Estimation of Oscillation Parameters for Power Grids

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

A power system grid can be modeled as a circuit of various RLC-meshes. In case of a switching event, some of those RLC-meshes are excited. These will produce additional frequency components within the *power signal*. In this paper, a concept which uses a priori information of these meshes for event-characterization is presented. Frequency estimations done inside specific nodes of the power system are mapped to entries of a lookup-table. Depending on this map, events can be identified/localized. This concept is based on the database-assisted parameter estimation algorithm (DaPT). In consequence, the advantages of that system (low-amplitude detection, extensibility) will be preserved.

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

I. Introduction

Current power transmission systems are going to be modernized due to the change in the generation strategies from conventional, central coal or nuclear power-plants to more decentralized and off-shore generation. To reduce the needed investment for network upgrades, companies try to utilize their transmission components to the highest possible load. This requires fast and informative metering [1].

One central aspect of metering is the detection of switching and failure events. To achieve on-line capabilities for various nodes, human personnel is not suitable. Such metering must become automatized. Automation can be done based on different sensor data. The most common sensor data includes symmetric components, synchrophasors, phase differences and environmental properties like temperature and humidity. Another class of data is the spectrum of the voltage or current signal. Next to the fundamental system component (50Hz/60Hz, region-dependent), additional components might emerge. These might originate in slightly non-synchronous rotating masses of large machines or power-electronic controllers. Therefore, these additional components are close to the fundamental component. They also might originate in excited oscillation meshes formed by the capacitances and inductances within the transmission network.

We focus on these excited oscillation meshes. In previous work, we developed a system named *DaPT* (database assisted parameter estimation) which is designed to capture the parameters of such signal [2]. Its main advantage is the capability of also detecting and rating low-amplitude components which would be counted as noise by common rank estimators. This is done by a database concept collecting and rating subspace-based frequency estimations over time.

In [3], the database was described based on the characteristics of a parameter estimation algorithm for a special kind of signal (see below). The properties of the network surrounding the measurement node were not taken into consideration. In this work, a priori information of this network is integrated into the algorithm. The resonance frequencies of surrounding oscillation meshes up to a defined *horizon* shall be lodged in a node-specific lookup-table (LUT). The algorithm maps the subspace-based measurements to the entries of the LUT. The resulting map provides the basis of subsequent event characterization and classification (not part of this work).

The rest of the paper organizes as follows: In the upcoming section, the signal model for this concept is described. The third section summarizes our previous work and gives an insight to subspace-based parameter estimation before it depicts the presented concept of LUT-supported parameter estimation. An example is given in the fourth section. It is based on a simulation examined in [3] running a model of the *New England Test System*. Conceptional data is added to illustrate the concept. The final section concludes this work and gives a glance at possible future work.

II. Line Modeling and Signal Model

The transmission network 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 or fault. In case of such event, each participating mesh in a node provides its resonance frequency as a superposed sinusoid in the voltage/current signal of this node.

Our concept involves theses resonance frequencies to be collected in a node-specific LUT. Of course, a LUT cannot hold a representation of a large network. However, this is not necessary since distant meshes are damped such that they are barely visible to measurements in the current node. The meshes that can possibly be measured are defined by a so-called *horizon*. The horizon defines the complexity of the current LUT and is influenced by characteristics like noise level or the signal's kind (voltage/current). In Fig. 1, an exemplary horizon is marked for a selected measurement node.

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

$$x(n) = \sum_{i=1}^{p} a_i(n) e^{j(2\pi n f_i + \varphi_i)} + w_{\text{awgn}}(n) \quad (1)$$

$$= \sum_{i=1}^{p} c_i(n) e^{j2\pi n f_i} + w_{\text{awgn}}(n). \quad (2)$$

The number of sinusoids (*rank*) is p. The component $\{c_1, f_1\}$ represents the fundamental component (complex amplitude and frequency). The resonance frequency of an excited LC-oscillation mesh is embodied in $f_i|_{i>1}$. The components' fading is not modeled explicitly, but may be extracted from the time-varying character of the $c_i|_{i>1}$.

III. Algorithms

A. Review of Previous Work

1) Subspace Estimation: The samples from the measurement are prepared with a sliding window before being fed to the subspace estimator. The samples' space can be described as a set of vectors forming a basis. Performing an eigenvalue/eigenvector decomposition of the estimated auto-correlation matrix (exponentially weighted averaging) creates an orthogonal basis of the samples' space in the form of eigenvectors. Knowing the rank p, the signal's subspace can be extracted by selecting the vectors corresponding to the p greatest eigenvalues. Consequently, the other vectors describe the noise subspace. A cheap alternative to the mentioned eigenvalue decomposition are subspace trackers [4]. In fact, they do not produce eigenvectors — they provide vectors forming a basis describing the same space as an eigenvector-basis does. Next to algorithms like PROTEUS [5] or YAST [6] the class of PAST-based algorithms [7], [8] are common in such context. We identified the OPAST algorithm to be a good choice [9].

2) Parameter Estimation: The selected signal describing basis-vectors are fed to ESPRIT [10]. This subspace-based parameter estimator is based on the analysis of the rotational invariance of two temporal sequent basis-vectors. Due to this principle, these vectors should only differ in a constant rotation $e^{j \cdot 1 \cdot \Omega_i}$ ($\Omega_i = 2\pi f_i / f_s$) resulting from the *eigenfrequency*, which is the desired parameter (with f_s being the sampling frequency).

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

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

The matrix $\mathbf{A}$ contains the exponential functions $e^{j\omega_i n / f_s}$ to form the superposition in one dimension and the burst description in the other dimension. On the right side of 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 (in a diagonal matrix) $\mathbf{D}(n)$:

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

One time-step can mathematically be described by multiplying a diagonal matrix $\mathbf{\Phi}$ with diagonal entries $e^{2\pi j \cdot f_i / f_s}$:

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

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 [2].

3) Database-assisted Parameter Estimation — DaPT: Assuming ESPRIT to use a few more basis-vectors than the rank p, these additional vectors usually belong to the noise subspace and are named auxiliaries. In contrast to the vectors of the signal subspace, theses will not result in a constant rotational invariance (and thus constant frequency). The idea of DaPT is to rate the temporal presence of each frequency.

Entries with high rating can be expected to be part of the desired signal and entries with a low rating are assumed to be noise and to be forgotten. By this the algorithm recognizes a change in rank by 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 used by ESPRIT.

In every recursion, the incoming frequency estimation is mapped to the most suitable database entry. For entries that have been successfully mapped, the quality index is increased (up to a maximum value); for the 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 to the raw frequency estimation. Another is based on the phase difference of two subsequent estimations of the complex amplitude. The measures' values are exponentially weighted over time and their severity index is updated sign-depended.

The procedure is explained in more detail in [3]. For now, the focus is set on the database fields *frequency* and *quality index*.

B. LUT Concept

Instead of dynamically collecting the measured frequencies and interpreting them generally, a priori knowledge of the surrounding meshes of the measurement node can be provided. The resonance frequencies can be derived off-line and provided as database entries prior to measuring. During the

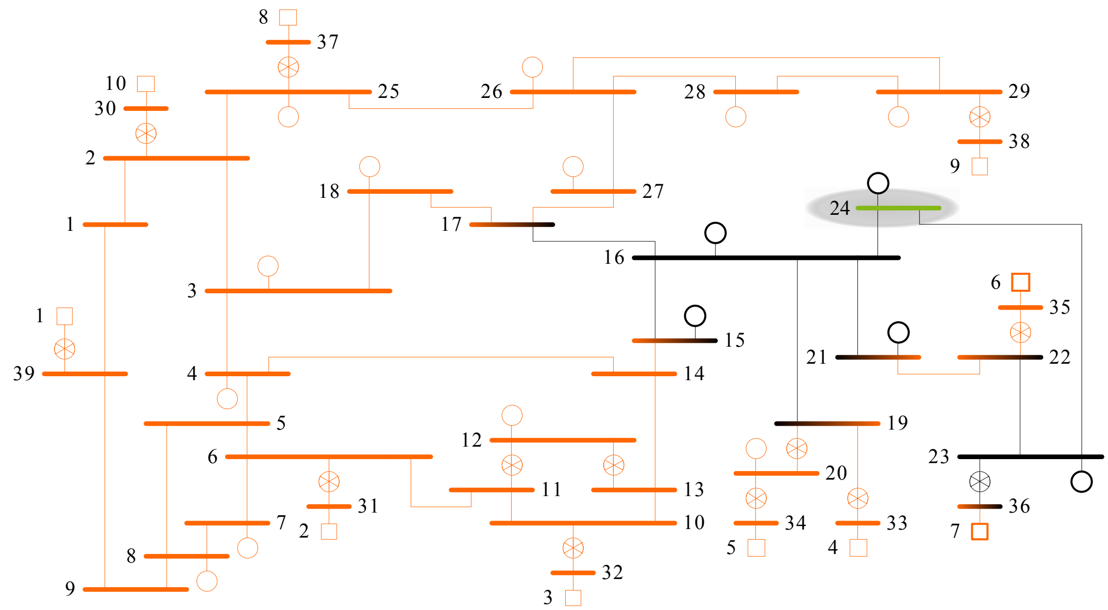

Figure 1: IEEE 39-bus New England Test System; here, node 24 is selected measurement node; exemplary horizon is marked black around selected node

on-line measurement process the estimated frequencies can be mapped to the most suitable and reasonable database entries.

In DaPT [3], entries for new-found frequencies are initiated and zero-quality entries are deleted. In contrast to that, zero-quality a priori entries are not deleted – they are *persistent*. Only components that cannot reasonably be mapped to *persistent* entries initiate new entries (which can be deleted). However, these entries have to be interpreted neglecting the oscillation-mesh-theory.

The quality indices of the a priori entries provide information on the excitation status of a resonance mesh. Additionally, further signal processing like e.g. phase and amplitude estimation via a least squares approach can be done. Based on this information, event detection can be executed. (This paper does not deal with the event detection.)

The generation of a priori knowledge can be done mathematically or numerically. Numerical solutions can be assisted by simulation tools like *DIgSILENT PowerFactory*® or *The Mathworks MATLAB*®. Mathematical solutions are based on solving exponential network equations. This is expensive and only suitable for small networks and for the verification of the numerical methods, respectively.

IV. Example Simulation

The concept of LUT-supported parameter-estimation-based event-detection is demonstrated by an example. In our previous work on DaPT [3], we presented a simulation on the basis of the *IEEE 39-bus "New England" Test System* (short: *NETS*, [11], [12]). We ran that simulation with a *DIgSILENT PowerFactory*® model of NETS. The model contained – inter alia – a switching event shortly after 1s. The signal processing regarding PAST, ESPRIT and DaPT was done with

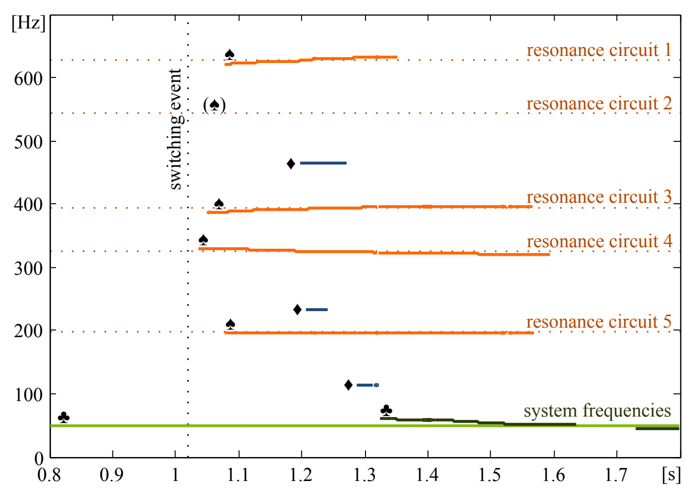

Figure 2: Frequency estimation from simulation of NETS with a line switching event shortly after 1s with an exemplary overlay of resonance frequencies; *green*, ♣: estimated system frequency (and power plant controller induced *out-of-sync* system frequency); *orange*, ♠: resonance frequencies and corresponding estimates; *blue*, ♦: other estimates

The Mathworks MATLAB® incl. *Simulink*. A more detailed description of the experiment can be found in [3].

Fig. 2 shows the frequency estimation done by DaPT for node 24 from the above mentioned simulation. The continuous lines show the estimates; the dotted lines are added afterwards to visualize the presented concept.

Throughout the complete displayed time range, the 50Hz fundamental system frequency can be found in light green (♣). An additional component near this 50Hz can be found

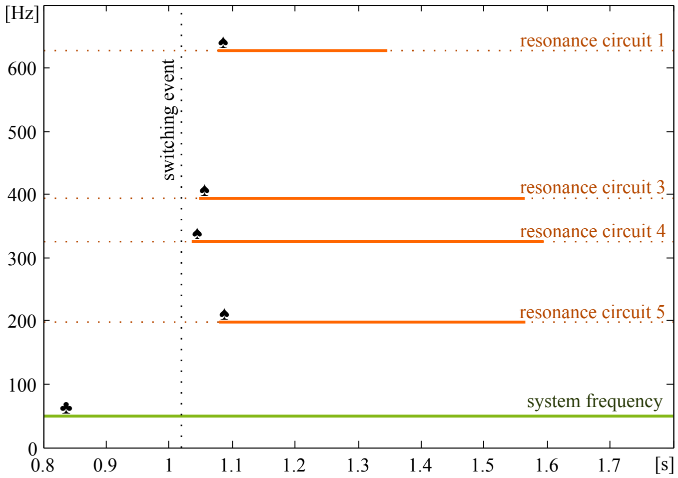

Figure 3: Tidied up version of Fig. 2; *green*, ♣: system frequency; *orange*, ♠: selected resonance frequencies

from 1.32s onwards. As already mentioned in our previous work, this component originates in a power plant controller. Those two close frequencies form a frequency beat which can clearly be seen in the waveform and looks like an amplitude modulation with low frequency. The second frequency is detected undesirably late after the switching event. There is a need for additional research to clear the ambiguity of beat and amplitude modulation for close frequencies.

The five dotted lines in dark orange (♠) visualize the resonance frequencies of the meshes within the horizon of the node. So, depending on the composition of estimates, a selection of these resonance frequencies provides information on the location of the switching event being responsible for the excitation of the oscillation meshes. In this example, meshes 3, 4, and 5 are detected for nearly 0.6s and mesh 1 is detected for about 0.3s. An additional amplitude estimation can support the event detection/localization by adding information about the initial amplitude and the damping of the components. Mesh 2 was not excited. Fig. 3 presents the time-dependent selection of resonance frequencies.

The short blue (♦) estimations are assumed not to belong to the a priori defined resonance frequencies. They could belong to oscillation meshes behind the horizon or they originate in another physical phenomenon. In consequence, these would create additional temporary database entries as described in [2], [3]. Those would have to be treated separately.

V. Conclusion

Assuming that a network of power transmission lines can be modeled as a circuit of inductances, capacitances, and resistances, it can be derived that a switching event – regardless, if it is intended or unintended – will excite different oscillation meshes. Knowing the line parameters of the network components around a designated measurement node up to a specific horizon, it should be possible to derive the corresponding resonance frequencies a priori. At this point of study, it is neglected that line parameters may not be constant when e.g. loads change.

Using these a priori frequencies in a database like in the DaPT algorithm makes the corresponding entries persistent. These are used to map estimated frequencies from a parameter estimation of the current or voltage signal. The resulting map can be used to identify the excited oscillation meshes. With this information, event detection and localization can be supported.

The presented concept extends our DaPT algorithm to use a priori information. The benefits of the original DaPT algorithm are preserved; this includes its capabilities to be extended for additional signal processing and its capability of detecting near-noise frequencies.

For further research, it is intended to focus on the calculation of resonance frequencies (for verification and as a priori information). It is also planned to do research regarding the interpretation of the parameter estimation in the context of event detection and classification.

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