Design of experiment for diagnosis of the temperatures in AC motor drive

M. Zygmunt*, M. Orkisz*, P. Joerg**, M. Wnek* and J. Nowak*

***Abstract*—the paper describes statistical methods used to diagnose power semiconductors in DTC drive system. Simulation was used to train the data-mining model and then trained model was used to diagnose temperatures. To select the most significant training points the design of experiment was applied.**

From the measurement point of view the challenge is in predicting the maximum temperature reached by the semiconductors (a momentary effect) based on signals that vary on much larger time scales, e.g., the cooling water temperature.

In this paper we present some requirements regarding collection and analysis of drive signals for the purpose of diagnosing temperatures.

***Index Terms*— AC motor drives, Fault diagnosis.**

I. Introduction

Voltage source inverter technology has entered the medium voltage drives applications in the past decade. Thanks to its flexibility and scalability, the new technology is now established in the low and mid power area (1 – 30MW). Fig. 1 shows ABB's MV Drives product portfolio, where LCI denotes the traditional thyristor based current source inverter and ACS the different families of voltage source inverters. Voltage source inverters gain their flexibility by employing so called turn-off semiconductors. These are solid state silicon switches, which can be turned on and off at any time. Advanced control schemes operate these switches so as to get perfect control over even the largest electrical motors.

One of the most advanced solutions is Direct Torque Control (DTC). DTC is known from publications [1] [5] as well as from academic books [2]. Core ideas of DTC are:

- the basic control loop runs every 25 µs
- torque and stator flux are controlled on every control cycle
- torque and flux is controlled using hysteresis control

Thanks to this hysteresis control, the converter only switches when required by the motor and its load. Contrary to predefined switching patterns (e.g. pulse width modulation PWM), this results in fewer switching actions per second for the same motor torque quality.

Knowing that the number of switchings per second is traded against available output power, DTC already greatly optimizes available output power. Several additional control procedures further increase power utilization, such as:

- adaptable DTC algorithms for low speed range
- changeable hysteresis bands
- utilization of the inverters thermal capacity for short term power increase

These methods are adjusted to the application by estimating how much thermal capacity of the drive is used for through putting power. For full utilization, the power semiconductors as the main source of heat have to be considered during design and – even better – during commissioning and operation phase.

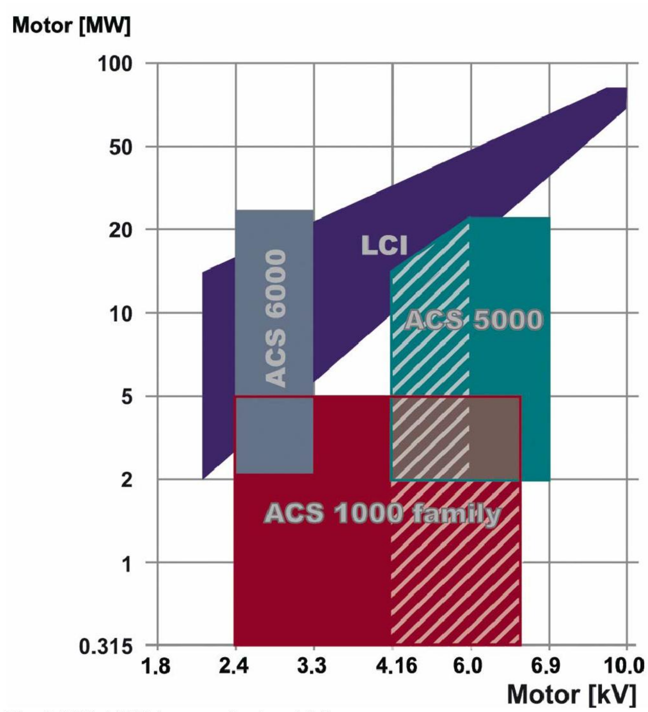

Fig. 1 MV AC Drives product portfolio

The idea presented in this paper is to treat the drive as a black box. We can predict the behavior of drive by looking at its inputs and outputs. Having in mind that not all outputs can be measured, we used simulation to model missing signals. We divided model signals into three basic groups: inputs, measured outputs and simulated outputs. Later on there will be a description how we have used these groups to train the database and how to use the trained database for diagnosis purpose. Diagnosis is done using predictive data-mining queries about signals which are not measured in the industrial environment. For a thermal diagnostic package interesting simulated outputs are power semiconductor temperatures. We use simulation tools for training the database. In order to be sure that simulation results are free from digital simulation errors we have performed extensive tests in industrial environments. Planning of these industrial tests has been done with the support of design of experiment theory.

Affiliation details:
*ABB Corporate Research Center
Starowiślna 13 A, 31-038 Kraków, Poland
e-mail: maciej.zygmunt@pl.abb.com
**ABB Switzerland Ltd
Austrasse, CH-5300 Turgi, Switzerland
e-mail: pieder.joerg@ch.abb.com

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II. SELECTIVE DATA COLLECTION

Drive monitor [4], ABB's commercial drive diagnostic framework, is capable of storing immense amount of data from production lines. Drawing conclusions out of this data however is not straight forward for several reasons:

- the majority of the time the drive under test is operating in good conditions
- data mining algorithms were developed for transactional systems similar to electronic cash registers: an event is always generated whenever the customer pays at the cash desk [3]. Applying this to every cycle of a mine hoist drive, all signals and parameters needed to be saved for analysis, resulting in gigabytes of data in few days, not providing any high level knowledge about the machine's condition, the drive's exploitation or possible energy saving opportunities caused by changing control parameters.

Therefore we used simulation and design of experiment to select triggering patterns for drive monitor. Instead of performing experiments according to a plan we can wait for a predefined condition pattern to measure most significant and important signals.

Drive Monitor might work in several possible modes:

- recording state of all variables and loggers whenever a trigger is fired
- recording selected variables upon occurrence of a condition

With Drive Monitor we are able to perform series of experiments for the purpose of data-mining and model training.

III. SIMULATION

A. *Diagnosis of the temperatures in AC converter.*

We have divided variables into three groups depending on the task context, i.e. whether it is simulation or diagnostics (see data flow on Fig. 4 and Fig. 5).

For simulation variable groups are (see Fig. 4):

- parameters: inputs
- measured signals: outputs
- simulated signals: outputs

For diagnostics variable groups are (see Fig. 5):

- parameters: inputs
- measured signals: inputs
- simulated signals: outputs

We did several simulation experiments to verify correlation between parameters, external conditions and internal state of the controlled device. The main effort of the simulations was to find a simple method to predict semiconductors temperature of ABB DTC MV Drives. The power part of these drives is using IGCT switching semiconductors. These semiconductors have high operating parameters like, for example, 4.5 kV. 91 mm IGCT is capable of switching current 3800 A with 2500 VDC or 3300 A with 2800 VDC, it has low on-state voltage drop and low turn-off switching losses, but nevertheless thermal losses at current measured in kiloamperes and voltage measured in kilovolts are the key design parameter of drives. Thermal losses are depending on current and switching frequency, see Fig. 2 where IGCT thermal limit characteristics are presented. Further on in this paper we will present some algebraic equations of semiconductor thermal model, but first look at Fig. 2 suggests that maximum switching current depends on the switching frequency, the ambient temperature and the case temperature. Due to the complexity of application and control, and due to high voltage in the drive, it is only possible to make simulation experiments to predict IGCT switching frequency and in effect semiconductors temperature.

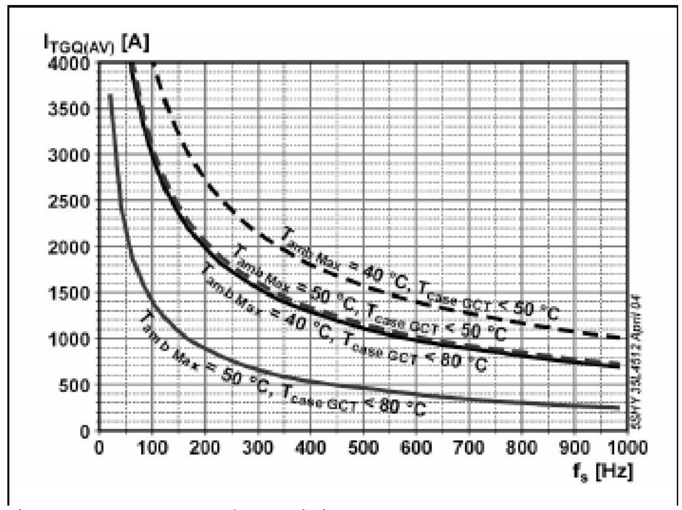

Fig. 2 IGCT temperature characteristics

We performed simulation of DTC drive behavior depending on different load and verified these results with a working application in industry. On Fig. 3 there is core idea of DTC from power electronics handbook [2].

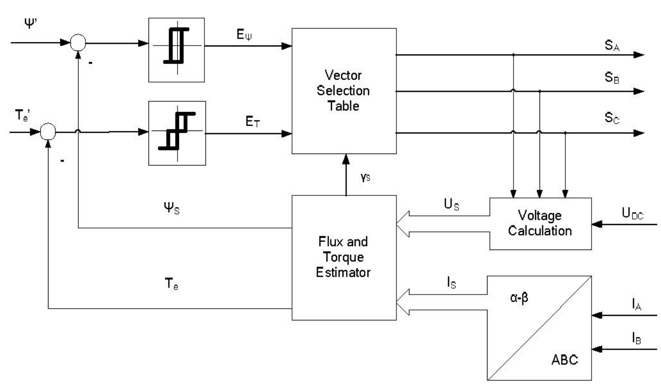

Fig. 3 DTC drive schematic diagram

Considered in this paper is a simulation of an AC converter under different load and final cooling system. In real drive temperatures are measured indirectly by measuring cooling liquid temperature and special probes inside the circuit. The thermal models have been established and validated already during the development of the drives. For training the diagnostics database, temperatures will be simulated and in the end simulation results will be compared with working industrial medium voltage installation once more. The target of these simulations and measurements is to find the most significant factors influencing semiconductors temperatures.

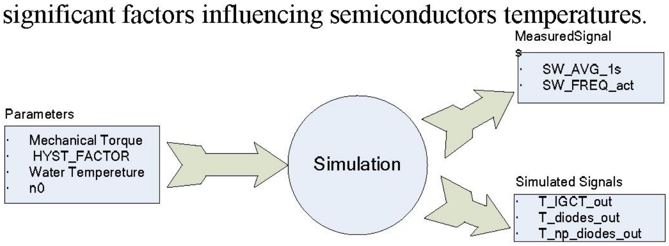

Fig. 4 Simulation data flow

The diagnostic process is similar to the simulation process, but measurement signals are now input to the diagnostic process. An example diagnostic process is shown on Fig. 5. Given a set of parameters and measured signals, diagnostic signals are obtained from the trained model.

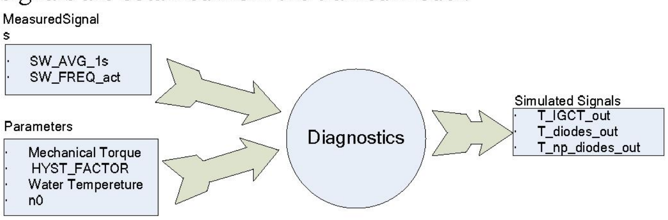

Fig. 5 Diagnostics data flow

IV. ALGEBRAIC CALCULATION

Algebraic calculations will be more deterministic: switching frequency is based on general hysteresis controller model shown on Fig. 6.

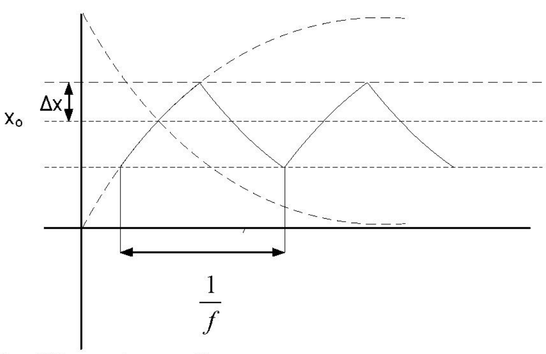

Fig. 6 Hysteresis controller

So switching frequency will be based on formula (1) , having in mind that there are two hysteresis controllers in DTC: one is flux controller and second one is torque controller, and consequently time constants are one electrical and second one electromechanical.

$$\frac{1}{f} = 2\tau \ln\left(\frac{1+\frac{\Delta x}{x_0}}{1-\frac{\Delta x}{x_0}}\right) \quad \textbf{(1)}$$

where

Δx: hysteresis band

x_0: controlled signal

τ time constant of the a dynamic system (either electrical or electromechanical)

Temperatures could be approximated with the following thermal model:

- thermal losses in IGCT depend on switching frequency and switching current
- heat transfer is usually calculated using equivalent RC model see Fig. 7, where formulas are presented in formula (2).

$$Z_{th}(t) = \sum_{n=1}^{m} R_{th(n)}\left[1-\exp(-t/\tau_n)\right] \quad \textbf{(2)}$$

Where:

$$\tau_n = R_{th(n)} C_{th(n)}$$

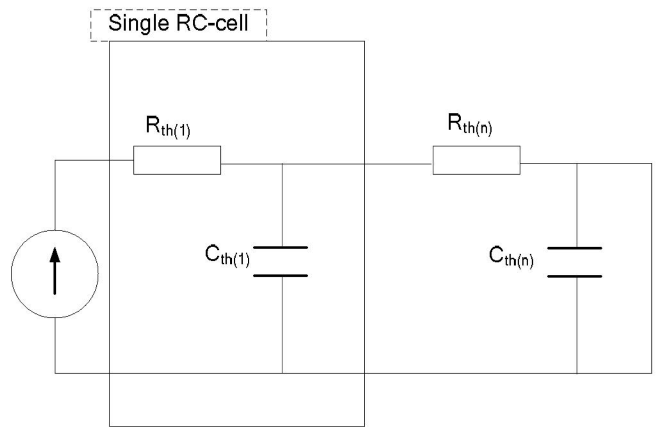

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Fig. 7 Equivalent RC model

Describing the whole system with algebraic formula would be the best solution, but due to some nonlinearities, and the overall system complexity, instead a dependency network (see Fig. 8) was constructed based on engineering knowledge of the system internals, then this network was verified with the simulation results.

Dependency graph:

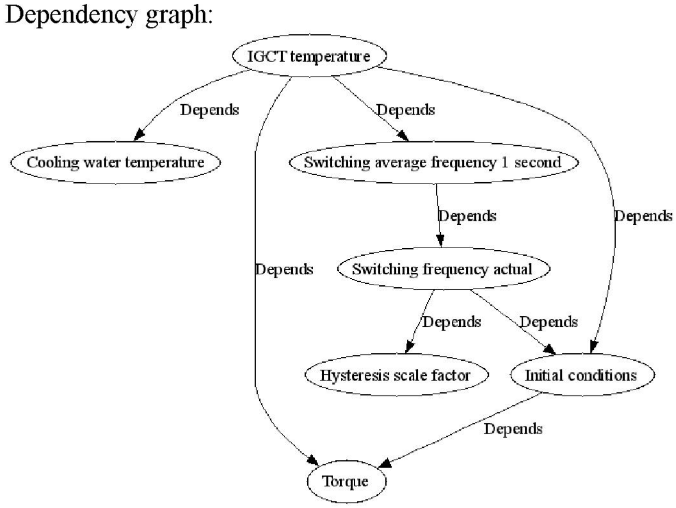

Fig. 8 Dependency graph

With algorithmic calculation it was possible to check model in several point to get confidence in diagnostics results.

V. Design of Experiment

Engineers usually use experience to select most significant parameters set, but it is beneficial to use analysis of variability (ANOVA) methods to select most significant parameters.

The design of experiment theory has been applied to select most significant points for the training model. Three level experiment plan was used for selected parameters. Parameters selection and parameter limits where dynamically changed during sequential iterations of the experiments. The whole simulation model has at least 200 input parameters, each simulation experiment takes about 2 minutes execution time on a modern PC. Calculating all parameters in 3 level design would take 3200 = 2.6 * 1096 times 2 minutes – a complexity impossible to handle. Therefore there was initial pre-selection of parameters based on engineering knowledge. In this paper there is proposed method for selecting parameters based on algebraic calculations and dependency graph.

VI. Data-Mining

We used simulation results to train the data mining model. On trained and tested model we can ask predictive queries. Testing model is performed on simulated data and will be performed in industrial environment.

A. *Data-mining model*

SQL server 2005 analysis services supports following data-mining algorithms:

- neural networks
- naive bayes networks
- clustering
- decision trees
- time series
- sequence clustering.

On the trained model one can perform several tasks:

- predict a discrete attribute
- predict a continuous attribute
- predict a sequence
- find a group of common items in transaction.

Detail description which algorithm is suitable for each task can be found in SQL Server 2005 literature [6].

Depending on the performed task, an appropriate algorithm should be used. In our work we get interesting results in predicting continuous attribute using neural networks. SQL Server provides flexible framework where trained model is accessed with high level query language hiding algorithms complexity from the programmer. During the designing of additional diagnostics packages we will use different tasks like predicting diagnostics sequences or predicting discrete attributes where different algorithms might be most appropriate.

We used data-mining process in the following scenario:

- train the model on simulated data from multiple runs of the model
- verify model on simulated data (or on real data).
- perform diagnostics predictive queries on the trained model.

B. *Predictive queries*

On trained model one can ask questions about not existing data, verify missing variable for example one can ask: "what will be IGCT temperature on [Sw Avg 1s] =200, [T_water] = 47" the trained model can give the answer, furthermore it can give the answer and tell you what is the confidence level, so the answer will be: temperature will be 65 with confidence level 92%.

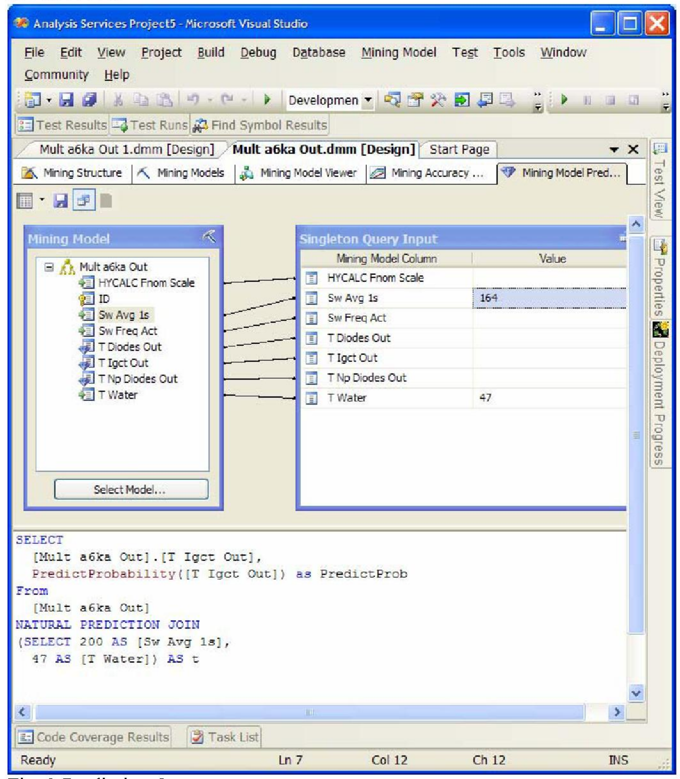

Fig. 9 Predictive Query

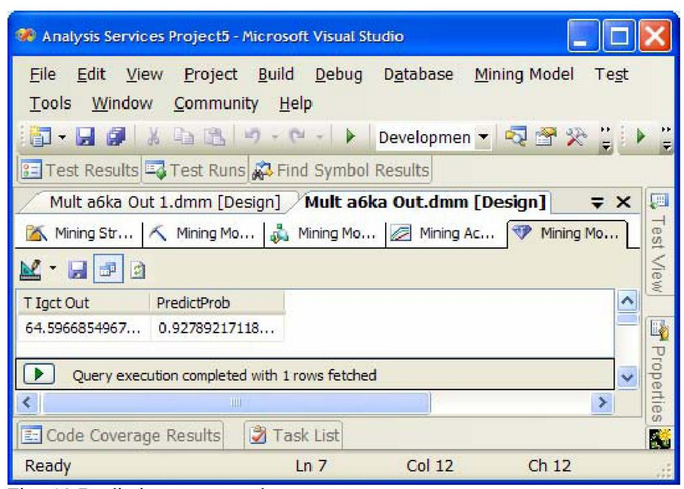

Fig.. 10 Predictive query result

VII. Black box approach versus simulation

If we have enough time for the simulation in real-time it would be most precise while simulator we have is very precise and was many time tested against real drive. Problem is that we would like to have answers in seconds how much further can we overload semiconductors without compromising safety limits. Further on we would like to somehow predict future or avoid points where will be now safe way to reduce load without risk of overheating semiconductors. Summarizing black box approach looks interesting for the following reasons:

- well trained model will give the answer fast and better then simple protection system;
- with design of experiment we can capture most important parameters influencing reaction of the system, which in case of the simulation can be simply not taken into account;
- we will answer not only what to do to avoid too big temperature, but also what to do to avoid "point of no return" see Fig. 11, means situation that reducing parameters will not guarantee safe functioning of the system.

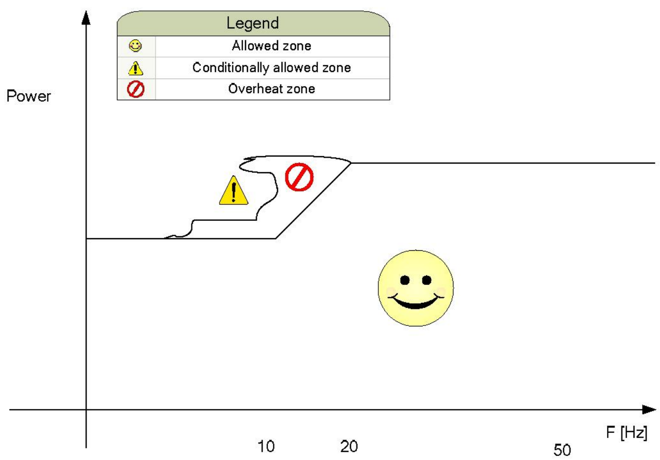

Fig. 11 Allowed load

VIII. CONCLUSIONS

Due to the complexity of a DTC-controlled MV AC drive, finding exact dependencies between system parameters and output temperatures was possible only with simulation, but algebraic formulas and dependency graph were helpful for more efficient planning of simulation experiments. The proposed methodology can be used for other diagnostic procedures, it allows making smart tabularization of non directly measurable signals and even it gives good background for planning experiments on physical objects.

In industrial environment it is not possible to measure semiconductor temperatures directly, but combining real measurements with computer simulation we are able to draw conclusions about possible peek overloading of the AC drive and allow to utilize more power out of the device without the risk of overheating semiconductors. The behavior of the drive has also been tested under some conditions where analytical formulas apply, in order to have more general methods than statistics and data-mining.

Diagnostics via predictive query is just one database select therefore it is much faster than online simulation. It gives the possibility to have nearly real-time predictive diagnostics. Further on it will be fine tuned and trained on the real object, so it will contain more accurate knowledge than only simulation data. In some circumstances the most probable load profile can be associated with drive's internal variables, and then in consequence algorithms can be trained for predicting load profiles and later on effectively predict load in extreme conditions.

Using selected method we where able to design high level asset optimization system. It can be tuned for selected applications - e.g. metal rolling - on a system level where the load diagram is known in advance for the selected application. This will reduce the risk of stopping the drive during work under extreme conditions.

IX. APENDIX A

Selected variables used in example diagnostics case study:

Varaiable Name	Description
HYCALC_fnom_scale	Hysteresis scale factor
T_water	Cooling water temperature
sw_avg_1s	Switching average frequency 1 second
sw_freq_act	Switching frequency actual
T_igct_out	IGCT temperature
T_diodes_out	Diodes temperature
T_np_diodes_out	Null point clamping diodes temperature

X. ACKNOWLEDGMENT

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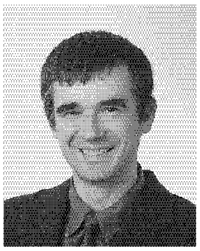
XII. Biographies

Maciej Zygmunt was born in Kraków, Poland. He received M.Sc. and Ph.D. in Computer Science from University of Mining and Metallurgy in Krakow in 1989 and 1999 respectively. 1989-2000 he worked at University of Mining and Metallurgy as Research and Teaching Assistant. Since 2000 he is with ABB Corporate Research working mainly in the area of condition monitoring, diagnostics, and manufacturing.



Michał Orkisz was born in Kraków, Poland. He received B.S. degrees in Computer Science, Physics and Mathematics at M.I.T. in 1988, and Ph.D. in Condensed Matter Physics in 1994 at M.I.T. He has worked in Gel Sciences, Inc., Genome Therapeutics, and, since 1998, in ABB's Corporate Research, where he has dealt with condition monitoring, risk analysis and computer vision.

Pieder Jörg (member IEEE) was born in Domat/Ems, Switzerland. He received his M.Sc. degree in electrical engineering from ETH Zürich in 1995. 1995 – 2002 he worked in the area of power electronics research at ABB Corporate Research. Since 2002 he is with ABB Medium Voltage Drives, dealing with product development of large medium voltage motor drives.

Maciej Wnek was born in Krakow, Poland on December 05th 1965. He received M.Sc. and Ph.D. In Physics from Jagiellonian University in Krakow in 1989 and 1993 respectively in the area of solid state matter. 1992-1995 temporarily he worked at Tohoku University, Sendai, Japan and Universita La Sapienza Rome, Italy in the area of liquid crystals displays (LCD). Since 1997 he is with ABB Corporate Research working mainly in the area of condition monitoring, diagnostics, and asset management.

Jarosław Nowak was born in Warsaw, Poland in June 24th 1974. He received M.Sc. in Automatic Control and Robotics from Warsaw University of Technology in 1999 in the area of industrial process diagnostics. Since 2000 he is with ABB Corporate Research working mainly in the area of condition monitoring and software development.