Classification of Low Voltage Distribution Networks by Means of Voltage Distortion

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Abstract—**Determination of power quality becomes more and more important in the future. Low voltage networks are usually large and very complex. Therefore the calculation of power quality parameters by modeling as equivalent network is hardly possible in practice. That's why new methods for efficient and exact estimation of power quality parameters in low voltage networks are necessary. The presented method is based on the fact that networks of similar structure have a similar behavior in power quality. The Points of Common Coupling (PCC) are divided into different classes, where each class consists of PCC's with similar characteristics. This way the method allows the estimation of power quality levels based on the class a PCC is assigned to. The paper demonstrates the method for the 5th voltage harmonic as an example power quality parameter. The above-mentioned classification of substations is based on probabilistic neural networks.**

***Index Terms*—Power distribution, power quality, harmonic distortion, power system identification, neural network applications.**

I. Introduction

THE growing number of electronic equipment in low voltage networks tends to result in a slightly but continuously decreasing power quality. On the other hand the equipment sensitivity increases. Due to both trends the determination of power quality becomes more and more important in the future. Low voltage networks are usually large and complex, which means that the calculation of power quality parameters by modeling as equivalent network is hardly possible in practice. Measuring the power quality at each node of interest is possible, but leads to quickly growing costs due to the huge amount of network nodes and time for data management. For these reasons new methods for efficient and exact estimation of power quality parameters in low voltage networks are necessary [1, 2, 3].

The power quality at a specific node in the low voltage network (referred to as Point of Common Coupling or PCC in the further text) significantly depends on structural characteristics. These can be divided into characteristics of network structure and consumer structure. The new method is based on the fact that networks of similar structure have a similar behavior in power quality. The PCC's are divided into different classes, where each class combines PCC's with similar characteristics. Now it becomes possible to infer from a few measurements of PCC's in each class to the power quality behavior at other PCC's of the same class.

The presented paper proves the above-mentioned assumptions by considering the 5th voltage harmonic as example power quality parameter. The 5th voltage harmonic is the dominant harmonic in public low voltage networks and affects the behavior of THD almost solely. The classification bases on the measurement data from 8 PCC's in the low voltage network of a half-million city. To classify the substations neural networks have been applied [4, 5]. In a first step the samples of the time-plot of the 5th voltage harmonic have been used as the input data for the neural network. In a second step the input data for the neural network are derived from the statistical distribution of the 5th voltage harmonic. In a step 2a) the percentiles of the cumulative distribution function (c.d.f.) and in step 2b) the histogram (discrete density function) of the 5th voltage harmonic are used s input data for the neural network.

II. Measurements

The measurements of the harmonics have been carried out for three weeks at each of 8 MS/NS-substations. While the network structure is nearly similar for all measurement sites, the consumer structure differs as shown in table 1.

A first analysis of the consumer structures in table 1 shows two generally different types of consumer structures. Group 1 combines PCC 1, 4, 7 and 8 (highlighted in gray) that mainly consist of offices and municipal buildings. The other PCC's are assigned to group 2 and are represented by a significant part of household consumers.

Figure 1 and 2 show the time-plot of the 5th voltage harmonics for PCC 1 and PCC 2. Overlaying the plots for the three weeks in each diagram shows the similar behavior between the weeks at each PCC more clearly. Comparing the plots of the different PCC's show differences in the behavior, which result from the differences in the consumer structures. PCC 2 (fig.2) with mainly household consumers (group 2) shows a small but distinctive evening peak, while the time plots measured at PCC 1 (fig.1) (group 1) can be divided, especially for working days, into two well distinguishable

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parts: higher levels during the daytime; smaller levels during nighttime.

TABLE 1 CHARACTERISTICS OF CONSUMER STRUCTURES

	PCC 1	*PCC 2*	*PCC 3*	*PCC 4*	*PCC 5*	*PCC 6*	*PCC 7*	*PCC 8*
one-family houses		x		x				
residential building		x	x		x	x		
building services eng.	x[4]		x			x[1]		x
street lighting		x						
offices/office buildings	x			x	x		x	x
municipal buildings	x						x[2]	
restaurants	x[3]			x				x
supermarkets	x							

1 – central heating station; 2 – health center; 3 – library; elevators

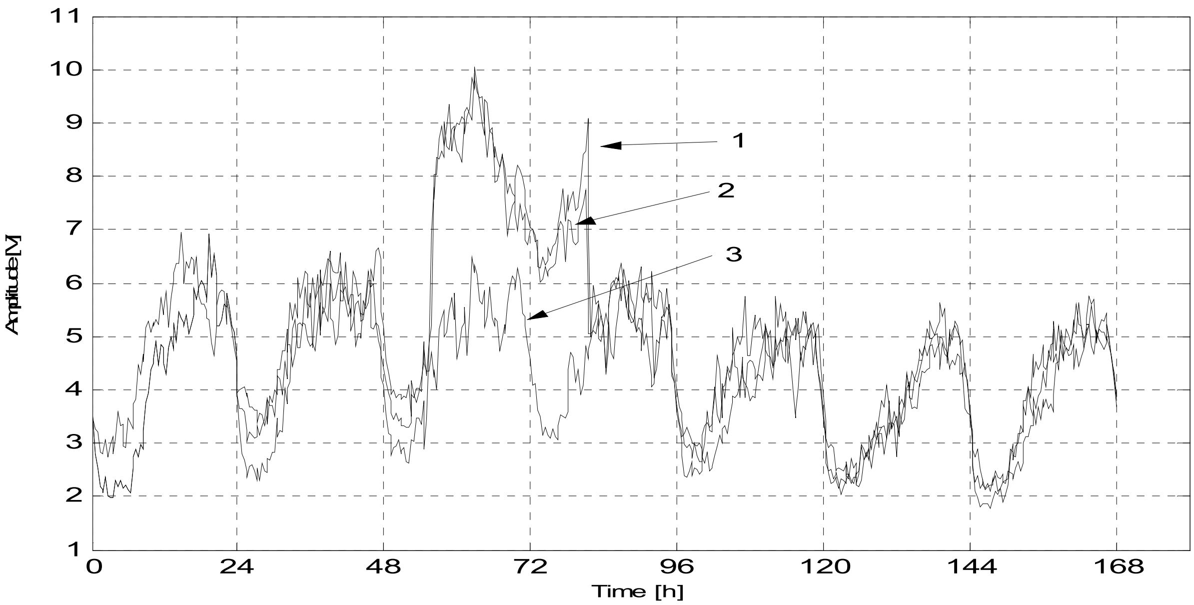


Fig. 1 Time-plot of 5th voltage harmonic for three consecutive weeks (1, 2, 3) at PCC 1

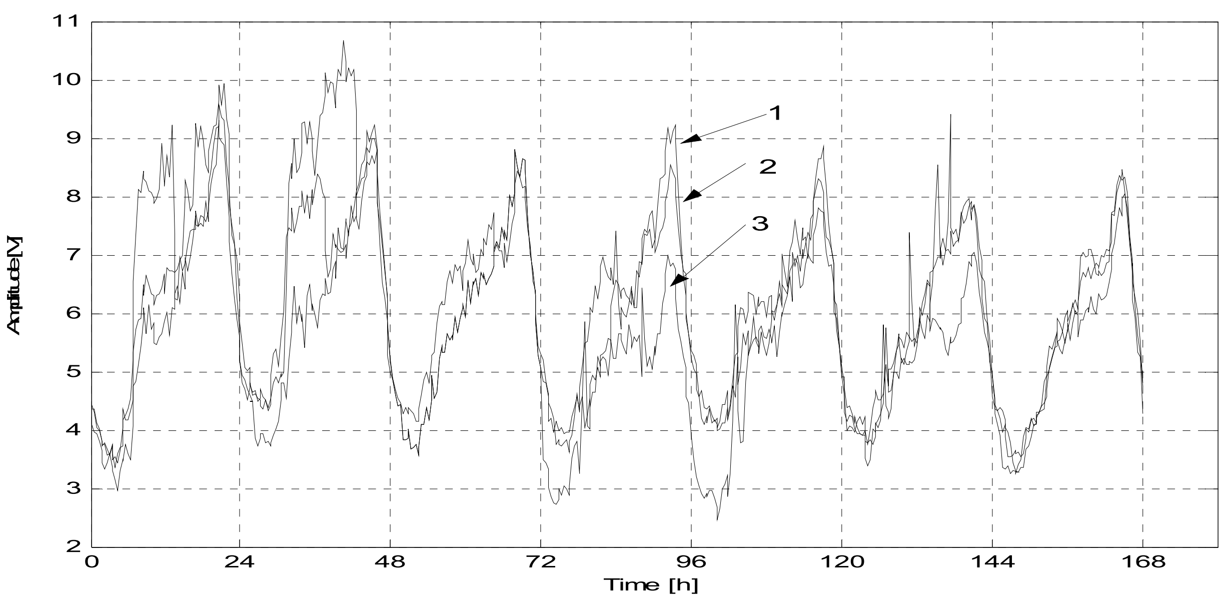


Fig. 2 Time-plot of 5th voltage harmonic for three consecutive weeks (1, 2, 3) at PCC 2

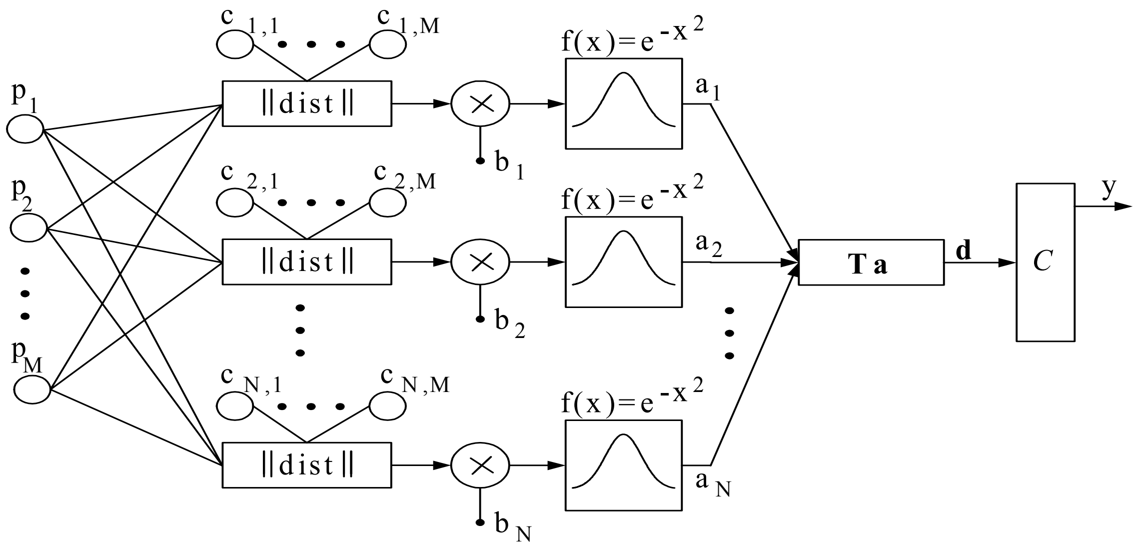


Fig. 3. Probabilistic neural network

III. Probabilistic neural network

Probabilistic Neural Networks (PNN) belong to the group of Radial Basis Neural Networks and are well suited for classification problems. The PNN is based on concepts used in classical pattern recognition problems. Design of the network structure is straightforward and does not depend on training [6]. It models a technique, which minimizes the expected risk of classifying patterns (in our case the input vectors) in a wrong category. The PNN has two layers: a hidden layer and an output layer (Fig. 3). The hidden layer acts like the hidden layer in radial basis function neural networks (RBF). Each hidden-layer neurons has a centroid $\mathbf{c}_i$ and smoothing factor (bias) b_i (i=1,2,…,N , where N is the number of vectors in hidden-layer). These neurons compute the vector distance between the input vector **p** and the centroid $\mathbf{c}_i$. The neuron outputs are a nonlinear, radial symmetric function of the distance. A commonly used transfer function for a radial basis neuron is the Gaussian exponential function:

$$f(x) = e^{-x^2} \tag{1}$$

This way the output of the neuron is strongest when the input vector **p** is nearest to $\mathbf{c}_i$. The bias b_i allows adjusting the sensitivity of the radial basis neuron. The network is initialized by setting the centroids $\mathbf{c}_i$ equal to the training patterns (training input vectors) $\mathbf{p}^{(T)}$. When an input is presented, the hidden layer computes distances from the input vector to the training input vectors, and produces a vector (vector **a** in Fig. 3) whose elements indicate how close the input is to training inputs. The output layer sums these contributions for each class of inputs (by multiplication **Ta,** where **T** is the matrix of target vectors) to produce a vector of probabilities **d**. Finally, a compete transfer function *C* picks the maximum of these probabilities. The PNN classifies the input vector into the class, for which the maximum probability is observed.

IV. Classification

A. Time Plots

For every substation and every week the input vectors were created. The values of the 5th harmonic were averaged over 20 min. This way 504 values per week have been obtained. That means, each vector $\mathbf{p_t}$ contains of 504 elements. In the first step it has been assumed that the substations can be classified into two groups. Training vectors for the first group were taken from PCC 1, while training vectors for the second group were taken from PCC 2. Next the neural network classifies the vectors from all substations. The results of the classifications are shown in the table 2.

TABLE 2 CLASSIFICATION RESULTS

Group 1	*Group 2*
PCC 1, PCC 4, PCC 7, PCC 8	PCC 2, PCC 5, PCC 6

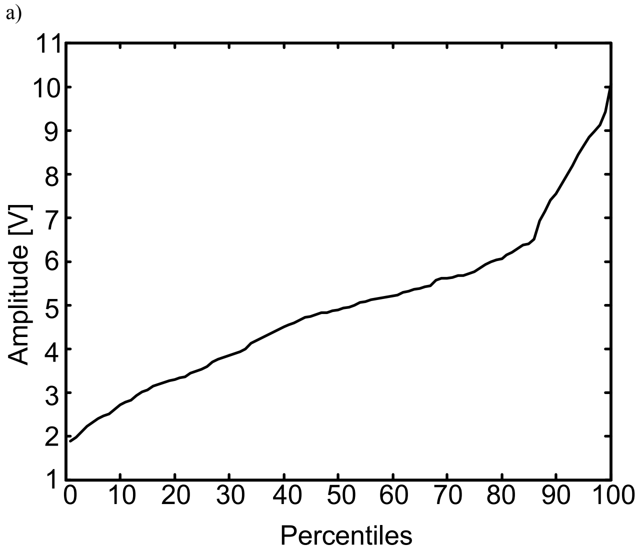
The results using the Neural Network fit the classification by hand (Table 1 – group 1: gray; group 2: white) very well. Only PCC 3 could not be assigned to one of the groups. In a next step three instead of two groups have been considered for classification, where vectors of PCC 3 became training vectors for group 3. The classification results for group 1 and group 2 have been retained unchanged; while Group 3 only contains PCC 3. The characteristics that cause PCC 3 to be classified to group 3 have to be analyzed in detail. Acquiring more measurement data it becomes possible to increase the performance of the classification method presented in the paper.

B. Statistical Distributions

In the previous chapter the time plots of the 5th voltage harmonic represented the input data for the network. Now the statistical distribution of the values of the 5^{th} voltage harmonic is used to derive the input data for the PNN.

In a first variant the input data for the PNN are the percentiles of the cumulative distribution function oft the 5^{th} voltage harmonic. The *k*th percentile is a value that is greater then *k* percent of values of the previously obtained vector $\mathbf{p_t}$, (the weekly time-plot of the 5th voltage harmonic for one week consisting of 504 elements. One hundred percentiles were calculated (k = 1,…,100) for each of the eight substations and for each of the three weeks. Fig. 4 shows the percentiles for PCC1 and for PCC2, for the first week. Thus the input vectors $\mathbf{p_p}$ for PNN contain 100 elements.

a)



b)

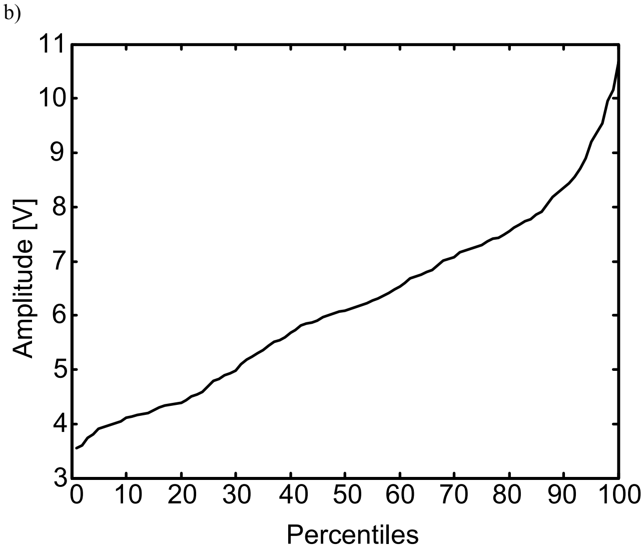
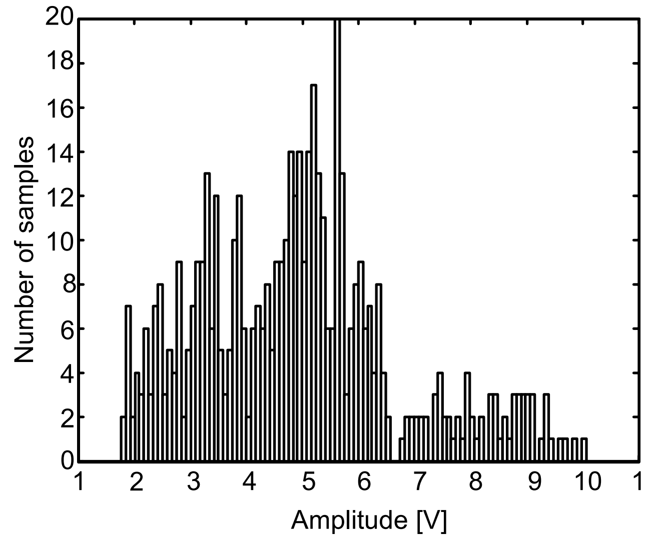


Fig. 4. The percentiles of the 5th voltage harmonic: a) for PCC1 b) for PCC2

In the second variant the histograms of 5^{th} voltage harmonic were used. To create input vectors, the element of each vector $\mathbf{p_t}$ was assigned to n equally spaced bins. The counts of elements in each of the n bins are the input data for the PNN. Thus the input vectors $\mathbf{p_h}$ contain n elements. To analyze the influences of different numbers of bins 2 different bin counts were carried out: n=100 (Fig. 5), n=20 (Fig. 6).

a)



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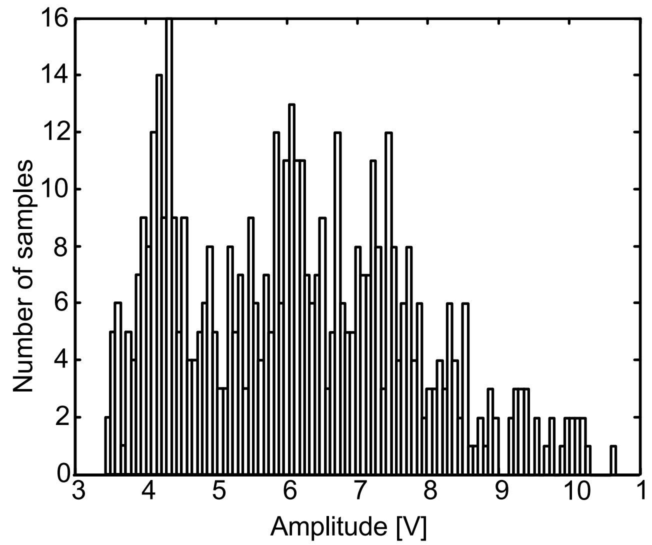
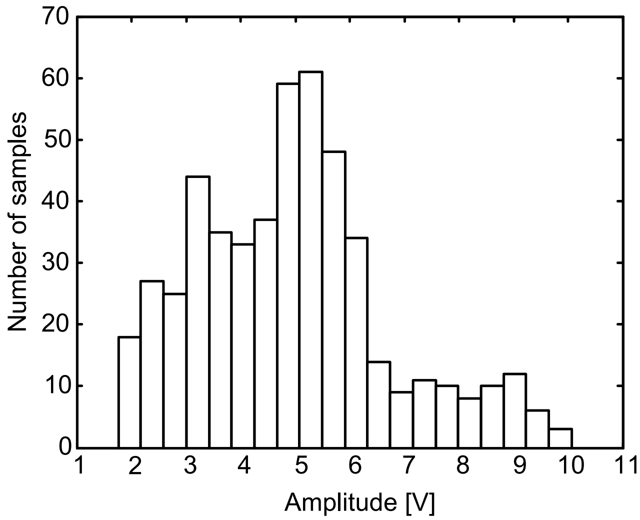


Fig. 5. The 100 bins histogram of 5th harmonic voltage for: a) PCC1 b) PCC2

It is significant that in the second case the input vectors contain only 20 elements; so the structure of the neural network is relatively simple.

For both variants (based on percentiles and histograms) the classification tests were carried out and results were compared with the time-plot method (IV.A). As before, it has been assumed that the substations can be classified into two groups; training vectors for the first group were taken from PCC 1, while training vectors for the second group were taken from PCC 2. The results of classification are very similar. For the variants based on percentiles and on histogram with number of bins n=20 the results are the same as in Tab. 2. Only in the case of histogram with n=100 bins a small difference has occurred. The classification of PCC 8 is not clear-cut; the two input vectors derived from two weeks were classified to *Group 2* and the third *week was classified to Group 1.*

a)



b)

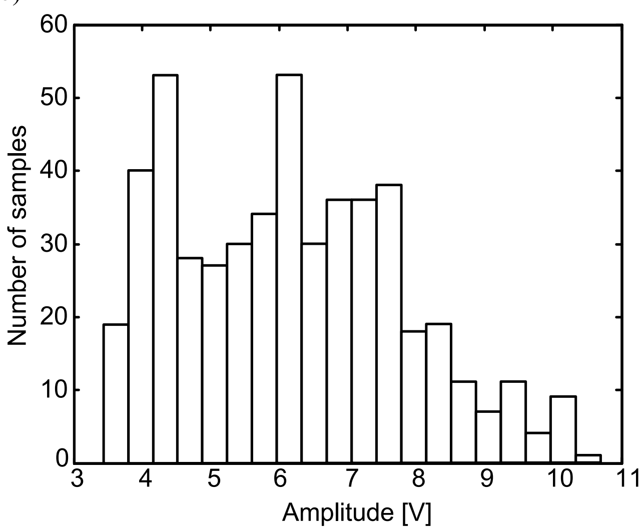


Fig. 5. The 20 bins histogram of 5th harmonic voltage for: a) PCC1 b) PCC2

VI. Conclusions

The paper presents a new method for efficient and exact estimation of power quality parameters in low voltage networks. The method is based on the fact that networks of similar structures have a similar behaviour in power quality, which is also proved by the results of the classification method. The 5th voltage harmonic, which is the dominant harmonic in low voltage networks, is considered as an example power quality parameter.

For classification of substations probabilistic neural networks have been applied. The classification bases on the measurement data at the substation busbars of 8 low voltage networks of a half-million city. The 8 substations were divided into two groups. Group 1 mainly consists of offices and municipal buildings. Household consumers mainly represent group 2.

The vectors from all substations were applied in classification process as input vectors. Different kinds of data representation for the neural network were analyzed:

- time-plot– 504 elements a week,
- percentiles of cumulative distribution function – 100 elements a week,
- histograms with 20 or 100 bins a week,

for each of the three weeks.
The results of classification were very similar for all the input vectors.

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VI. Biographies

Peter Schegner (M' 1999) studied Electrical Power Engineering at the Darmstadt University of Technology (Germany) where he received the M.Sc. degree in 1982. After that he worked as a system engineer in the field of power system control and became a member of the scientific staff at the Saarland University (Germany), receiving the PH.D. degree in 1989 with a thesis on the earth-fault distance protection. From 1989 until 1995 he worked as head of the development department of protection systems at the AEG, Frankfurt a.M./Germany. In 1995 he became a Full Professor and Head of the Institute of Electrical Power Systems and High Voltage Engineering at the Dresden University of Technology (Germany).

Jan Meyer received the M.Sc. in 1995 and the Ph.D. in 2004 from the Technische Universität Dresden, Germany. He works at the Institute of Electrical Engineering at the TUD since 1995. His field of interest are new, statistically based methods to calculate power quality in low and medium voltage networks, as well as the development of efficient methods for power quality benchmarking.
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Tadeusz Lobos received the M.Sc., Ph.D. and Habilitate Doctorate (Dr Sc.) degrees, all in electrical engineering, from the Wroclaw University of Technology., Poland in 1960, 1967, and 1975, respectively. He has been with the Department of Electrical Engineering, Wroclaw University of Technology, since 1960, where he became a Full Professor in 1989. From 1982 to 1986, he worked at the University of Erlangen-Nuremberg, Germany. His current research interests are in the areas of transients in power systems, control and protection, and especially application of neural networks and signal processing methods in power systems.
The Alexander von Humboldt Foundation, Germany awarded Dr. Lobos a Research Fellowship in 1976 and he spent this fellowship at the Technical University of Darmstadt. He received the Humboldt Research Award, Germany in 1998.

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Michael Mühlwitz received the M.Sc in electrical engineering from Technische Universität Dresden in 1993. He is with local multi utility DREWAG - Stadtwerke Dresden GmbH since 1994 up to now. Till 1999 he works on the field of protection in power distribution systems. Since 1999 he manages the sub department Electrical Service.