresponding threshold within a finite time. A fault is considered isolated when all the potential faults but one are excluded. In practice a case is feasible when two distinct faults can be hardly identified and isolated, when their corresponding fault functions are not distinctive enough.

# 4. SAMPLE APPLICATION – A DIRECT FREQUENCY CONVERTER CONTROLLED AC (INDUCTION) DRIVE

In their investigation the authors used an induction motor drive rated at 5,5 kW, fed from a direct (matrix) frequency converter. A simplified block diagram of the selected drive is depicted in Fig.2. As may be noted the system control follows the field oriented current vector method.

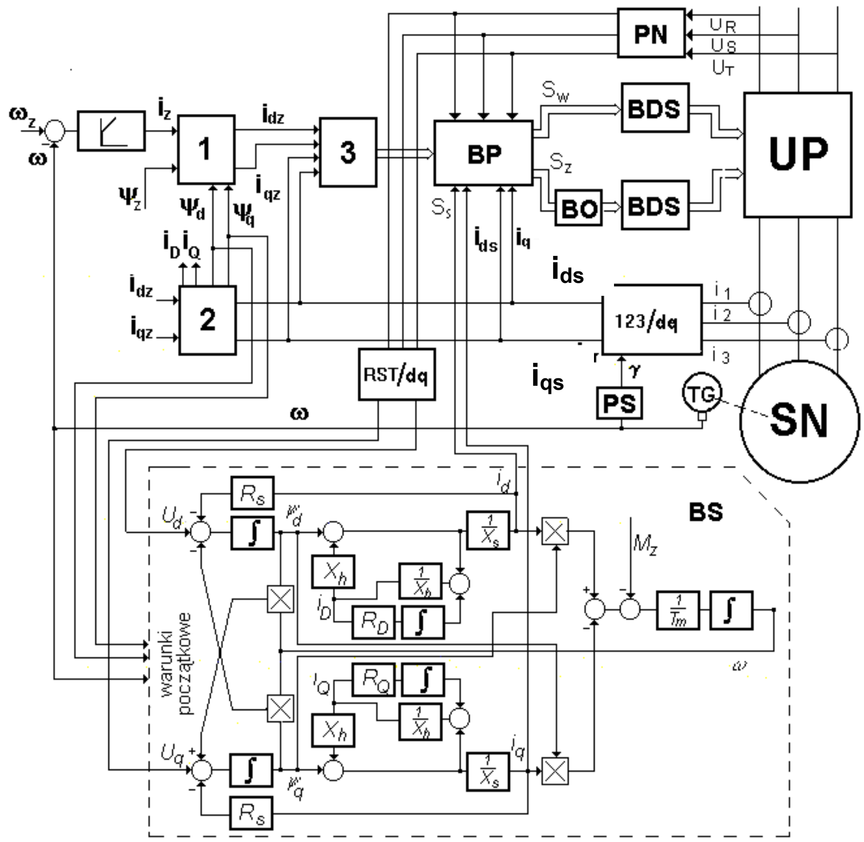


**Fig.2. Block diagram of the frequency converter control system.**

As can be seen from the diagram the set (motor speed and flux) and measured signals are applied on the system input. Additionally block 2 acted as observer of the state variables, which performed reckoning hardly measurable values, necessary for completing calculation of the algorithm: the components of the stator flux linkage and constituents of the rotor current. Using set values of the state variables Block 1 calculates the components $i_{dz}$ and $i_{qz}$ of the stator current. Block 3 produces pattern current waveforms that then are used in the comparison and optimization block BP. In this block the pattern waveforms are compared to the signals SS that were obtained as a result of the simulation block BS operation. The optimal arrangement of the converter's connections - following minimum deviation criterion – is also produced in this block. Blocks BDS adjust the real signals level according to the requirements imposed by the control system so they are good to switch the valves of the converter. Finally block BO provides a delay of the "on" signal against the "off" signal.

## 5. THE RESULTS

As mentioned earlier, the authors in their investigation had to consider the two factors that sometimes influence the converter's dynamics in a somehow intermingled way. They are: uncertainty in finding the exact values of the drive parameters, and the appearing faults.

In order to find out how uncertain evaluation of the drive parameters influences possible fault diagnosing a simulation of a fault-free operation of the drive was carried out and another one for a minor fault in one of the power electronic converter's switches. This fault manifested as increased resistance of the switch in the conduction direction. Investigated was also the coincident influence of small uncertainties in evaluating two selected parameters of the motor (they were the mutual inductance of the motor windings $x_h$ and the rotor resistance $R_R$ ).

The obtained sample waveforms of the stator current rotational vector are depicted in Figs.3 through 5. The drawings show the plots of the current starting at the fault instant, which occurs in the steady state operation of the motor at $t$ = 0.75 s. Included in it is also the effect of a coincident change in the determination accuracy of both of the mentioned motor parameters. The units on the $x$-axis of the co-ordinates are relative, while on the $y$-axis are absolute values.

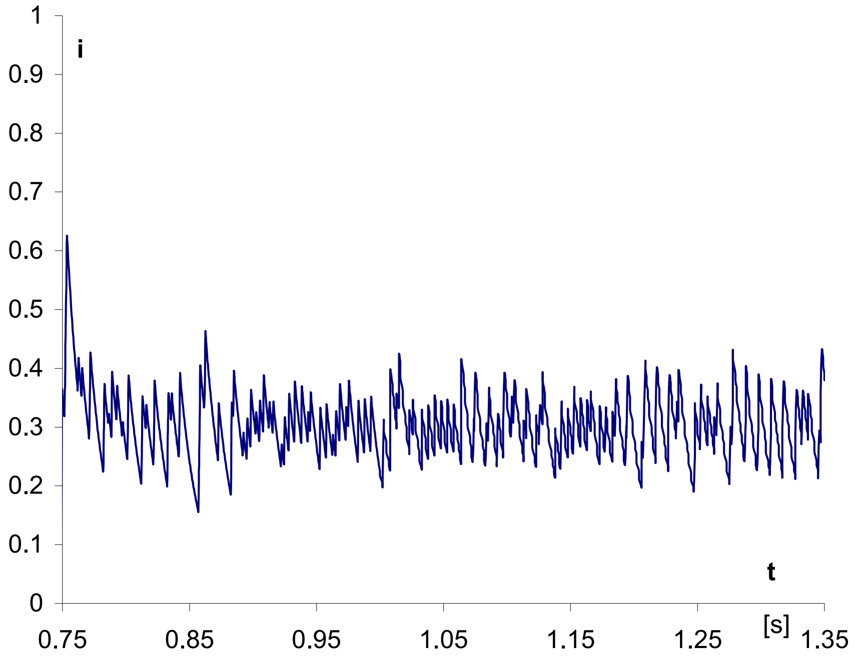


**Fig.3. Rotational current vector vs. time under a fault and with accurate motor parameters.**

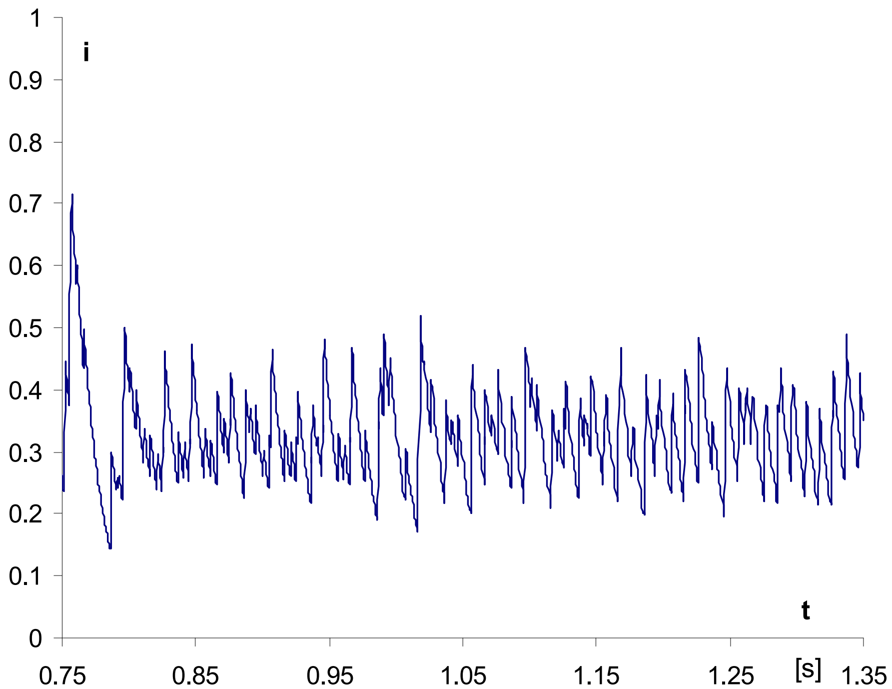


**Fig.4. Rotational current vector vs. time under a fault and with underestimated parameters.**

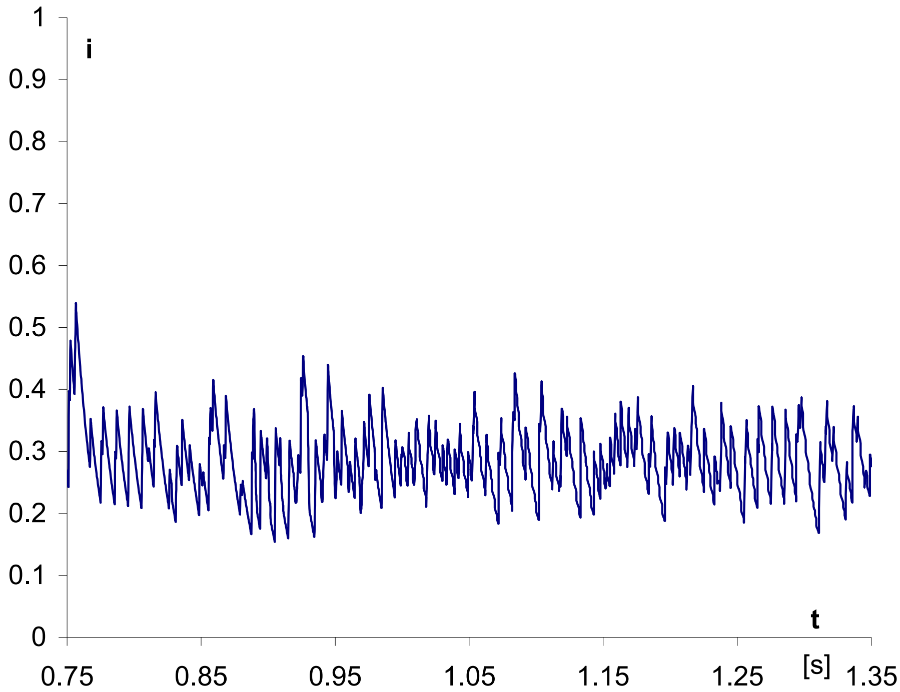


**Fig.5. Rotational current vector vs. time under a fault and with overestimated parameters.**

The analysis of the obtained waveforms of the individual state variables in time domain leads to a conclusion, that their changes are quite small and hardly conclusive. It is difficult to determine clear rules governing the relation of the parameter accuracy and the resulting time plots of the individual state variables.

The diagnostics of faults was based on analyzing the signals in frequency domain. In order to meet the requirements of real time processing (i.e. for the diagnosis to be made fast enough) the selected discrete system signals were analyzed using Haar transform. Every 128 spectra lines of the rotational vector of the converter output current were investigated for all the simulated cases. The obtained sample Haar spectra of the stator rotational current vector with damaged switch in the converter are presented in Figs.6 through 8 for accurate, overestimated and underestimated parameters, respectively.

For better comparison in Figs.9 through 11 there are Haar spectra of the rotational current vector with damaged thyristor switch of the frequency converter for the three different cases of the motor parameters determination accuracy, covering different aspects relevant to the accuracy of the selected elements. And so the individual plots depict:

- Fig.9 deals only the accuracy of the mutual inductance of the windings,
- Fig.10 –the rotor resistance only is considered,
- Fig.11 – accuracy coincidence of both of the mentioned parameters.

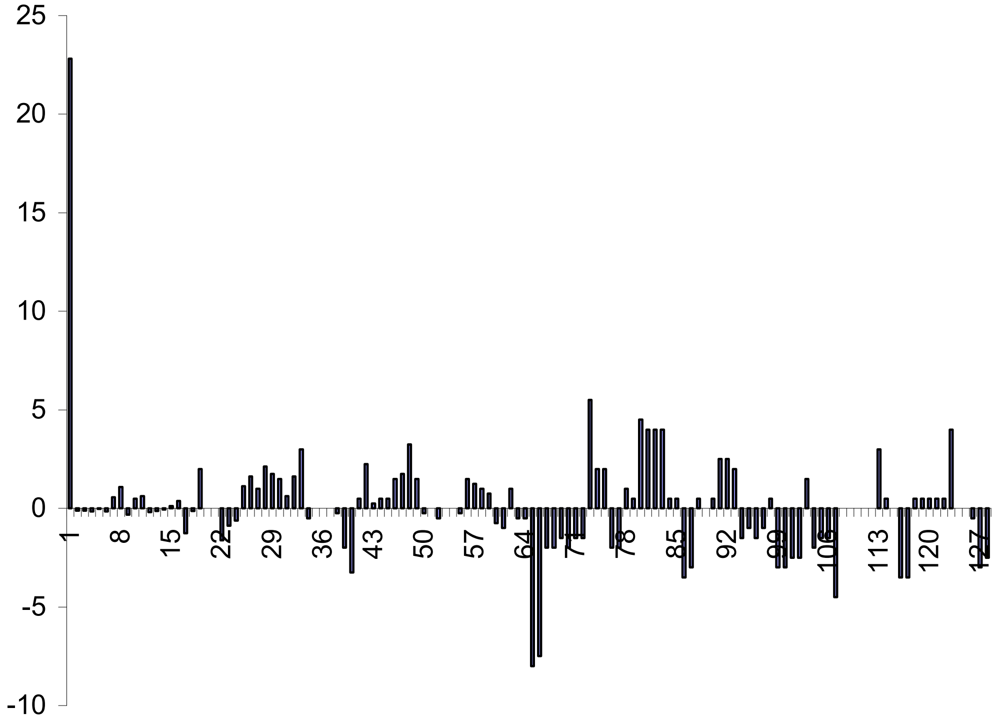


**Fig.6. Haar spectrum of the current signal with damaged switch and accurate parameters.**

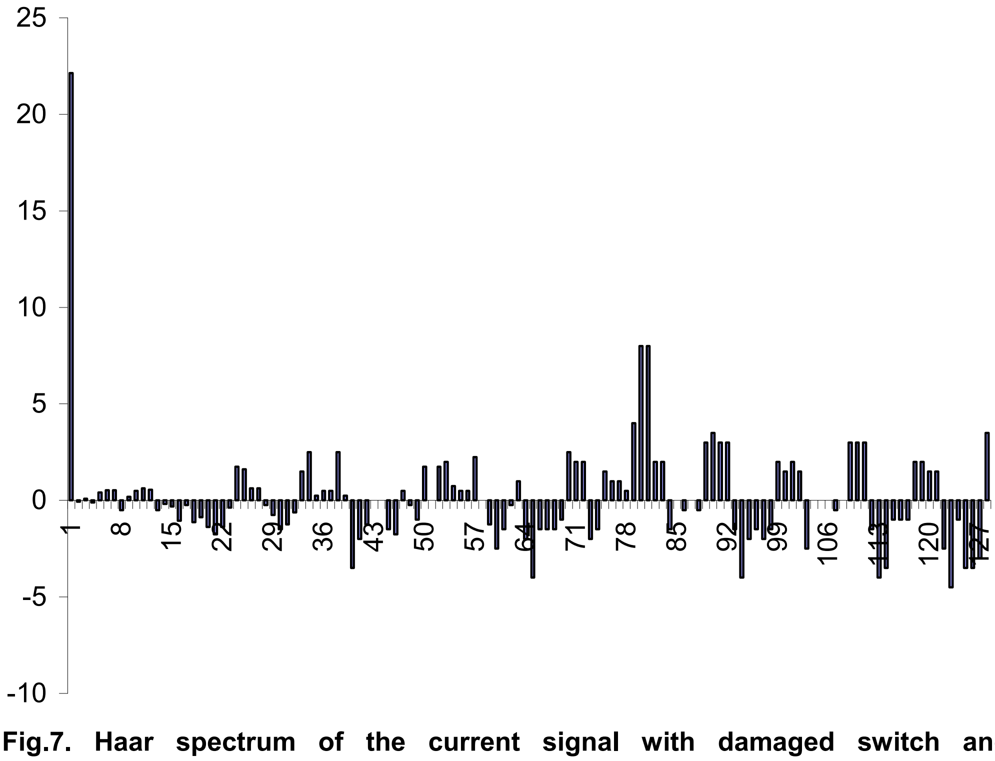


**Fig.7. Haar spectrum of the current signal with damaged switch and overestimated parameters.**

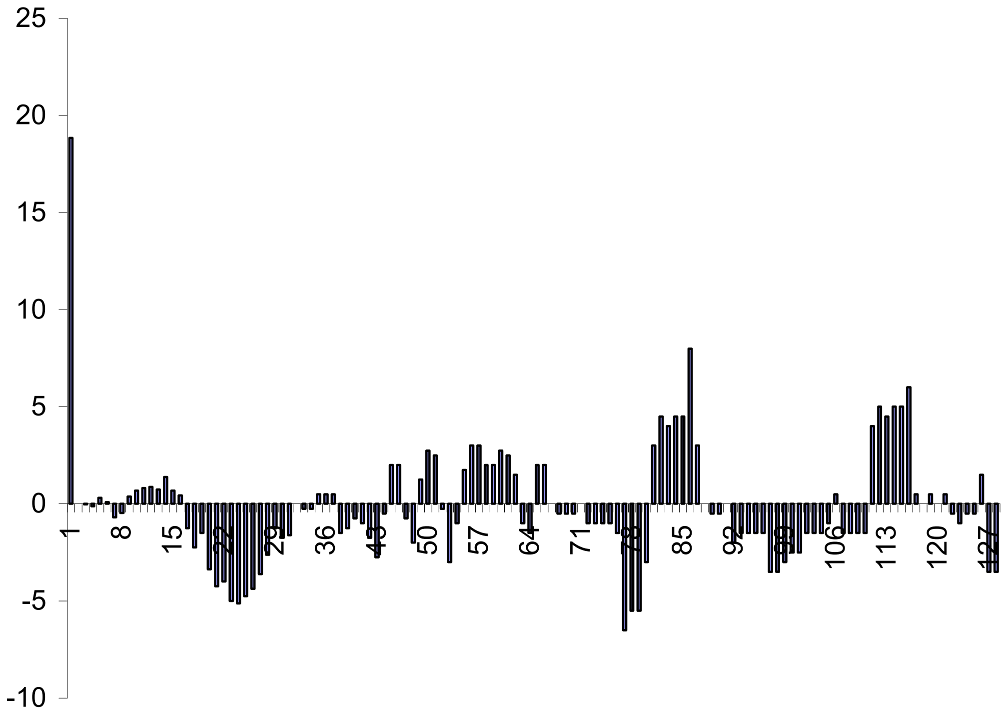


**Fig.8. Haar spectrum of the current signal with damaged switch and underestimated parameters.**

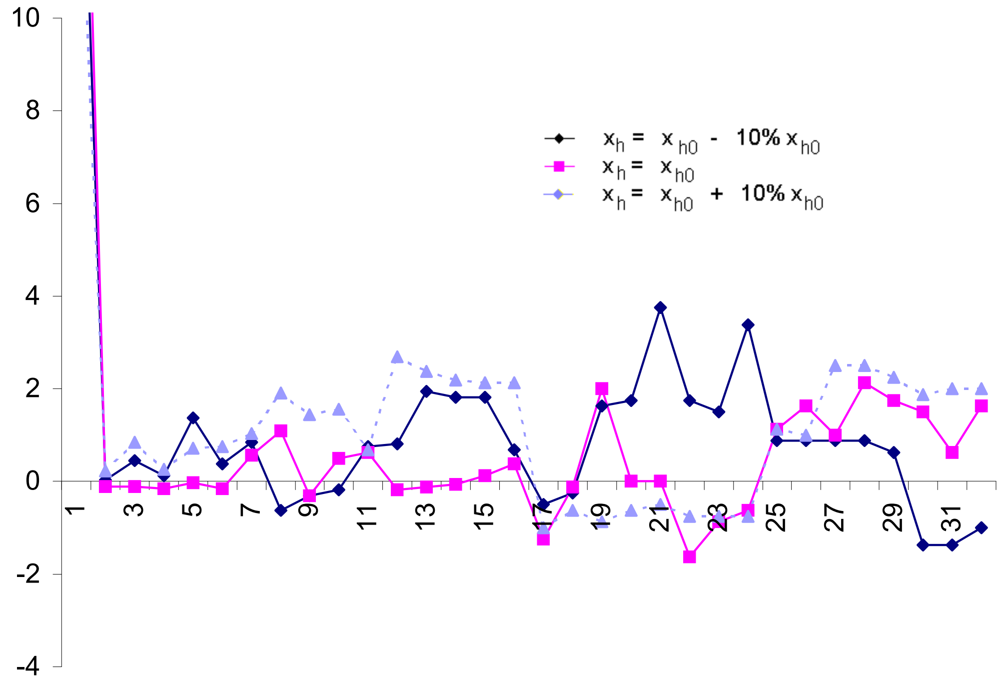


**Fig.9. Haar spectra envelope for inaccurate $x_h$ and defective thyristor.**

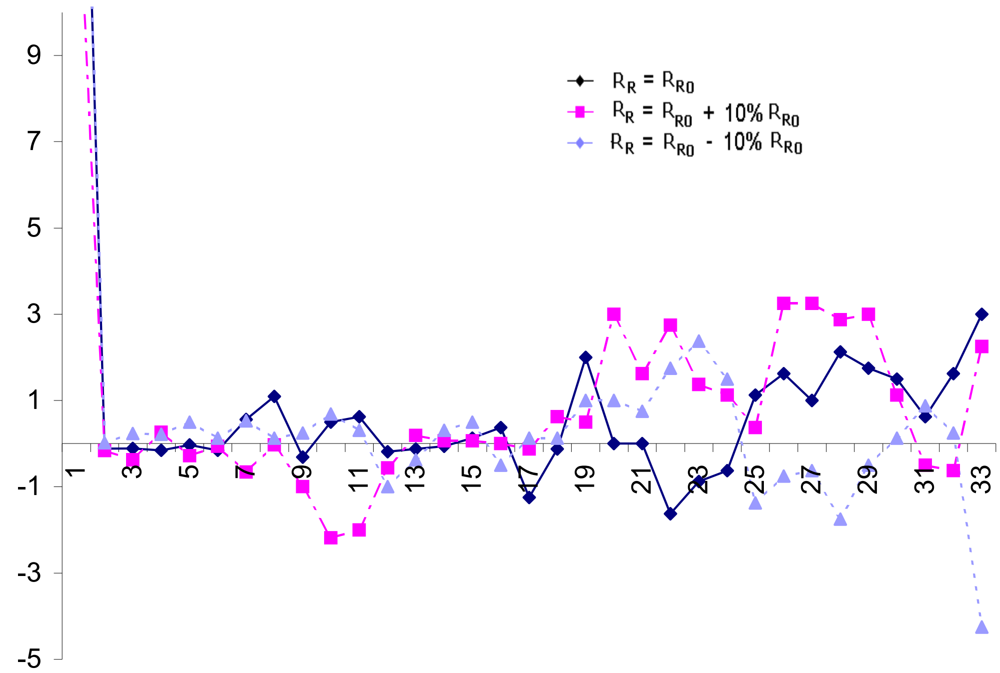


**Fig.10. Haar spectra envelope for inaccurate $R_R$ and defective thyristor.**

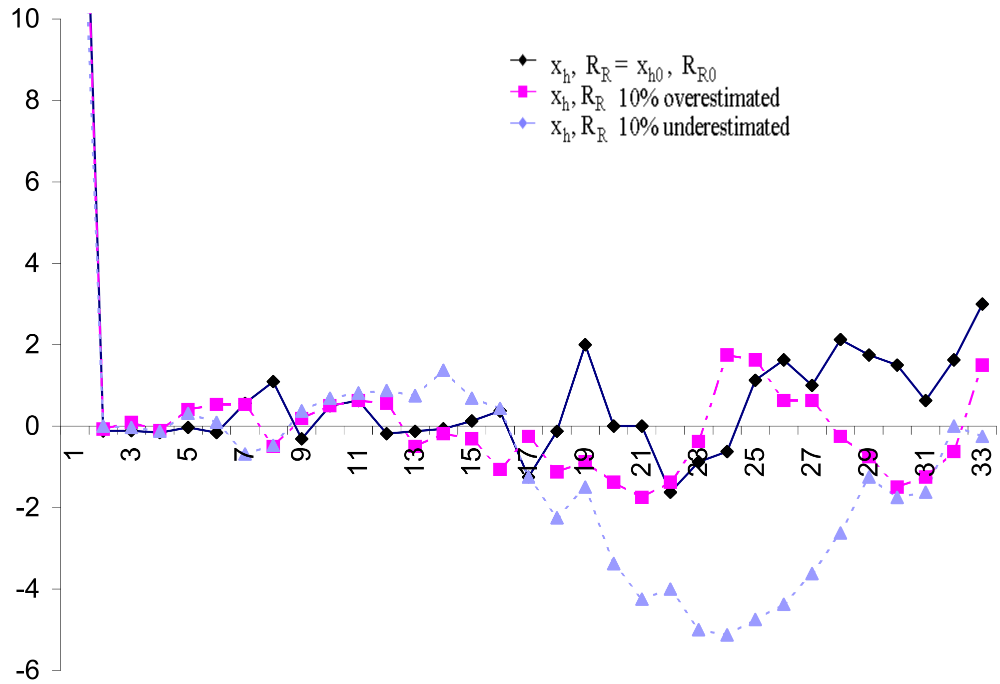


**Fig.11. Haar spectra envelope for inaccurate $R_R$ and $X_h$ a fault present.**

For better legibility the plots in these figures are presented in a linear mode (adversely to the conventional bar diagrams). However, the values of the individual spectra lines are denoted with marked points in individual segmented lines. Also for the sake of legibility only 33 spectra lines are included.

Analysis of the obtained diagrams makes it possible to determine how inaccuracy in evaluation of the motor parameters influences the resulting Haar spectra of the current signals both at normal and flawed operation of the system. This influence differs with inaccurate determination of different parameters.

The values of the first spectrum line vary in the above analyses with uncertain motor parameters. The values of these spectra lines are gathered in Table 1 (they are truncated in the plots).

**TABLE 1**

| Accurate $R_R$ and $X_h$ | $R_R$ +10% | $R_R$ -10% | $X_h$ +10% | $X_h$ -10% | $R_R$, $X_h$ +10% | $R_R$, $X_h$ -10% |
|---|---|---|---|---|---|---|
| 22,82 | 14,20 | 23,11 | 15,52 | 18,71 | 22,13 | 18,84 |

## 6. SUMMARY AND CONCLUSIONS

The authors presented in this paper one of the feasible methods for real-time diagnostics of power electronics, that takes account of the uncertainty in the evaluation of the parameters. In the course of the investigation the authors came to a conclusion that the problem is hard, as the uncertainty in evaluating the parameters may make it difficult to identify the emerging faults, since both those factors may manifest similarly.

Considering this the authors employed a diagnostic algorithm that can accomplish fault detection and isolation based on models, the structures of which were modified.

The presented algorithm may be used irrespective of the implementation and the architecture of the computer. Also it can be modified by decomposing a full task of modeling, and then executed on distributed computing systems [5]. This is essential with the presented approach since for the complete model a problem of computing complexity reduction arises.

Considering probable increase in the effectiveness of the computation possible reconfiguration of the computational algorithm was preliminary analyzed as well as the perspectives for fault detection using more accurate model.

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## DETEKCJA I LOKALIZACJA USZKODZEŃ UKŁADU ENERGOELEKTRONICZNEGO ZAWIERAJĄCEGO NIEDOKŁADNIE OKREŚLONE PARAMETRY

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**STRESZCZENIE** *W pracy przyjęto, że monitorowanie przekształtnika i jego sterowania jest prowadzone w sposób ciągły (cyklicznie) poprzez automatyczne formułowanie diagnoz jego stanu przez komputerowy system diagnostyczny. Innymi słowy diagnozowanie jest prowadzane w czasie rzeczywistym. Autorzy zakładali, że jako* *sygnały diagnostyczne użyte będą sygnały procesu, ponieważ wprowadzanie dodatkowych sygnałów testowych mogło by zakłócać jego dynamikę. Praca przedstawia układ wykrywania i lokalizacji uszkodzeń układu energoelektronicznego zawierającego niedokładnie określone parametry przy braku możliwości pomiaru wszystkich zmiennych stanu. Zaproponowana architektura diagnostyki uszkodzeń obejmuje estymator ich wykrywania oraz zbiór estymatorów lokalizacji. Każdy estymator lokalizacji odpowiada konkretnemu typowi uszkodzenia. Zastosowanie przekształceń ortogonalnych umożliwia przedstawienie zmiennej stanu układu energoelektronicznego w postaci odpowiednich kombinacji liniowej funkcji bazowych, dotychczas aproksymowanej szeregiem czasowym. W badaniach zastosowano rodziny binarnych funkcji ortogonalnych Walsha i Haara. Opisane podejście można zaliczyć do metod analityczno – numerycznych. Badanie własności sygnałów przekształtników energoelektronicznych przeprowadzono w oparciu o opracowane przez autorów algorytmy szybkich przekształceń.*

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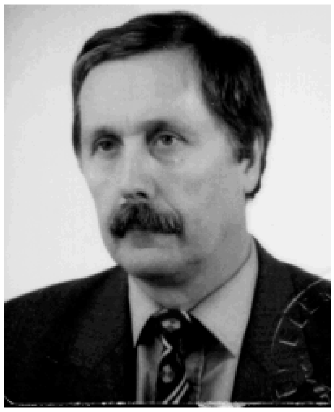
In 1980 he joined the Department of Fundamental Research in Electrotechnics of the Polish Academy of Sciences at the Institute of Electrical Engineering. He has been involved there in simulation and parallel computations in the control of electric drive systems.

He is the author or contributor of a number of papers and reports, of which several were presented in scientific conferences.



**Mieczysław Zając D. Sc.**, was born in Kraków in 1949. During his university studies and thereafter he was involved in control theory and application of computer systems in modeling and optimization of industrial processes. The scope of his M. Sc. Comprised problems encountered in the construction of optimization algorithms using probabilistic methods.

After graduation he joined the Institute of Automatic Control and Industrial Electronics in the Mining and Metallurgy University of Kraków, while at the same time attending post-graduate studies for doctor's degree. In his disseration he investigated problems of the use of stochastic methods in the construction of a dynamic model of the hot-strip mill drives. In 1976 he passed a one year practise in Metallurgical Works in Kraków and then joined the Institute of Electric Drive Control.

In 1980 he joined the Department of Fundamental Research in Electrotechnics of the Polish Academy of Sciences at the Institute of Electrical Engineering. There he has been focused his scientific interest on the computer control of complex drive systems. In recent he has been involved in the use of parallel processing in the synthesis of drive systems' control.