Database-Assisted Frequency Estimation for Power System Measurement

Matthias Lechtenberg†, Kay Görner‡, Jügen Götze†and Christian Rehtanz‡ Information Processing Lab†, Institute of Energy Systems, Energy Efficiency and Energy Economics‡
TU Dortmund University
44227 Dortmund, Germany
Email: {matthias.lechtenberg,kay.goerner,juergen.goetze,christian.rehtanz}@tu-dortmund.de

In modern power transmission systems, monitoring of transient processes becomes more important. Analyzing a transient process is hard since the process is not only transforming from one steady state into another, but it also includes event-driven oscillations from LC-circuits within the net. The number of such oscillations is unknown and not constant. Furthermore, the oscillations can have a small amplitude. The knowledge of such oscillations can help understanding what happens where in the net. To estimate these oscillations, we present a signal processing method based on subspace estimation and history-based data ranking. It enables the estimation of an a-priori unknown number of oscillations and so the rank, although their amplitude might be small compared to dominating components.

***Index Terms*—ESPRIT, OPAST, Rank Estimation, Frequency Estimation, Database, Power System Measurement, Transient Processes**

I. Introduction

A. Context of Power Distribution

Power supply strategies have changed during the last decade because of new framework conditions such as the increase of regenerative power and the liberalization of energy markets. Load flows across several different control regions stress transmission lines so that in case of an emergency cascading outages may occur. Subsequently, the net must be upgraded for a reliable and stable operation. However, it might not be possible to keep step with the power plant development due to (mainly) political and economical reasons. In addition, the power generation will not be as homogeneous as before, since regenerative power generation depends on environmental influences like weather [1].

Signal processing for power systems in steady-state usually covers e.g. symmetrical components transformation, extraction of the fundamental frequency's harmonics and synchrophasor generation — just to name a few. However, some of this analysis is also relevant for fast electromagnetic transients. A focus is set on the event-driven transient periods. One group of transient processes is invoked by intended or unintended switching events like line-switchings, line faults or compensating capacitances [2].

B. Line Modeling and Signal Model

The transmission net can be modeled as a circuit of resistances, inductances and capacitances with partly overlaid meshes. Each mesh with inductances and capacitances taken from the circuit has its own resonance frequency and can be excited by a switching event. In case of such a switching event, each participating mesh in a node provides its resonance frequency as a superposed sinusoid in the voltage/current signal of this node.

These sinusoids appear during a transient process when the transmission net merges from one steady-state condition into another. In consequence, there are short-term components of the signal appearing suddenly and fading out within a short time. In addition, they usually have an amplitude which is significantly smaller than the fundamental frequency's amplitude. A resulting signal model may be written as follows:

$$x(n) = \sum_{i=1}^{p} a_i(n) e^{jn\omega_i + \varphi_i} + w_{\text{awgn}}(n) \quad (1)$$

$$= \sum_{i=1}^{p} c_i(n) e^{jn\omega_i} + w_{\text{awgn}}(n) \quad (2)$$

The number of sinusoids (*rank*) is p. The complex amplitude $c_i(n) = a_i(n)\exp(j\varphi_i)$ is built of the amplitude $a_i(n)$ and the (initial) phase φ_i. The component $\{c_1, \omega_1\}$ represents the fundamental frequency. The resonance frequency of an excited LC-oscillation mesh is embodied in $\omega_i|_{i>1}$. The components' fading-out is not modeled explicitly, but may be extracted from the time-varying character of the $c_i|_{i>1}$.

C. Frequency Estimation

The resonance frequencies are typically in the range of 100Hz to 1000Hz. Depending on the examined net, some of the resonance frequencies may have similar values. In

M. Lechtenberg (matthias.lechtenberg@tu-dortmund.de) and J. Götze (juergen.goetze@tu-dortmund.de) are with the Information Processing Lab, TU Dortmund.

K. Görner (kay.goerner@tu-dortmund.de) and C. Rehtanz (christian.rehtanz@tu-dortmund.de) are with the Institute of Energy Systems, Energy Efficiency and Energy Economics, TU Dortmund.

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consequence, conventional transformation-based parameter estimation like *DFT/FFT*, *STFT* or *Wavelets* may render disadvantageous since — inherent to their functional principle — they suffer from problems like spectral leakage and low resolution. Other parameter estimation algorithms not suffering from these effects should be preferred. Subspace-analyzing algorithms like *MUSIC* [3] and *ESPRIT* [4] belong to this group of algorithms as well as Prony's method [5], [6] and its derivations. However, we chose ESPRIT since Prony's method is known to be more affected by noise, which can be considered a strong argument in the context of variable rank [7].

Another problem emerges from the small amplitudes. This signal constellation is not covered by typical rank estimation via model assessment (*AIC*, *MDL*, *ITC*, *MAP*; [8], [9], [10]). However, rank estimation is necessary for subspace-based parameter estimation. In most publications, this challenge is not addressed, e.g. [6], [11].

A different approach is modeled on a kind of database. This database gathers the estimated frequencies (under consideration of an overestimated rank). Although some noise will be mistaken as signal, this will enable the discovery of new, emerging components. The estimated frequencies are rated over time. A reoccurring frequency is rated high, thus it is regarded as present and a part of the signal, respectively. Counting the relevant components provides a more robust rank estimation. A potential drift of such frequency over time is tracked via threshold-controlled drift statistics.

In the upcoming sections, we will present the database-assisted algorithm chain in the context of a transient process in the 39-node-containing *New England Test System* having a line fault. The method will be used to extract the instantaneous values of the fundamental frequency and the frequencies caused by event-driven excitations of LC-oscillation circuits.

Section two will detail the signal processing methods. This includes the algorithms involved, their theoretical background and their relation. Section three focuses on the simulation. It describes the corresponding environment, the simulation itself and the results. Section four concludes this work.

II. Process Chain

A. Subspace Estimation

The concept of the presented parameter estimation was already discussed in [12], [13], [14]. The samples from the measurement are prepared with a sliding window before the respective data is fed to the subspace estimator.

The samples' space can be described by a set of vectors forming a basis. One way to do this is to use windowed sample data to estimate the auto-correlation matrix (e.g. via exponentially weighted averaging) and to perform an eigenvalue/-vector decomposition of this matrix. These eigenvectors form one possible basis of the samples' space. Knowing the rank p, the signal's subspace can be extracted by selecting the p vectors corresponding to the greatest eigenvalues. Consequently, the other vectors describe the noise subspace.

Another way to find a basis for the signal's subspace is depicted by the so-called subspace trackers. They are often mentioned as cheap alternative to the above-mentioned eigenvalue decomposition. In fact, they do not produce eigenvectors — they provide vectors forming a basis describing the same space as a basis defined by eigenvectors does. Next to algorithms like PROTEUS [15] or YAST [16] the class of PAST-based algorithms [17], [18] is common in such context. In a former work [14], the OPAST algorithm was identified to be a good choice.

B. Parameter Estimation

The a priori selected basis-vectors describing the desired signal are fed to the subspace-based parameter estimator ESPRIT. It is based on the analysis of the rotational invariance of two subsequent basis-vectors. Due to the principle of rotational invariance, these vectors should only differ in a constant rotation $\exp\left(j \cdot n \cdot \Omega_i\right)\big|_{n=1}$ (with $\Omega_i = 2\pi f_i/f_s$) resulting from the *eigenfrequency*, which is the desired parameter.

Remembering the signal model in Eq. (2), the signal can also be described by subspaces like in the equation

$$\vec{x}(n) = \mathbf{A}(n, \vec{\omega})\vec{c}(n) + \vec{w}_{\text{awgn}}(n) = \mathbf{S}(n) + \sigma^2_{\text{awgn}}\mathbf{I}. \qquad (3)$$

The matrix $\mathbf{A}$ contains the exponential functions $\exp(j\omega_i n/f_s)$ to form the superposition in the horizontal dimension and the burst description in the vertical dimension. Within that equation, $\mathbf{S}(n)$ describes the signal subspace, which can be written as a product of the eigenvectors $\mathbf{W}(n)$ and the eigenvalues (on a diagonal matrix) $\mathbf{D}(n)$:

$$\mathbf{S}(n) = \mathbf{W}(n)\mathbf{D}(n)\mathbf{W}(n)^H \qquad (4)$$

One time-step can be described by a multiplication with a diagonal matrix $\mathbf{\Phi}$ having diagonal entries $\exp(2\pi j \cdot f_i/f_s)$:

$$\mathbf{S}(n+1) = \mathbf{W}(n)\mathbf{D}(n)\mathbf{\Phi}\mathbf{W}(n)^H. \qquad (5)$$

The key idea of ESPRIT is to estimate the rotation $\mathbf{\Phi}$. Due to noise, $\mathbf{\Phi}$ will have off-diagonal elements. So an EVD is performed on $\mathbf{\Phi}$. The frequencies can be extracted from these eigenvalues by calculating their angle. These frequencies are the input of DaPT [13].

C. Database-assisted Parameter Estimation — DaPT

Assuming the feed of ESPRIT to contain a few more basis-vectors than the rank of the signal, these additional vectors belong to the noise subspace and are named auxiliaries. In contrast to the signal's vectors, theses will not result in constant parameter estimations within the ESPRIT algorithm. The idea of DaPT (*Database-assisted Parameter Estimation*) is to rate the temporal presence of each frequency.

Entries with high rating can be hypothesized as part of the desired signal and entries with a low rating are assumedly noise and to be forgotten. By this, the algorithm recognizes a change in rank by simply counting entries with high ratings. This rank is advanced by a small number (the *auxiliaries*) and looped back to the block that selects the vectors to be fed to ESPRIT.

In every recursion, the incoming frequency estimation is mapped to the most suitable database entry. Ideally, both values match neglecting the measurement noise. For entries that have been successfully mapped, the quality is increased (up to a maximum value); for others, it is decreased (down to zero). A zero-quality-entry will be deleted. The frequency-entry is corrected according to the drift measures' severity indexes exceeding a threshold. One measure is based on the difference of frequency estimation and is double-staged, i.e. it has two thresholds for small and large steps. Another is based on the phase difference of two subsequent estimations of the complex amplitude. The measures' values are exponentially weighted over time (*double-exponential smoothing*) and its severity index is updated sign-depended.

This database has entries for each signal component containing frequency f_i and (complex) amplitude c_i. The complex amplitude is to be estimated separately. Additional fields hold:

1) *Frequency drift*: This field tracks the change of the frequency estimations against the database field for threshold-based frequency field updates.
2) *Phase difference*: It tracks the change of the phase gradient as second indicator for a mis-estimated frequency. The phase is assumed to be constant, so a monotonically changing phase estimation (based on the database's frequency) indicates a mismatch.
3) *Severity of frequency drift/phase difference*: These are the indicators for the previously mentioned threshold-based updating rules.
4) *Quality of entry*: This is the actual rating. It rates how often a frequency has been part of the last estimation recursions. Based on that, components can be marked reliable (i.e. *present*), and therefore are accounted for rank estimation and output.

D. Symmetrical Components Transformation

The delay introduced by the subspace tracking (considering its exponential averaging) and the database (considering the thresholds to be reached) shall not only be quantitatively but also qualitatively evaluated. For the qualitative evaluation, we incorporate the symmetrical components transformations as the negative and zero sequence provide indicators for system changes. In an advanced implementation, this transformation may also be incorporated as trigger for adaptive parameter changes within the database rules.

The symmetrical components transformation transforms the three phase-measurements (of a three-phase system) into a positive, a negative and a zero sequence. A steady-state transmission (without unsymmetrical faults) only produces a significant value in the positive sequence, since all phases are rotated to be added *in-phase*. Rotations for the other sequences rotate contrarily, so unsymmetrical loads can be detected through these. A switching event invokes significant values in the negative and zero sequence since the phases will not be switched at the same time but each $120°$ ($\hat{=}6\,{}^{2}\!/_{3}\mathrm{ms}$) phase-shifted. The transformation is defined as

$$\begin{bmatrix} U_+ \\ U_- \\ U_0 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} U_A \\ U_B \\ U_C \end{bmatrix} \quad \text{with} \quad a = e^{j\,2\pi/3} \tag{6}$$

E. Additional Signal Processing

Phase and amplitude estimation can be obtained by a simple LS approach referring to the signal model in Eq. (3). Since time index and frequency are known, the matrix $\mathbf{A}$ can be built. Together with the samples, the complex amplitude can be estimated. Using the same method, the synchrophasor can be determined by referencing a constant frequency — i.e. the system's fundamental frequency — and calibrating an offset-phase to adapt to the UTC-time [19]. However, a real-time system like FPGA is recommended for meeting the temporal requirements of PMU measurements.

F. Signal Processing Node

Considering the application of signal processing for power transmission systems, these algorithms can be grouped to nodes. Such node could replace a PMU or advance a net of PMUs. Providing a data-link between such nodes enables further processing for load-flow estimation, localizing and categorizing system events etc. As an example, in the upcoming simulation, the phase estimation is also done using the sample-data from neighboring nodes. By doing so, the phase difference of a frequency-component between two nodes can be calculated. The phase difference can be an indicator for the load flow of the respective transmission line.

III. Simulation Environment

The upcoming simulation demonstrates an application for assessing the transmission system state and/or health. This simulation is based upon the common *New England Test System* and incorporates the above mentioned signal processing nodes in a set of the test system's nodes.

A. New England Test System

The *IEEE 39-bus New England Test System* (short: *NETS*, [20], [21]) is a commonly used test system for power simulations introduced in 1979 for the analysis of faulted transmission systems. Its use grants basic comparability to other researches and is described well in various literature. Fig. 1 views a schematic view of *NETS*. It contains 39 buses (—), 10 generators (□) and 17 subnets/loads (○). Different voltage levels are separated by transformers indicated by the symbol ⊛. All items are interlinked with transmission lines (—).

The *NETS* is initialized for steady-state, fault-free, nominal service. After one second of nominal service, the transmission line from node 22 to 23 will be opened. Two seconds later, it will be closed again. For the here-presented simulation, nodes 16 and 21 are equipped with the above described signal processing block.

B. Simulation Parameters

The power system simulation is done with *DIgSILENT PowerFactory*® *4.1* using the simulation method for *instantaneous values* regarding electromagnetic transients. The three phase voltages for each bus equipped with a signal processing node as described above are exported. The sampling frequency

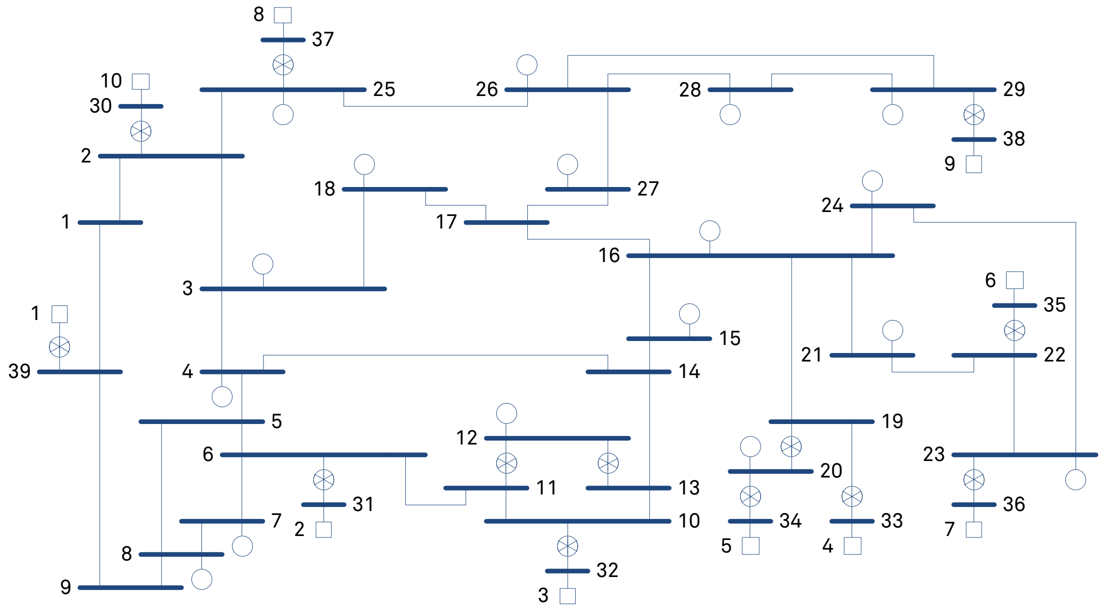

Figure 1: IEEE 39-bus New England Test System

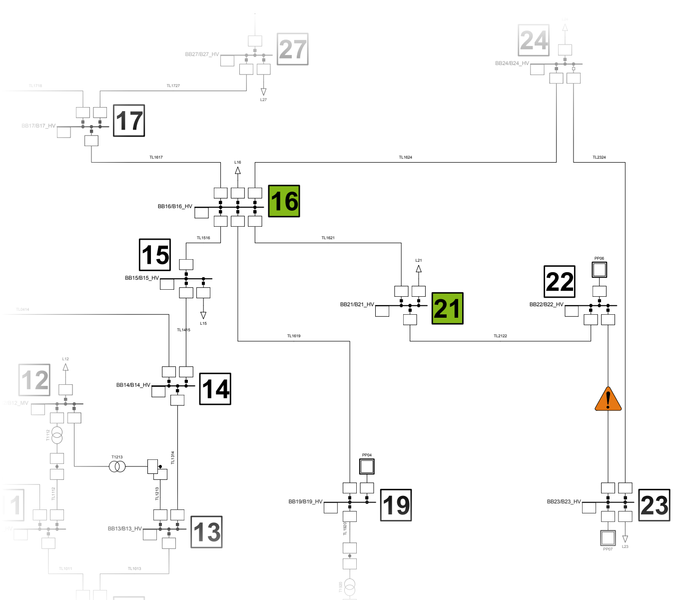

Figure 2: Cutout of the *New England Test System* (Fig. 1) as modeled in *PowerFactory*

is $f_s = 10\text{kHz}$. The signal processing is done with *The Mathworks MATLAB® R2011b* including *Simulink*. The sample window length is $w = 128$. The subspace tracker (OPAST) is parametrized with a forgetting-factor $\beta_{\text{PAST}} = 0.95$, which results in a pseudo-window-length of $T_\beta = w_\beta \cdot {}^1/_{f_s} = {}^1/_{1-\beta} = 20 \cdot {}^1/_{f_s} = 2\text{ms}$. ESPRIT is fed with $p + 4$ (rank plus auxiliaries) vectors. The thresholds of DaPT are $50 \;\hat{=}\; T_{\text{fd1}} = 5\text{ms}/100 \;\hat{=}\; T_{\text{fd2}} = 10\text{ms}$ for the frequency drift and $50 \;\hat{=}\; T_{\text{pd}} = 5\text{ms}$ for the phase difference drift. The forgetting factor for averaging the frequency drift is $\beta_{\text{fd}} = 0.95$ and for the phase difference drift $\beta_{\text{pd}} = 0.99$ ($w_\beta \cdot {}^1/_{f_s} = \frac{1}{1-\beta} \cdot {}^1/_{f_s} = 100 \cdot {}^1/_{f_s} = 10\text{ms}$).

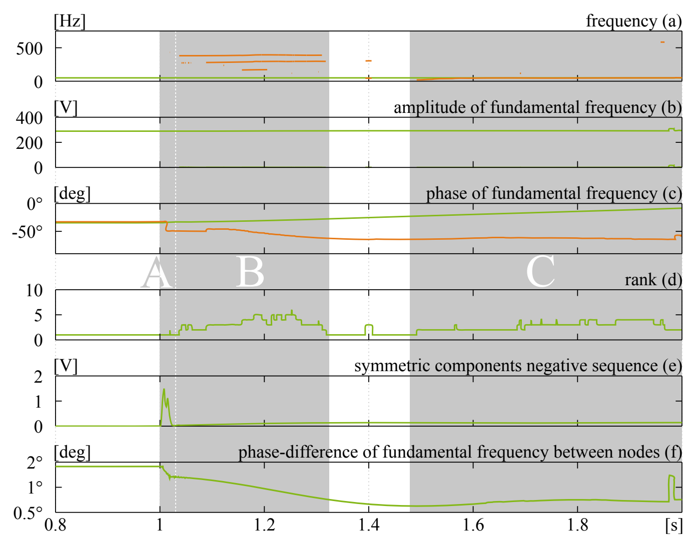

Figure 3: Graphs of simulation of node 16, transient components

C. Simulation Results

The primarily estimated parameter is the frequency. The expectation is that the fundamental frequency is present continuously, and that there are some additional components after each switching.

This estimation is visualized in Fig. 3a), especially in region B. The result supports the expectation. The uncertainty about the additional components in the transient sequence is an impact of the very low amplitudes of these components. As can be found in Fig. 3b), compared to the amplitude of the fundamental component, these amplitudes are hardly visible.

The rank estimation in Fig. 3d) is robust in consideration of the low amplitudes of the above mentioned additional frequencies.

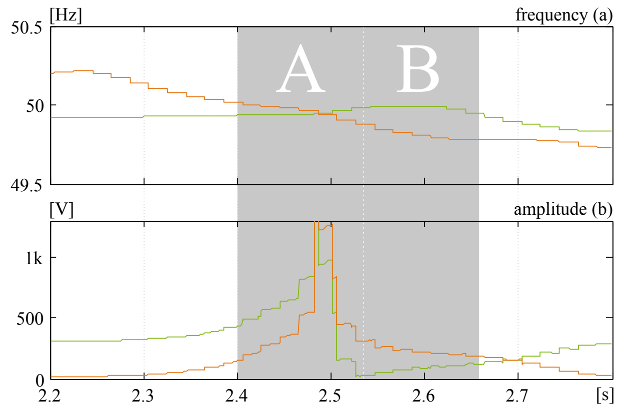

Figure 4: Graphs of simulation of node 16, additional component by power plant controller

Although the simulated three-phase-system is symmetric, the symmetrical components transformation helps identifying the points in time when the system change is applied. This is since not all three phases are switched at the very same moment but each a little phase-shifted ($6^2/3$ms), so that each phase is switched in the moment of crossing zero. In Fig. 3e), the negative sequence is presented. As expected, shortly after 1s (region A) significant non-zero values become noticeable. Examining the frequency estimation in Fig. 3a) again, the first additional components emerge at 1.02s. This is consistent taking into account that the PAST sampling window (128 samples), its forgetting-factor linked pseudo-window-length (20 samples) and DaPT's quality-threshold (100 samples) would justify a worst-case-delay of 248 samples (equal to 24.8ms).

Fig. 3c) showing two phase estimations exemplifies that after the first switching power is missing in that specific region of the net. A power deficit is indicated by a reduced system frequency. There are two perspectives of frequency and phase. When keeping the frequency constant, the phase has to be monotonically (in this case) increasing. Since the estimation is designed to keep the phase constant, a reduced frequency is expected. In the focused subfigure Fig. 3c), one estimation is done with the constant system frequency 50Hz (green/upper); the other is done with DaPT, which is intended to keep a constant phase (orange/lower).

The last subfigure, Fig. 3f), displays the phase difference of two neighboring nodes. As depicted, the difference changes during the transient time (region B) and approaches a different value (region C). This is another indication that the load situation (regarding the transmission line connecting both nodes) has changed.

The frequency plot in Fig. 3a) additionally shows a component from $t = 1.5$s on (region C) which was not expected. This indicates the net has not yet reached steady-state again. A possible explanation is supported by controllers of nearby power plants not yet adapted to the new load situation. This additional component is roughly valued 50Hz, which is close to the fundamental frequency.

This renders two problems (although the database correctly maps them to their entries) that will be pointed out with the help of Fig. 4. In Fig. 4a) both — additional (orange, *curvy*) and fundamental (green, constant) — components are visible. The first problem can be inspected in region A. Both frequency estimation graphs cross each other. Subsequent estimations like the here-applied phase-/amplitude-estimation by a least-squares approach obviously cannot deal with this situation, see Fig. 4b).

The second problem is buried inside the subspace tracking algorithm. Two very close components can be tracked, but they become biased during that period resulting in two estimations being more separate than they should. This due to the subspace basis of the signal. The vectors describing it have a small angle to each other. This similarity, which results in a high matrix condition, leads to inaccurate ESPRIT estimations.

IV. Conclusion

Transient processes that take place in consequence of a net switching event may contain information on the system's state. One kind of such information is the signal understood as superposed sinusoids. Considering the net as being a circuit of various overlapped oscillation meshes, a change in these meshes should induce oscillations at the resonance frequencies of each mesh.

Our estimation concept with adaptive rank (DaPT) is capable of estimating theses frequencies, even if their corresponding amplitude is very low. In future work, our research group is intending to present a theoretical net calculation that verifies the estimated frequencies to correspond to the resonance frequencies of the mentioned oscillation meshes. However, there are some systematic problems for components with very close frequencies.

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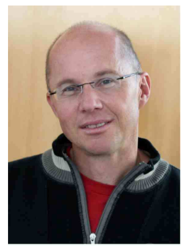
Matthias Lechtenberg (M’2010) was born in Coesfeld in Germany, on June 13, 1984. He studied Electrical Engineering at the TU Dortmund University. He received his Dipl.–Ing. in 2009.

Since 2010 he is a staff member of Information Processing Lab, TU Dortmund University, and studying for a PhD in Engineering. His special interests are parallel computing, signal processing and, more specific, parameter estimation.



Jürgen Götze (M’1987) received his Dipl.–Ing. and Dr.–Ing. degrees in Electrical Engineering from Munich University of Technology in 1987 and 1990, respectively.

From 1991 to 1992 he held a research position at the Computer Science Department of Yale University. From 1992 to 1995 he was with the Department of Electrical Engineering and Information Technology of Munich University of Technology. From 1995 to 1996 he was with the DSP group of the Electrical and Computer Engineering Department of Rice University. Since 1997 he is Professor (Information Processing Lab) at the Department of Electrical Engineering and Information Technology of TU Dortmund University.

He served as Associate Editor of *IEEE Transactions on Circuits and Systems, Part I: Fundamental Theory and Applications* from 1997 to 1999. His research interests include: signal and array processing, wireless communications, parallel algorithms and architectures, system-on-chip.

Kay Görner received his diploma degree in 2007 at Technische Universität Dortmund, Germany.

Since then he is a staff member of the Institute of Energy Systems and Power Economics at the Technische Universität Dortmund. His main research interests are investigation and development of power system applications for the integration of Wide Area Monitoring Systems as well as improvement of measurement-algorithms in Phasor Measurement Units.

Christian Rehtanz (SM’)received his diploma degree in Electrical Engineering in 1994 and his Ph.D. in 1997 at Technische Universität Dortmund, Germany.

From 2000 he was with ABB Corporate Research, Switzerland and from 2003 Head of Technology for the global ABB business area Power Systems. From 2005 he was Director of ABB Corporate Research in China.

From 2007 he is professor and head of chair for power systems and power economics at Technische Universität Dortmund. His research activities include technologies for network enhancement and congestion relief like stability assessment, wide-area monitoring, protection, and coordinated FACTS- and HVDC-control.