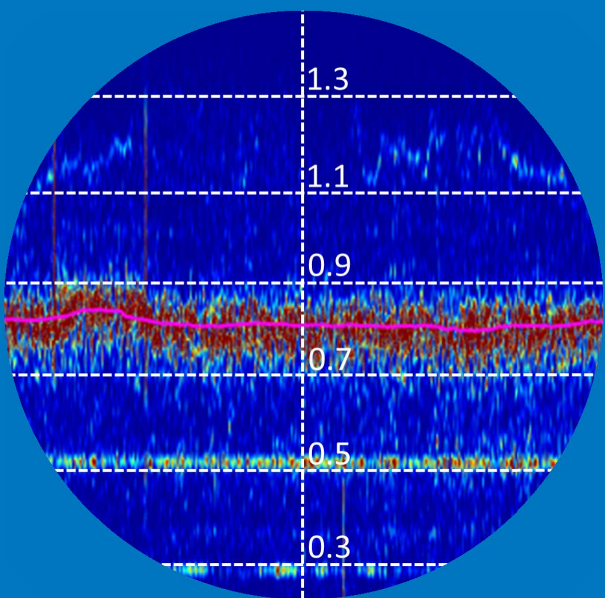
Department of Electrical Engineering and Automation

Methods for Monitoring Electromechanical Oscillations in Power Systems

Janne Seppänen



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Methods for Monitoring Electromechanical Oscillations in Power Systems

Janne Seppänen

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Abstract

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Abstract

Electromechanical oscillations are an inherent property of power systems and the damping of the oscillations is the limiting factor for the transmission capacity of certain transmission corridors. In the most severe situations, unstable oscillations may lead to blackouts. Thus, it is important to monitor the characteristics of the oscillations.

The oscillations can be monitored for example by using phasor measurement units (PMU). The development of wide area monitoring systems (WAMS) consisting of several PMUs has enabled the use of multiple synchronized measurement signals received from several locations in the power system to be used for the monitoring and analysis of the oscillatory modes.

This thesis presents four new multivariate methods (i.e., use several measurements from different locations of the grid) for the monitoring of the electromechanical modes. The methods are able to continuously identify electromechanical modes using ambient oscillations, which are mainly excited by load variations and are constantly present in power systems. The performance, characteristics and limitations of the methods are studied using simulated data as well as real measured data. This thesis also presents comparisons of different modal identification methods and illustrates additional analysis tools that can be used to support the modal identification in real power systems.

This thesis shows that the proposed methods are functional for monitoring of electromechanical modes. Due to certain limitations in modal identification methods, the thesis also highlights the need of using additional tools, such as spectral analyses, which may significantly help the interpretation of modal identification results. The methods presented in this thesis can be used as building blocks for transmission system operators (TSO) to create functional applications for real-time and offline modal analysis of power systems. Consequently, the information given by the methods may be used to improve the security and reliability of power systems.

Keywords Ambient oscillation, electromechanical oscillation, modal identification, PMU, power system dynamics, WAMS

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Tiivistelmä
Sähkömekaanista heilahtelua esiintyy sähkövoimajärjestelmissä jatkuvasti. Joissain voimajärjestelmissä sähkömekaanisen heilahtelun vaimennus rajoittaa verkon siirtokapasiteettia ja pahimmissa tapauksissa vaimenematon heilahtelu voi aiheuttaa laajoja sähkökatkoja. Mm. näistä syistä johtuen on tärkeää valvoa sähkömekaanista heilahtelua sähkönsiirtoverkoissa.

Heilahtelua voidaan valvoa hyödyntäen osoitinmittalaitteita (phasor measurement unit, PMU). Useista PMU:ista koostuvien laajan alueen valvontajärjestelmien (wide area monitoring systems, WAMS) kehittymisen myötä sähkömekaanisten heilahtelumoodien valvonnassa ja identifioinnissa voidaan hyödyntää useita synkronoituja mittauksia.

Tässä väitöskirjassa esitetään neljä uutta monimuuttujamenetelmää, jotka on tarkoitettu sähkömekaanisten heilahtelumoodien identifiointiin ja jatkuvaan valvontaan. Esitettävät menetelmät hyödyntävät WAMS-mittauksia useasta eri paikasta sähköverkossa ja käyttävät moodien identifiointiin verkossa esiintyvää jatkuvaa heilahtelua, jonka herätteenä toimivat mm. kuormien muutokset. Väitöskirjassa analysoidaan esitettyjen menetelmien toimintaa, ominaisuuksia ja rajoitteita sekä simuloidun että mitatun datan perusteella. Väitöskirjassa myös esitellään apumenetelmiä, joita voidaan käyttää hyödyksi moodien identifiointimenetelmien tulosten tulkinnassa ja visualisoimisessa.

Väitöskirjan tulokset osoittavat, että esitetyt moodien identifiointimenetelmät soveltuvat sähkömekaanisen heilahtelun valvontaan. Tulosten perusteella väitöskirjassa suositellaan lisäksi moodien identifiointitulosten tulkintaa helpottavien apumenetelmien, kuten spektrianalyysimenetelmien, hyödyntämistä sähkömekaanisen heilahtelun valvonnassa. Kantaverkkoyhtiöt voivat käyttää väitöskirjassa esitettyjä menetelmiä WAMS-järjestelmissään ja tätä kautta saada tarkempaa tietoa sähkömekaanisen heilahtelun esiintymisestä ja ominaisuuksista voimajärjestelmässä. Tarkempaa tietoa voidaan mm. käyttää voimajärjestelmän käyttövarmuuden analysoimisessa ja kehittämisessä.

Avainsanat Sähkömekaaninen heilahtelu, moodien identifiointi, PMU, sähkövoimajärjestelmän dynamiikka, WAMS

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Preface

I started my PhD work in the beginning of 2012 in the department of electrical engineering at Aalto University. In 2013, I started working for Fingrid, but continued my PhD work alongside my main work. The road to graduation has been long and not without challenges, but looking back, I feel privileged getting the opportunity to work with such an interesting research theme and highly competent people.

I am grateful to everyone I have worked with among the thesis work. Firstly, my instructor Dr. Liisa Haarla, who was also the supervisor of my work during the first years, deserves my warmest gratitude. I am also very grateful to my second instructor Dr. Jukka Turunen. This thesis would not exist without the guidance, ideas, and numerous interesting discussions with Liisa and Jukka. My gratitude goes as well to Prof. Matti Lehtonen, who has supervised and guided me in the end part of the thesis work.

During my PhD work, I had the pleasure of co-operating with Dr. Matti Koivisto, Prof. Siu-Kui Au, Dr. Francesco Sulla, Dr. Nand Kishor and many others. These collaborations turned out to be very productive and taught me that scientists coming from different backgrounds can produce fruitful results working in collaboration around a common research theme.

During my work at the university, my research was funded by the STRONgrid project. I am grateful to all the people who participated the steering group during the project, especially Antti-Juhani Nikkilä, Stig Lovlund, and Jan-Åge Walseth. They are kindly acknowledged for the industrial expertise and providing simulation models and measurement data for me to analyze.

Most importantly, I want to thank my family and especially my parents for the encouragement and support throughout my studies. Also, I would like to thank my friends for providing lots of joy in my life outside the research work. Thank you Sanna for all the love and support during the end part of my thesis work.

Tuusula, 31 December 2016
Janne Seppänen

Contents

List of Abbreviations

AR	Autoregressive (model)
BSS	Blind signal separation
CWT	Continuous Wavelet Transform
DOF	Degree of freedom
ERA	Eigensystem realization algorithm
FFT	Fast Fourier transform
MAR	Multivariate Autoregressive (model)
MPV	Most probable value
NExT	Natural excitation technique
NLLF	Negative log-likelihood function
PDC	Phasor data concentrator
PDF	Probability density function
PMU	Phasor measurement unit
PSD	Power spectral density
RD	Random decrement
SBC	Schwarz Bayesian criterion
SNR	Signal-to-noise ratio
SOBI	Second order blind identification

STFT	Short time Fourier transform
TSO	Transmission system operator
VAR	Vector Autoregressive (model)
WAMS	Wide area monitoring system

List of Symbols

In this doctoral dissertation, the symbols written in bold refer to matrix or vector variables. The symbols written in non-bold refer to scalar variables.

$\boldsymbol{A}$	Coefficient matrix of the MAR model, mixing matrix, state-space matrix
a	Scale in calculation of wavelet coefficients
$\boldsymbol{B}$	State-space matrix
B	Data length factor
b	Position in calculation of wavelet coefficients
$\boldsymbol{C}$	Covariance matrix, matrix of damping coefficients, state-space matrix
C	Wavelet coefficients
$\boldsymbol{D}$	Measured data, matrix of damping coefficients
D	Damping coefficient
D_{yy}	Random decrement auto signature (of signal y)
$\boldsymbol{e}$	Noise
$\boldsymbol{F}$	Vector of natural excitation to system
$\hat{F}_k$	Scaled FFT of measured data at FFT frequency f_k
f	Frequency
f_i	Natural frequency of the i-th mode
f_{k}	FFT frequency
$\boldsymbol{H}$	Hankel matrix
$\boldsymbol{H}_k$	Transfer matrix at FFT frequency f_k

h_{ik} Transfer function of the i-th mode at FFT frequency f_k

$\mathbf{I}$ Identity matrix

i, j Index

j Imaginary unit ($\mathrm{j}^2 = -1$)

$\boldsymbol{K}$ Matrix containing the synchronizing power coefficients

K Synchronizing power coefficient

L Negative log-likelihood function

$\boldsymbol{M}$ Matrix containing the inertia coefficients

M Inertia coefficient

m Number of modes within selected frequency band

N Number of measured time instants (total number of samples collected)

N_q Fast Fourier transform (FFT) frequency index at Nyquist frequency

N_f Number of FFT frequencies in the selected frequency band

n Number of measured degrees of freedom

$\boldsymbol{P}$ Left singular vector

P_{M} Turbine power

P_{E} Air gap power of a generator

p Order of the MAR model, number of columns in the Hankel matrix

p_i Modal excitation of the i-th mode

p_{ik} Scaled FFT of modal excitation at FFT frequency f_k

$\boldsymbol{Q}$ Right singular vector

$\boldsymbol{R_x}$ Covariance matrix of variable $\boldsymbol{x}$

R_{xy} Correlation function of variables x and y

r Number of rows in the Hankel matrix, impulse response of the system

$\boldsymbol{S}$ PSD matrix of modal excitations

$\boldsymbol{S}_e$ Power spectral density (PSD) of prediction error

$\boldsymbol{S}_{ij}$	Cross PSD between modal excitations of the i-th and j-th mode
$\boldsymbol{s}$	Source signals
s	Sample number
T_s	Sampling time
t	Time
$\boldsymbol{U}$	Unitary matrix
$\boldsymbol{W}$	Whitening matrix
$\boldsymbol{x}$	Vector of states, observations, vector of rotor angles of system
$\boldsymbol{y}$	Vector of outputs, vector of impulse responses, signal part of the observations
$\boldsymbol{y}_k$	Vector of measured data at time instant k
y	Ambient response (recorded data)
$\boldsymbol{z}$	Whitened process
α	Real part of the eigenvalue
Δt	Sampling time interval
δ	Rotor angle, posterior coefficient of variation of the damping ratio
$\boldsymbol{\varepsilon}$	Noise
ε_k	Scaled FFT of prediction error at FFT frequency f_k
ζ	Damping ratio
ζ_i	Damping ratio of the i-th mode
η_i	Modal response of the i-th mode
η_{ik}	Scaled FFT of $\eta_i(t)$ at FFT frequency f_k
$\boldsymbol{\theta}$	Set of modal parameters to be identified
κ	Bandwidth factor characterizing the usable bandwidth
λ	Eigenvalue
$\boldsymbol{\Pi}$	State matrix
$\boldsymbol{\Sigma}$	Matrix of singular values
$\boldsymbol{\sigma}$	Vector consisting of the variance of the noise

σ	Standard deviation of a signal, singular value
τ	Time lag, length of a sample
$\mathbf{\Phi}$	Partial mode shape matrix of the measured DOFs
φ_i	Partial mode shape of the i-th mode of the measured DOFs
Ψ	Wavelet function
$\boldsymbol{\psi}_i$	Mode shape vector of the i-th mode with all DOFs
$\boldsymbol{\omega}$	Vector of intercept terms
ω	Angular frequency
ω_i	Natural frequency of the i-th mode

List of Publications

This doctoral dissertation consists of a summary and of the following publications which are referred to in the text by their Roman numerals

I. J. Seppänen, L. Haarla, and J. Turunen, "Modal analysis of power systems with eigendecomposition of multivariate autoregressive models," *in proceedings of the 2013 IEEE PowerTech*, Grenoble, France, June 16-20, 2013.

II. J. Seppänen, J. Turunen, M. Koivisto, N. Kishor, and L. Haarla, "Modal analysis of power systems through natural excitation technique," *IEEE Transactions on Power Systems*, vol. 29, no. 4, pp. 1642-1652, July 2014.

III. J. Seppänen, J. Turunen, M. Koivisto, and L. Haarla, "Measurement based analysis of electromechanical modes with second order blind identification," *Electric Power Systems Research*, vol. 121, pp. 67-76, April 2015.

IV. J. Seppänen, S. K. Au, J. Turunen, and L. Haarla, "Bayesian approach in the modal analysis of electromechanical oscillations," *IEEE Transactions on Power Systems,* vol. 32, no. 1, pp. 316-325, Jan. 2017.

V. J. Seppänen, A. Tuononen, A. J. Nikkilä, J. Turunen, and L. Haarla, "Experiences in using damping estimation methods in real-time oscillation monitoring," *in proceedings of the 2015 IEEE PowerTech*, Eindhoven, Netherlands, June 29 - July 2, 2015.

VI. J. Turunen, **J. Seppänen**, A. J. Nikkilä, and L. Haarla, "Using spectral analysis and modal estimation for identifying electromechanical oscillations: A case study of the power system in northern Norway and northern Finland," *in proceedings of the IEEE International Conference on Power Engineering, Energy and Electrical Drives (POWERENG)*, Riga, Latvia, May 11-13, 2015.

Author's Contribution

Publication I: Modal analysis of power systems with eigendecomposition of multivariate autoregressive models

The author adapted and implemented the multivariate autoregressive model based analysis for identification of electromechanical modes from ambient power system data. The author performed all the analyses and wrote the manuscript.

Publication II: Modal analysis of power systems through natural excitation technique

The author formulated the equations of the natural excitation technique and implemented the method for identification of electromechanical modes from ambient power system data. The author performed all the analyses and wrote the manuscript.

Publication III: Measurement based analysis of electromechanical modes with second order blind identification

The author adapted and implemented the second order blind identification method for identification of electromechanical modes from ambient power system data. The author performed all the analyses and wrote the manuscript.

Publication IV: Bayesian approach in the modal analysis of electromechanical oscillations

The author instructed and participated the analyses, which were mainly carried out by Prof. Siu-Kui Au (second author). The author wrote a significant part of the manuscript including interpretation of the results, discussion and conclusions.

Publication V: Experiences in using damping estimation methods in real-time oscillation monitoring

The author performed the modal analyses for the measured data using the multivariate autoregressive model and the spectral analyses. The author was the main writer of the manuscript.

Publication VI: Using spectral analysis and modal estimation for identifying electromechanical oscillations: A case study of the power system in northern Norway and northern Finland

The author performed the damping and frequency identification part of the analyses, apart from the analyses with the wavelet method. In addition, the author wrote significant parts of the manuscript including the modal identification parts of the results and discussion.

1. Introduction

1.1 Background and Motivation

Electromechanical oscillations have been observed in electrical transmission systems as long as interconnected systems with several synchronous generators have existed [1]. The oscillations are an inherent property of power systems and they cannot be completely eliminated [2]. The oscillations are observable in several different measurable quantities, such as the generator speeds, power flows in the grid, voltage magnitudes and angles.

In some transmission systems (e.g., the Nordic power system) the damping of the oscillations is the limiting factor for the transmission capacity of certain transmission corridors, and thus, the thermal capacity of the lines cannot be fully utilized. Moreover, in the most severe situations, unstable oscillations may lead to local blackouts or even to the collapse of the entire system [3].

Electromechanical oscillations can be classified according to their interaction characteristics to inter-area mode oscillations, local plant mode oscillations, intraplant mode oscillations, torsional (subsynchronous) mode oscillations, and control mode oscillations [2]. Inter-area mode oscillations are typically most critical in terms of security of the entire system. Furthermore, the oscillations can be classified with respect to the operating condition of the power system to ambient (spontaneous) oscillations, transient oscillations, and forced oscillations [2].

Ambient oscillations are constantly present in power systems and they are excited mainly by loads, which are randomly varying by nature. Transient oscillations are caused for example by faults or certain switching events in the system. [2] Forced oscillations are typically associated with inadequate tuning of control systems [4]. Ambient oscillations, transient oscillations, and forced oscillations may also be present in power systems simultaneously, as illustrated for example in Publications V and VI of this thesis. Figure 1 shows example measurements of different types of electromechanical oscillations.

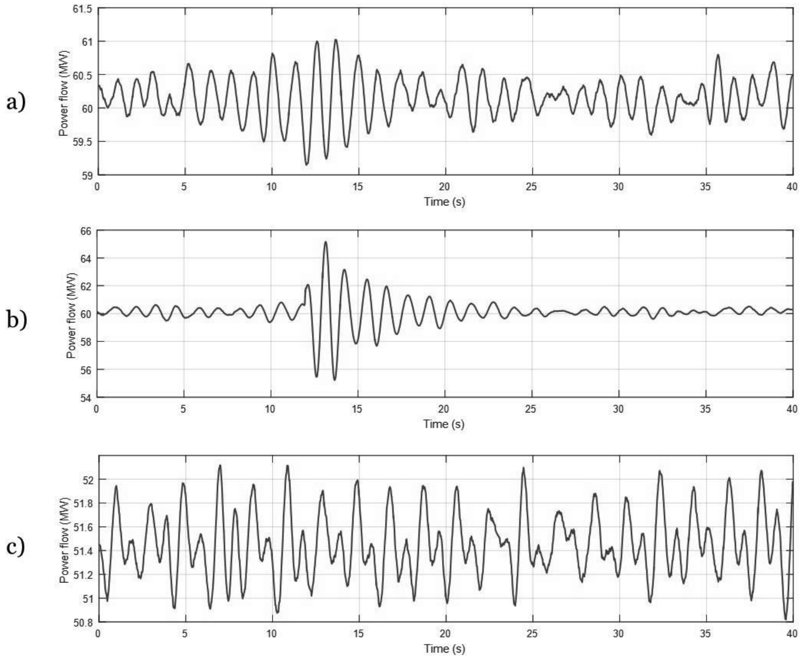

Figure 1. Example oscillation measurements: a) ambient oscillations, b) transient oscillation (between 12 – 22 s), and c) forced oscillations. The measurements are collected from the northern parts of the Nordic power system (i.e., Vajukoski and Ivalo substations, see Figure 15 for more details on the measurement locations).

A traditional way to analyze the oscillatory stability of power systems is to conduct an extensive set of simulation studies. However, the simulations can be performed only for a limited set of operational situations of the system. Furthermore, many issues may cause differences between the simulation models and real dynamic behavior of the power system. Due to differences in the simulated and real dynamic behavior of the system, transmission system operators (TSO) usually maintain a specific margin between the allowed power transfer capacity and the simulated maximum capacity.

Different types of oscillations may be sometimes observed in power systems even though the simulation models do not indicate their existence [5]. If these oscillations are poorly damped, they may threaten the security of the system. In addition, interaction or resonance effects between different modes [6] may cause large oscillations to the system, which might not be shown by the simulation models. Consequently, measurement based approaches in the monitoring of the oscillatory modes can improve the operational security and enhance the situational awareness of power system operators. Furthermore, such approaches may yield important information for specialists to conduct different types of offline analyses, such as model validation, root cause analysis of certain events and identifying erroneously operating components.

Due to reasons discussed above, it is important to monitor (in real-time) the oscillatory stability of power systems. The oscillatory stability can be monitored for example by using measurements from phasor measurement units (PMU).

The development of wide area monitoring systems (WAMS) consisting of several PMUs has enabled the use of multiple synchronized measurement signals received from several locations in the power system to be used for the monitoring and analysis of the oscillatory modes. To illustrate the use of WAMS systems, an example structure of such system is shown in Figure 2.

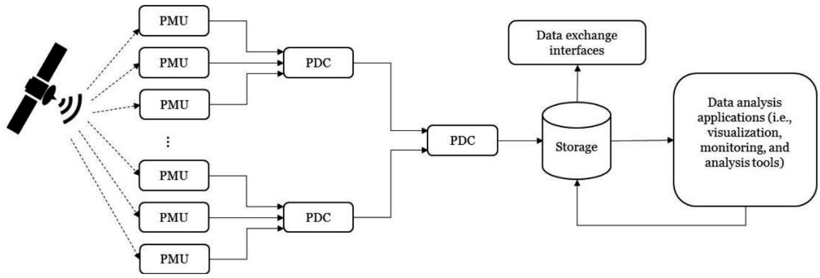

Figure 2. Example structure of a WAMS system (PDC refers to Phasor Data Concentrator).

Electromechanical oscillatory modes can be monitored by using modal identification methods and measurements collected from WAMS systems. In continuous monitoring of the modes, it is practical to use measurements from ambient power system conditions since ambient oscillations are constantly present in the system. Ambient modal analysis methods are often called *mode-meters* [7]. Another approach is to identify the modal characteristics from transients by using *ringdown* [7] methods, such as those discussed in [8]–[13]. However, using transients is not often practical in continuous monitoring of the modes since transients are rather seldom present in power system measurements.

In the past, several methods have been proposed for identifying the modes from ambient measurements [14]–[41]. These methods can be classified into different categories in several ways, such as: parametric vs. non-parametric methods, univariate vs. multivariate methods, and methods that are based on fitting a specific model to the measurements vs. methods that use signal processing instead of models. Figure 3 presents an example flow chart of a general ambient modal analysis method.

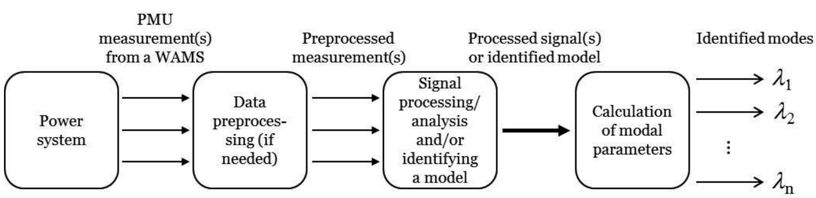

Figure 3. Example flow chart of modal estimation from ambient data.

Most of the ambient identification methods presented in the literature, such as [14]–[23], [30]–[40] are parametric – i.e. they require a set of parameters to be defined for the identification of the modes. There exist also certain non-parametric methods, which do not require the selection of parameters and work directly on the data [7], [24], [28]. However, the damping estimation capability of the non-parametric methods is often limited or does not exist [7], [28].

Certain methods, such as [2], [14]–[19], [29], [32], [35], [37]–[40] use only a single measurement (i.e., univariate) collected from the system to identify the modal parameters. However, using a single measurement signal does not always lead to the best observability of the oscillatory modes [20]. In addition, univariate methods running in parallel based on different measurements may yield different results due to varying modal observability in separate measurements, and thus, interpreting the results may be difficult [20]. Using several measurements and multivariate methods may improve the observability of the oscillations, and consequently, the accuracy of the modal identification.

Several methods, such as [14]–[21], [29], [30], [31], [35], [36], [38]–[40], are based on fitting a certain model to the measurements to represent the dynamics of the studied power system. Usually, a linear model is assumed since the power system is considered linear in the vicinity of the operating point (i.e., in ambient operation). The modal parameters of interest can be calculated from the identified linear model. On the other hand, certain methods [2], [22], [32] rely entirely to signal processing techniques instead of a model.

Even though several methods for identifying the modal characteristics from ambient measurements exist in the literature, there is still much room for development of the methods. Developing new methods may, for example, improve the accuracy and reliability of the modal identification. Furthermore, new methods may often have highly different characteristics compared with the existing methods, and thus, they may be better suited for modal identification in certain power systems or operating conditions.

Since several methods with very different characteristics are available for modal identification, it may be difficult for a TSO to select the most suitable method for its purposes. Thus, it is important for a TSO to obtain experiences regarding the application, performance and limitations of the methods. Based on extensive testing of different methods, TSOs can select the most appropriate methods for their applications.

This thesis presents four new multivariate methods for the monitoring of modes from ambient measurements. The theoretical background of the methods is presented, the application of the methods to ambient power system data is illustrated, and the different characteristics of the methods are described. The performance of the methods is also analyzed using both simulated and real data sets.

Furthermore, the thesis presents experiences of using ambient modal analysis methods for the monitoring of real modes. The thesis also illustrates supporting analysis tools that can be used to support the modal identification in real power systems. TSOs may utilize the results of this thesis when designing and configuring tools for the real-time monitoring and offline analyses of electromechanical modes.

1.2 Scope and Objectives

This thesis focuses on continuous monitoring and identification of electromechanical modes from ambient measurements, where mainly normal load variations excite the oscillations. Detecting the modes from transients with ringdown methods, nonlinear analysis methods, use of simulation model based approaches or external probing signals are not considered. The main focus is on identifying the frequencies and damping ratios of the electromechanical modes since these quantities give an insight on the oscillatory stability, and thus, the security of the system.

The main objective of this thesis is to develop novel multivariate methods for the monitoring of electromechanical modes and show that they are functional for identifying the modes from ambient measurements. The thesis aims to investigate the performance of the new methods extensively using both simulated data as well as real measured PMU data and illustrate the different characteristics of the methods.

Another objective is to present experiences in using ambient modal identification methods for the monitoring of real modes. Furthermore, the goal is to show how supporting analysis tools (i.e., spectral analyses) can be used in the interpretation and visualization of the identification results given by different modal identification methods.

1.3 Contribution of the Thesis

The main contribution of this thesis is to propose four new multivariate ambient modal identification methods for the monitoring of electromechanical modes. These methods are:

- **Multivariate autoregressive model (MAR) method (Publications I, V and VI)**. The MAR method is a multivariate method, which is based on fitting a MAR model to the ambient measurements collected from the studied power system. The modal parameters (i.e., frequency and damping ratio of the modes) are calculated from the eigenvalues of the estimated MAR model. In addition, the confidence intervals for the modal parameters can be calculated by the method, thus providing information on the accuracy of the estimates.
- **Natural Excitation Technique – Eigensystem Realization Algorithm (NExT-ERA) method (Publications II, V and VI)**. The NExT technique estimates the impulse responses of the studied power system from ambient PMU measurements. The ERA is used to identify a state-space model of the power system using the impulse responses estimated with the NExT. The modal parameters are calculated from the eigenvalues of the identified state-space model. The NExT-ERA method is also able to utilize unsynchronized (i.e., relay recorder) measurements with certain limitations.
- **Second Order Blind Identification (SOBI) based method (Publication III)**. The SOBI algorithm is used to extract the modal responses from ambient PMU measurements. After extracting the

modal responses, the Random Decrement (RD) technique is used to calculate the single mode impulse response for each extracted mode. The state-space representation concerning each mode separately is then obtained using the ERA and the modal parameters are calculated from the eigenvalues of the identified state-space model.

- **Bayesian approach (Publication IV)**. In the Bayesian approach, the identification information about the parameters are expressed using the Bayes Theorem in terms of a probability distribution conditional on the data and modeling assumptions. The Bayesian approach to system identification recognizes the fact that it is philosophically impossible to identify exactly the values of the modal parameters, because of limited amount of available data, measurement noise, modeling error, etc. Thus, the Bayesian approach identifies the most probable values for the modal parameters, and also, yields information regarding the uncertainty of the parameters.

In addition to the presentation of the new methods, the contribution of this thesis includes:

- Presentation of **experiences and comparisons of using different modal identification methods** for the monitoring of real power systems (Publications V and VI).
- Presentation of experiences in using **additional analysis tools** (spectral analysis) that can be utilized in the visualization and interpretation of the modal identification results (Publication VI).

1.4 Dissertation Structure

This thesis is structured as follows. Chapter 2 provides a detailed description of the MAR, NExT-ERA, SOBI and Bayesian approaches, in the respective order. Chapter 3 presents results to validate and analyze the performance of the methods. Chapter 4 presents experiences in using modal analysis methods for the monitoring and analysis of real power systems and illustrates the use of supporting analysis tools in the interpretation of the modal identification results. Chapter 5 summarizes the publications included in this thesis, discusses the main findings and reflects recommendations for future research work.

2. Modal Analysis Methods for Ambient Data

This chapter presents four new measurement based ambient modal analysis methods for the analysis of electromechanical modes: MAR, NExT-ERA, SOBI and Bayesian methods. The theoretical background of the methods is presented and their application to ambient power system data is illustrated. In addition, characteristics and parameter selection of the methods are discussed.

2.1 Multivariate Autoregressive Model (MAR)

2.1.1 Introduction

The MAR model (also called VAR, Vector Autoregressive model) is a time series model that has been widely used in various applications in several different fields of research [42]. Previously, it has been used for ambient modal analysis of oscillating structures in the field of civil engineering [43]. This thesis and Publications II, V-VI show that the MAR model is also applicable for modal analysis of electromechanical oscillations, and thus, suitable for wide area monitoring of power systems.

The MAR model utilizes data, which are synchronously measured from several locations in the power system through a WAMS. The MAR model can be fitted to the collected ambient measurement data and the modal characteristics of the studied system can be calculated from the parameters of the model.

Previously used univariate AR models [14]–[19] utilize only a single measurement signal to model the entire system, whereas a MAR model contains not only a model of each signal but also a model of the relationships between the signals. Even though univariate AR models can be used to deal with multivariate measurement data [21], the relationships between the signals (and consequently, information regarding the process) are still left unmodeled.

MAR model of any order can be decomposed into eigenvalues with characteristic oscillation frequencies and damping ratios [44]. In a power system, these eigenvalues correspond to the electromechanical modes, and therefore, the modal parameters (frequency and damping ratio) can be calculated from the eigendecomposition of the MAR model. Uncertainty information (i.e., confidence intervals) can be also calculated from the estimated parameters of the MAR model. Confidence intervals give an insight on the achieved estimation accuracy of the modal parameters and they can be utilized for example in interpretation of the received modal identification results.

2.1.2 Theoretical Background

Consecutive measurements of a time series contain information regarding the process that generated them. An autoregressive model identifies this underlying process by modeling the current value of the series as a weighted linear sum of its previous values. In a MAR model, the current values of all variables in a multivariate time series are modeled as a linear sum of their previous values. Furthermore, the relationships between the individual time series are included in the model.

A MAR model of order p for an m-variate stationary time series $\boldsymbol{y}_k$, observed at equally spaced instants k, can be defined by

$$\boldsymbol{y}_k = \boldsymbol{\omega} + \sum_{l=1}^{p} \boldsymbol{A}_l \boldsymbol{y}_{k-l} + \boldsymbol{\varepsilon}_k \qquad \boldsymbol{\varepsilon}_k = \text{noise}(\boldsymbol{C}) \tag{1}$$

where the matrices $\boldsymbol{A}_1, \dots, \boldsymbol{A}_p$ are $m \times m$ dimensional coefficient matrices of the MAR model. The parameter vector $\boldsymbol{\omega}$ is a $m \times 1$ dimensional vector of intercept terms that may be included to consider a nonzero mean of the time series. The $m \times 1$ dimensional vectors $\boldsymbol{\varepsilon}_k$ representing white noise are random vectors with mean zero and $m \times m$ dimensional covariance matrix $\boldsymbol{C}$.

The unknown model parameters $\boldsymbol{A}_1, \dots, \boldsymbol{A}_p$, $\boldsymbol{\omega}$ and $\boldsymbol{C}$ can be estimated using several different algorithms [42], [44]–[48]. In Publications I, V and VI of this thesis, the least squares algorithm [44], [47] is used. However, other algorithms such as the Yule-Walker algorithm [46] can be also used in the estimation of the electromechanical modes, as presented in [48].

When the coefficient matrices $\boldsymbol{A}_1, \dots, \boldsymbol{A}_p$ of the MAR model of order p have been estimated, the modal parameters can be calculated as follows. Firstly, the coefficient matrices are positioned into the following state matrix:

$$\boldsymbol{\Pi} = \begin{bmatrix} \boldsymbol{A}_1 & \boldsymbol{A}_2 & \cdots & \boldsymbol{A}_{p-1} & \boldsymbol{A}_p \\ \boldsymbol{I} & \boldsymbol{0} & \cdots & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} & \cdots & \boldsymbol{0} & \boldsymbol{0} \\ \cdots & \cdots & \ddots & \cdots & \cdots \\ \boldsymbol{0} & \boldsymbol{0} & \cdots & \boldsymbol{I} & \boldsymbol{0} \end{bmatrix} \tag{2}$$

Secondly, the eigendecomposition of the state matrix is calculated:

$$\boldsymbol{\Pi} = \boldsymbol{L} \begin{bmatrix} u_1 & 0 & 0 & 0 \\ 0 & u_2 & 0 & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & u_{mp} \end{bmatrix} \boldsymbol{L}^{-1} \tag{3}$$

Thirdly, the poles of the system $\lambda_1 \dots \lambda_{mp}$ representing the oscillatory modes can be calculated by:

$$\lambda_i = \frac{\ln(u_i)}{T_s}, \quad (4)$$

where T_s is the sampling time of the observed signals. The angular frequency ω_i and damping ratio ζ_i of the oscillatory mode i can be calculated as follows:

$$\lambda_i = \alpha_i + \mathrm{j}\omega_i \quad (5)$$

$$\zeta_i = \frac{-\alpha_i}{\sqrt{\alpha_i^2 + \omega_i^2}} \quad (6)$$

In addition, the confidence intervals for the estimated modal parameters can be calculated by utilizing the approach presented in [44].

2.1.3 Application to Power System Data and Selection of Method Parameters

Figure 4 presents the flow chart of the MAR method when applied to data collected from a power system. The MAR method requires selection of certain parameters, which are also shown in Figure 4. The selection of the parameters is discussed below.

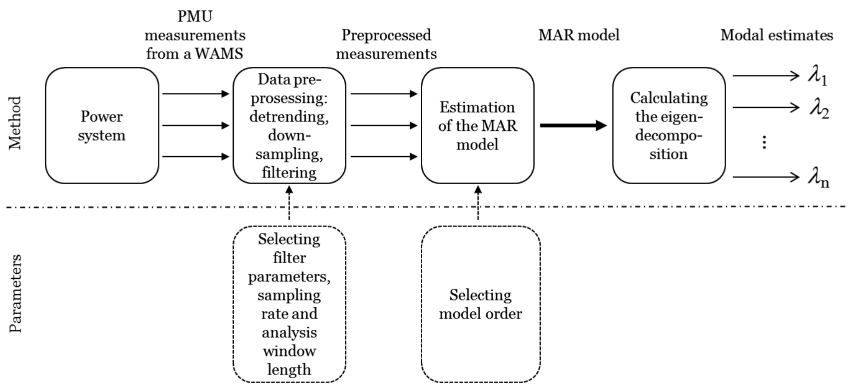

Figure 4. Flow chart of the MAR model when applied to power system data.

Data Preprocessing

Prior to analyzing real PMU data, the measurement data have to be usually preprocessed (however, data preprocessing is often not required for analysis of simulated data). The mean values or slow trends of the measurement signals should be removed and data downsampling may be needed, depending on the sampling rate of the original data. In addition, the signals have to be filtered.

In Publications I, V and VI the data have been downsampled to 10 Hz sampling frequency (if the original sampling frequency of the data has been higher). The required sampling frequency depends on the frequency of the studied mode, but often 10 Hz is sufficient, and there are no benefits in using higher sampling frequencies in the analyses.

In Publications I, V, VI and in this thesis, low order high-pass or low order band-pass filters have been used for the data preprocessing. The goal is not to distort the original data significantly with filtering. The cut-off frequencies of the filters should be selected such that they remove the low frequency components situated outside the range of interest, and if band-pass filters are used, the high frequency noise can be removed as well.

Selecting the Model Order

The selection of the model order, has a clear effect on the modal estimates, as shown for example in [48]. In Publications V and VI, a fixed model order was used. There are also different algorithms [43], [44] for selecting the model order automatically. In Publication I, the Schwarz Bayesian criterion (SBC) was used in conjunction with a rather low upper limit for the model order. However, based on practical experience, a fixed order (i.e., in the range of 20–24 for data with 10 Hz sampling frequency) is often suitable for modal identification with MAR. In future research, automated algorithms for model order selection should be further investigated.

2.2 Natural Excitation Technique – Eigensystem Realization Algorithm (NExT-ERA)

2.2.1 Introduction

The NExT-ERA method has been widely utilized for the modal analysis of oscillating structures, such as buildings and bridges [49]–[53]. However, prior to this thesis and Publications II and VI, the method has not been applied for the modal analysis of power systems. Publications II, VI and this thesis show that the method is functional for analyzing the electromechanical modes in power systems and formulate the equations in the NExT technique to deal with analyses of electromechanical modes.

The NExT-ERA is a multivariate method utilizing data that are measured from several locations in the power grid. The method is capable of utilizing synchronously measured data from a WAMS as well as unsynchronized measurements, such as measurements of individual relays' recorders. Using unsynchronized measurements can further improve the observability of the oscillations and improve the estimation accuracy in certain cases. According to the author's knowledge, other existing ambient modal analysis methods have not been shown to be capable of simultaneously utilizing both synchronized and unsynchronized measurements for the analysis of electromechanical modes.

In the NExT technique, cross-correlation functions calculated using measurements collected from the studied system are utilized to estimate the impulse responses of the system. Based on the estimated impulse responses, the ERA estimates a linear state-space model to determine the system dynamics. The modal parameters (frequency and damping ratio) can be calculated from the eigenvalues of the estimated state-space model.

2.2.2 Theoretical Background

NExT

The starting point in deriving the equations for the NExT technique is the well-known swing equation describing the oscillatory motion of the rotor of a single generator:

$$M\frac{\mathrm{d}^2\delta}{\mathrm{d}t^2} = P_\mathrm{M} - P_\mathrm{E} - D\frac{\mathrm{d}\delta}{\mathrm{d}t} \tag{7}$$

where M denotes the inertia coefficient, P_M the turbine power, P_E the air gap power of the generator, D the damping coefficient, and δ the rotor angle. Modeling the generator using a classical generator model with a constant flux linkage, and linearizing (7) in the vicinity of the operation point, yields

$$M\frac{\mathrm{d}^2\Delta\delta}{\mathrm{d}t^2} + D\frac{\mathrm{d}\Delta\delta}{\mathrm{d}t} + K\Delta\delta = 0 \tag{8}$$

where K is the synchronizing power coefficient and $\Delta\delta$ denotes the rotor angle deviation around the equilibribrium point. [54]

Let all the generators in the electrical power system be modeled with classical generator models. Consequently, M, D, and K in (8) transform into diagonal matrices, containing the inertia coefficients, damping coefficients, and the synchronizing power coefficients of each generator, respectively. Furthermore, in actual power systems, each generator is constantly exposed to a random accelerating power – the natural excitation of the system. The main causes of the natural excitation are the loads, which are randomly varying by nature. In addition, minor transients such as minor changes in production, minor switching events, or minor faults can be considered as the natural excitation of the system [2]. By taking the natural excitation into consideration, (8) can be extended to describe the oscillatory behavior of each generator in the power system:

$$\boldsymbol{M}\Delta\ddot{\boldsymbol{\delta}}(t) + \boldsymbol{D}\Delta\dot{\boldsymbol{\delta}}(t) + \boldsymbol{K}\Delta\boldsymbol{\delta}(t) = \boldsymbol{F}(t)\ , \tag{9}$$

where $\Delta\boldsymbol{\delta}(t)$ is the angle displacement vector, $\boldsymbol{F}(t)$ the excitation vector, and $\dot{(\cdot)}$ indicates the derivative with respect to time. Post-multiplying (9) by a reference angle displacement, $\Delta\delta_\mathrm{r}(s)$, and taking the expected value of each side yields

$$\begin{aligned}&\boldsymbol{M}E\left[\Delta\ddot{\boldsymbol{\delta}}(t)\Delta\delta_\mathrm{r}(s)\right] + \boldsymbol{D}E\left[\Delta\dot{\boldsymbol{\delta}}(t)\Delta\delta_\mathrm{r}(s)\right] + \boldsymbol{K}E[\Delta\boldsymbol{\delta}(t)\Delta\delta_\mathrm{r}(s)]\\ &= E[\boldsymbol{F}(t)\Delta\delta_\mathrm{r}(s)]\end{aligned} \tag{10}$$

where $E[\cdot]$ denotes the expected value. Equation (10) can be written

$$\boldsymbol{M}\boldsymbol{R}_{\Delta\ddot{\boldsymbol{\delta}}\Delta\delta_\mathrm{r}}(t,s) + \boldsymbol{D}\boldsymbol{R}_{\Delta\dot{\boldsymbol{\delta}}\Delta\delta_\mathrm{r}}(t,s) + \boldsymbol{K}\boldsymbol{R}_{\Delta\boldsymbol{\delta}\Delta\delta_\mathrm{r}}(t,s) = \boldsymbol{R}_{\boldsymbol{F}\Delta\delta_\mathrm{r}}(t,s)\ , \tag{11}$$

where $\boldsymbol{R}(\cdot)$ denotes a vector of correlation functions.

Assuming that $A(t)$ and $B(s)$ are stationary processes, the following yields:

$$R_{A^{(m)}B}(\tau) = R_{AB}^{(m)}(\tau)\ , \tag{12}$$

where $\tau = t - s$ and $A^{(m)}$denotes the mth derivative of the random process $A(t)$ with respect to time and $R_{AB}^{(m)}$ denotes the mth derivative of the correlation function $R_{AB}(\tau)$ with respect to τ. [49], [55]

The reference angle displacement $\Delta\delta_{\mathrm{r}}(s)$ is uncorrelated to the natural excitation of the system $\boldsymbol{F}(t)$ for $\tau > 0$ if the excitation is assumed to be a white noise process (i.e., the past values of $\Delta\delta_{\mathrm{r}}(s)$ do not correlate with the future values of $\boldsymbol{F}(t)$). Thus, $\boldsymbol{R}_{\boldsymbol{F}\Delta\delta_{\mathrm{r}}}(t,s) = 0$ yields for $\tau > 0$. In addition, assuming that the rotor angle displacements $\Delta\ddot{\boldsymbol{\delta}}(t)$, $\Delta\dot{\boldsymbol{\delta}}(t)$, $\Delta\boldsymbol{\delta}(t)$, and $\Delta\delta_{\mathrm{r}}(s)$ are stationary processes, (11) can be written

$$\boldsymbol{M}\ddot{\boldsymbol{R}}_{\Delta\boldsymbol{\delta}\Delta\delta_{\mathrm{r}}}(\tau) + \boldsymbol{D}\dot{\boldsymbol{R}}_{\Delta\boldsymbol{\delta}\Delta\delta_{\mathrm{r}}}(\tau) + \boldsymbol{K}\boldsymbol{R}_{\Delta\boldsymbol{\delta}\Delta\delta_{\mathrm{r}}}(\tau) = 0 \,, \qquad \tau > 0 \,, \qquad (13)$$

Thus, the vector of rotor angle displacement correlation functions, $\boldsymbol{R}_{\Delta\boldsymbol{\delta}\Delta\delta_{\mathrm{r}}}(\tau)$, satisfy the homogeneous differential equations describing the oscillatory behavior of each generator. Consequently, the correlation functions yield an estimate of the impulse responses of the power system. In the vicinity of the operating point, the generator rotor angles have a linear coupling to other variables of the grid, such as power flows, voltages, and voltage angles. Thus, the impulse responses of the system can be estimated also from the correlation functions of the respective variables. This enables the use of cross-correlation functions calculated between PMU measurements to be used to estimate the oscillatory behavior of the complete power system.

Application of NExT to Unsynchronized Data

If the measurements received from the power system are not time synchronized (i.e., relay measurements), a time synchronization error t_{E} is introduced in the estimated cross-correlation functions. Consequently, the correlation function $R_{\Delta\delta_{\mathrm{E}}\Delta\delta_{\mathrm{r}}}(t - t_{\mathrm{E}}, s)$ of an unsynchronized rotor angle displacement measurement $\Delta\delta_{\mathrm{E}}$ and the reference measurement $\Delta\delta_{\mathrm{r}}$ does not satisfy (8). However, by selecting $\tau_{\mathrm{E}} = t - t_{\mathrm{E}} - s = (t - s) - t_{\mathrm{E}} = \tau - t_{\mathrm{E}}$, the correlation function can be written:

$$R_{\Delta\delta_{\mathrm{E}}\Delta\delta_{\mathrm{r}}}(\tau_{\mathrm{E}}) = R_{\Delta\delta_{\mathrm{E}}\Delta\delta_{\mathrm{r}}}(\tau - t_{\mathrm{E}}) \quad . \qquad (14)$$

As shown by (14), the correlation function of the unsynchronized measurements is shifted by t_{E} compared with the correlation function of the synchronized measurements. An example of the correlation functions of synchronized and unsynchronized measurements from an underdamped oscillating system is shown in Figure 5.

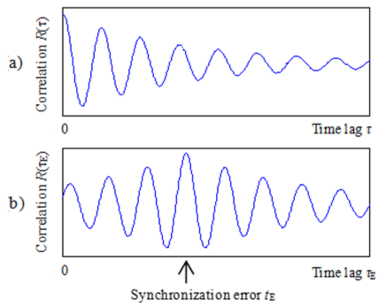

Figure 5. A schematic example of cross-correlation functions of a) two synchronized and b) two unsynchronized measurements from an underdamped oscillating system.

In the context of oscillation analysis, the part of (14), where $\tau_{\mathrm{E}} < t_{\mathrm{E}}$, has negative damping even though the studied system would be stable in reality [56]. This phenomenon can be observed in Figure 5 b). Thus, the impulse responses of the system cannot be directly estimated from the unsynchronized measurements (i.e., the unsynchronized correlation functions shown by (14) do not satisfy (8)). However, the part $\tau_{\mathrm{E}} \geq t_{\mathrm{E}}$ of (14) corresponds to the synchronized correlation functions described by (13), and can be utilized to estimate the impulse responses of the system.

If the part, where $\tau_{\mathrm{E}} < t_{\mathrm{E}}$ is truncated from (14), the resulting correlation function satisfies (8), and thus, yields an estimate of the impulse response of the power system. Since the part $\tau_{\mathrm{E}} < t_{\mathrm{E}}$ of (14), has negative damping, and the part $\tau_{\mathrm{E}} \geq t_{\mathrm{E}}$ has positive damping (assuming that the studied power system is stable and the analyzed measurements are stationary), the time synchronization error t_{E} can be approximated from the following equation:

$$R_{\Delta\delta_{\mathrm{E}}\Delta\delta_{\mathrm{r}}}(t_{\mathrm{E}}) \approx \max_{\tau_{\mathrm{E}}} \left|R_{\Delta\delta_{\mathrm{E}}\Delta\delta_{\mathrm{r}}}(\tau_{\mathrm{E}})\right| . \tag{15}$$

This enables the use of truncated cross-correlation functions of unsynchronized measurements to be used to estimate the impulse responses of the power system. Thus, measurements from unsynchronized devices, such as relays' recorders, can be utilized for the modal analysis with the NExT.

ERA

The ERA was originally introduced by Juang and Pappa [57]. The goal of the ERA is to find the minimum realization to obtain a state-space representation of the studied system. ERA is based on the following state-space representation of the studied system:

$$\begin{aligned} \boldsymbol{x}(k+1) &= \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) \\ \boldsymbol{y}(k) &= \boldsymbol{C}\boldsymbol{x}(k) \end{aligned} \tag{16}$$

where $\boldsymbol{x}(k)$ is the vector of states, $\boldsymbol{u}(k)$ is the vector of system inputs and $\boldsymbol{y}(k)$ is the vector of system outputs at the kth step, and $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$ are the discrete-time state-space matrices [57].

The ERA starts with forming the following Hankel matrix [57], [49]:

$$\boldsymbol{H}(k-1)=\begin{bmatrix}\boldsymbol{y}(k) & \boldsymbol{y}(k+1) & \cdots & \boldsymbol{y}(k+p)\\ \boldsymbol{y}(k+1) & \ddots & & \\ \vdots & & & \vdots \\ \boldsymbol{y}(k+r) & & & \boldsymbol{y}(k+r+p)\end{bmatrix}, \tag{17}$$

where $\boldsymbol{y}(k)$ is the vector of the measured impulse responses of the system at time k. When used in conjunction with the NExT, $\boldsymbol{y}(k)$ is the vector of correlation functions calculated with the NExT. The parameters p and r correspond to the number of columns and rows in the Hankel matrix.

Next step in the ERA is to perform the singular value decomposition of $\boldsymbol{H}(0)$ [57], [49]:

$$\boldsymbol{H}(0)=\boldsymbol{P\Sigma Q}^{\mathrm{T}}\ , \tag{18}$$

where $\boldsymbol{P}$ and $\boldsymbol{Q}$ are left and right singular-vectors of $\boldsymbol{H}(0)$, respectively, and $\boldsymbol{\Sigma}$ is the diagonal matrix of singular values. Relatively small singular values along the diagonal of $\boldsymbol{\Sigma}$ correspond to computational or noise modes [49]. The rows and columns associated with computational modes are eliminated to form condensed matrices $\boldsymbol{\Sigma}_{\mathrm{c}}$, $\boldsymbol{P}_{\mathrm{c}}$, and $\boldsymbol{Q}_{\mathrm{c}}$.

The final step in the ERA is to estimate the state-space matrices of the studied system. By using the condensed matrices, the estimates of the discrete-time state-space matrices can be calculated as follows [57], [49]:

$$\widehat{\boldsymbol{A}}=\boldsymbol{\Sigma}_{\mathrm{c}}^{-1/2}\boldsymbol{P}_{\mathrm{c}}^{\mathrm{T}}\boldsymbol{H}(1)\boldsymbol{Q}_{\mathrm{c}}\boldsymbol{\Sigma}_{\mathrm{c}}^{-1/2} \tag{19}$$

$$\widehat{\boldsymbol{B}}=\boldsymbol{\Sigma}_{\mathrm{c}}^{-1/2}\boldsymbol{Q}_{\mathrm{c}}^{\mathrm{T}}[\mathbf{I}\ \ \mathbf{0}]^{\mathrm{T}} \tag{20}$$

$$\widehat{\boldsymbol{C}}=[\mathbf{I}\ \ \mathbf{0}]\boldsymbol{P}_{\mathrm{c}}\boldsymbol{\Sigma}_{\mathrm{c}}^{-1/2}\ . \tag{21}$$

For the modal estimation, the estimated state-space matrices are transformed into continuous time. After the transformation, the modal estimates (frequencies and damping ratios of the modes) can be calculated from the eigenvalues of $\widehat{\boldsymbol{A}}$.

2.2.3 Application to Power System Data and Selection of Method Parameters

Figure 6 presents the flow chart of the NExT-ERA method when applied to data collected from a power system. Certain steps and characteristics of the NExT-ERA method that are important in its practical application are discussed below.

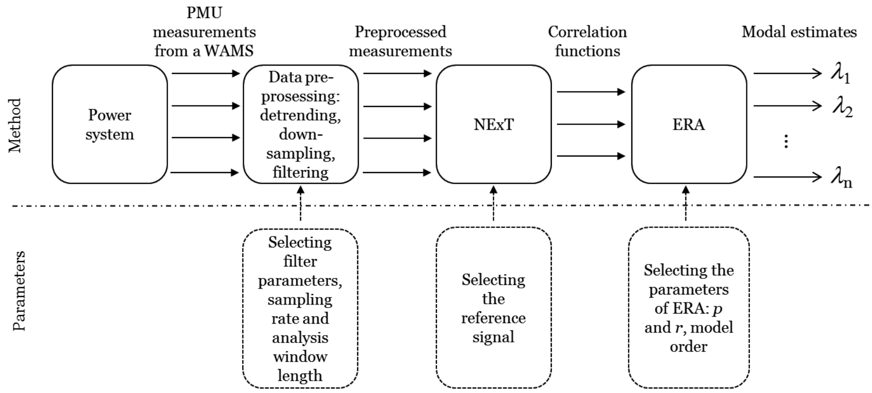

Figure 6. Flow chart of the NExT-ERA method when applied to power system data.

Data Preprocessing

Data preprocessing (filtering etc.) for the NExT-ERA method is similar to the MAR method (see Section 2.1.3).

Selecting the Reference Signal for NExT

The NExT requires the selection of a reference variable (e.g., the reference rotor angle displacement $\Delta\delta_r$ in (13)) for the calculation of the cross-correlation functions. When the NExT is applied to power systems, the reference variable should be a PMU measurement having a high observability of the mode of interest, and high signal-to-noise ratio. In this thesis and Publication II, the power spectral densities from the available measurements were calculated and the reference variable was selected to be the measurement having the highest peak in the power spectrum at the frequency of the mode of interest. However, if a certain measurement is known to typically have a high observability of the mode of interest, such measurement may be constantly used as a reference measurement.

Selecting the Parameters of ERA

The parameters of the ERA include the dimensions p and r of the Hankel matrix $\boldsymbol{H}$ and the model order. p and r describe how many samples of the estimated correlation functions (using the NExT) are used in the estimation of the state space representation of the system. There are different methods for selecting p and r [58]. In this thesis and Publications II and VI, p and r are selected as follows: p is 10 times the number of expected poles (i.e., 20 times the number of frequencies) and r is 2 times p (this approach is also recommended in [57]). Another commonly used approach to select the dimensions is based on the quality of the free responses (i.e., correlation functions). In such an approach, the Hankel matrix is built using the whole length of the decaying signal provided the signal-to-noise ratio is high [58].

The model order of the estimated state-space model can be selected for example based on the singular values along the diagonal of matrix $\boldsymbol{\Sigma}$ in (18). Relatively small singular values correspond to computational or noise modes and they can be neglected [58]. In this thesis and Publication II, the singular values that were smaller than $0.1 \cdot \sigma_{\max}$, where $\sigma_{\max}$ is the largest singular value, were assumed to correspond computational modes (noise modes). Thus, the model order is selected according to the number of singular values larger than $0.1 \cdot \sigma_{\max}$. However, the model order can be also selected based on *apriori* knowledge of the studied system (i.e., a constant model order can be used in some cases).

2.3 Second Order Blind Identification (SOBI)

2.3.1 Introduction

SOBI is a Blind Source Separation (BSS) technique. The fundamental objective of BSS is to retrieve unobserved source signals from their observed mixtures. [59] A well-known example of BSS is the cocktail party problem, where the individual speech signals of several people speaking simultaneously in a room are retrieved utilizing only the signals recorded by a set of microphones located in the room. In the field of modal analysis, BSS has been widely applied for analyzing oscillating structures [60]. Recently, a BSS technique called Independent Component Analysis (ICA) was also applied to analyze the electromechanical modes in power systems [22]. The SOBI technique, however, has not been used in the field of analyzing electromechanical oscillations prior to this thesis and Publication III. This thesis and Publication III show that the SOBI algorithm, along with the Random Decrement (RD) technique and the ERA, is applicable for analyzing the electromechanical modes of power systems.

The goal of the SOBI, in the context of analyzing electromechanical modes, is to recover the oscillatory signals from noisy ambient measurement data collected from power systems. The SOBI algorithm identifies and separates the blind sources (i.e., electromechanical modes) utilizing their temporal structure. The SOBI relies entirely on second order statistics, whereas for example ICA techniques are based on higher order statistics (non-Gaussianity of the sources). Therefore, the SOBI has an advantage compared to ICA techniques since the calculation of higher-order statistics is laborious, and also difficult in the case of scarce data [61].

After processing the signals with the SOBI, the impulse response of the system is estimated with the RD technique [62], [63]. The impulse responses can be estimated for each mode separately, since single-mode ambient responses have been recovered from the original data with the SOBI. The modal parameters (modal frequency and damping ratio) are identified with the ERA [57]. The use of the SOBI-RD-ERA method to measurement data received from a power system is illustrated in the block diagram of Figure 7.

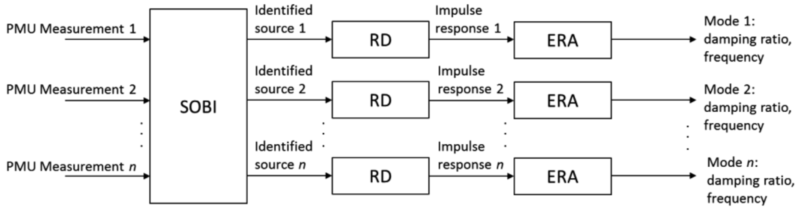

Figure 7. A block diagram of the SOBI-RD-ERA method.

2.3.2 Theoretical Background

SOBI

The model used in the SOBI algorithm assumes that the observations $\boldsymbol{x}(t)$ gathered from the studied system consist of mixed independent source signals $\mathbf{s}(t)$ and additive noise $\boldsymbol{e}(t)$. The goal of the algorithm is to recover the unobserved source signals $\boldsymbol{s}(t)$ from the observed mixtures of the source signals and noise. The model used in the SOBI can be written

$$\boldsymbol{x}(t) = \boldsymbol{y}(t) + \boldsymbol{e}(t) = \boldsymbol{A}\boldsymbol{s}(t) + \boldsymbol{e}(t)\,, \tag{22}$$

where $\boldsymbol{y}(t)$ is the signal part of the observations, and $\boldsymbol{A}$ is referred to as the mixing matrix [64], [61].

In the SOBI algorithm, the sources are assumed to be mutually uncorrelated and stationary. If the sources are scaled to have a unit variance, their covariance matrix is

$$\boldsymbol{R}_s(0) = E[\boldsymbol{s}(t)\boldsymbol{s}^*(t)] = \mathbf{I}\,, \tag{23}$$

where * denotes the conjugate transpose of a vector. The covariance matrix of the observations is

$$\boldsymbol{R}_x(0) = E[\boldsymbol{x}(t)\boldsymbol{x}^*(t)] = \boldsymbol{A}\boldsymbol{A}^{\mathrm{H}} + [\boldsymbol{\sigma}(t)\boldsymbol{\sigma}^*(t)] = \boldsymbol{A}\boldsymbol{A}^{\mathrm{H}} + \boldsymbol{\sigma}^2\mathbf{I}\,, \tag{24}$$

where $\boldsymbol{\sigma}$ is a vector consisting of the variance of the noise, and H denotes the complex conjugate transpose of a matrix. [64], [61].

The first step of SOBI consists of whitening the signal part $\boldsymbol{y}(t)$ of the observation such that

$$E[\boldsymbol{W}\boldsymbol{y}(t)\boldsymbol{y}^*(t)\boldsymbol{W}^{\mathrm{H}}] = \boldsymbol{W}\boldsymbol{A}\boldsymbol{A}^{\mathrm{H}}\boldsymbol{W}^{\mathrm{H}} = \mathbf{I} \tag{25}$$

From (25), it follows that for any whitening matrix $\boldsymbol{W}$, there exists a unitary matrix $\boldsymbol{U}$ such that $\boldsymbol{W}\boldsymbol{A} = \boldsymbol{U}$. If $\boldsymbol{x}(t) \neq \boldsymbol{y}(t)$ (i.e., noise is present in the observations), the whitened process $\boldsymbol{z}(t) = \boldsymbol{W}\boldsymbol{x}(t)$ yields:

$$\begin{aligned} E[\boldsymbol{z}(t)\boldsymbol{z}^*(t)] &= E[\boldsymbol{W}\boldsymbol{x}(t)\boldsymbol{x}^*(t)\boldsymbol{W}^{\mathrm{H}}] = \boldsymbol{W}\boldsymbol{A}\boldsymbol{A}^{\mathrm{H}}\boldsymbol{W}^{\mathrm{H}} + \boldsymbol{W}\boldsymbol{\sigma}^2\boldsymbol{W}^{\mathrm{H}} \\ &= \boldsymbol{W}(\boldsymbol{R}_x(0) - \boldsymbol{\sigma}^2\mathbf{I})\boldsymbol{W}^{\mathrm{H}} + \boldsymbol{W}\boldsymbol{\sigma}^2\boldsymbol{W}^{\mathrm{H}} = \boldsymbol{W}\boldsymbol{R}_x(0)\boldsymbol{W}^{\mathrm{H}} \end{aligned} \tag{26}$$

Consequently, the whitening matrix $\boldsymbol{W}$ can be determined from the covariance matrix $\boldsymbol{R}_{\boldsymbol{x}}(0)$ of the observations (more details are presented in [64]).

The second step of SOBI is finding the unitary matrix $\boldsymbol{U}$. To determine $\boldsymbol{U}$, spatially whitened time lagged covariance matrices $\boldsymbol{R}_{\boldsymbol{W},\boldsymbol{x}}(\tau)$ are considered:

$$\begin{aligned}
&\boldsymbol{R}_{\boldsymbol{W},\boldsymbol{x}}(\tau) = E[\boldsymbol{z}(t+\tau)\boldsymbol{z}^{*}(t)] = \boldsymbol{W}E[\boldsymbol{x}(t+\tau)\boldsymbol{x}^{*}(t)]\boldsymbol{W}^{\mathrm{H}} \\
&= \boldsymbol{WA}E[\boldsymbol{s}(t+\tau)\boldsymbol{s}^{*}(t)]\boldsymbol{A}^{\mathrm{H}}\boldsymbol{W}^{\mathrm{H}} = \boldsymbol{U}\boldsymbol{R}_{\boldsymbol{s}}(\tau)\boldsymbol{U}^{\mathrm{H}} \quad \forall\tau \neq 0
\end{aligned} \tag{27}$$

Since $\boldsymbol{U}$ is unitary and $\boldsymbol{R}_{\boldsymbol{s}}(\tau)$ is diagonal, (27) shows that any whitened covariance matrix $\boldsymbol{R}_{\boldsymbol{W},\boldsymbol{x}}(\tau)$ can be diagonalized with the unitary transform $\boldsymbol{U}$. Consequently, the matrix $\boldsymbol{U}$ can be determined through the eigenvalue decomposition of the time-lagged whitened covariance matrices. After determining $\boldsymbol{U}$, the mixing matrix $\boldsymbol{A}$, and the sources $\boldsymbol{s}(t)$ can be directly calculated since $\boldsymbol{U} = \boldsymbol{WA}$, and $\boldsymbol{x}(t) = \boldsymbol{As}(t)$. [64], [61]

To estimate the unitary matrix $\boldsymbol{U}$, the SOBI algorithm jointly diagonalizes several whitened covariance matrices $\boldsymbol{R}_{\boldsymbol{W},\boldsymbol{x}}(\tau)$ with different time lags. The simultaneous diagonalization of the covariance matrices is carried out to improve the robustness of the algorithm (i.e., several time lags are considered instead of a single time lag, and thus, a poor choice for the lag is less probable). The diagonalization is carried out using an extension of the Jacobi technique [64].

Figure 8 illustrates the application of the SOBI algorithm to mixtures of three sinusoidal signals. As shown in the figure, the SOBI is able to separate different sinusoidal signals with high accuracy.

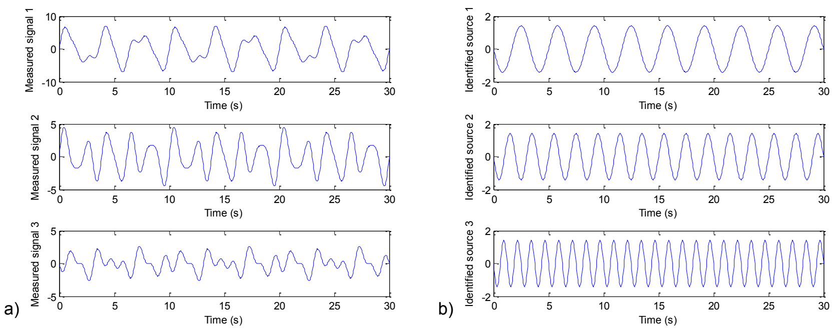

Figure 8. a) Mixtures of three sinusoidal signals (frequencies 0.3 Hz, 0.5 Hz and 0.8 Hz) and b) the identified source signals.

RD Technique

The Random Decrement (RD) (introduced in [62], [63]) is a univariate time domain averaging technique. The goal of the technique is to estimate the impulse response of the studied system from ambient observations collected from the system. When used in conjunction with the SOBI, the RD technique is applied to the source signals identified by the SOBI algorithm.

If the studied system is assumed to be linear and the excitation (i.e., disturbance) of the system is Gaussian distributed random variation, the RD auto signature $D_{\mathrm{yy}}(\tau)$ yields an estimate of the impulse response of the system [65]. The above-mentioned assumptions are justified during the ambient operation of power systems [2]. The RD estimate of the impulse response of the system $r(t)$ is

$$r(t) = D_{yy}(\tau) = \frac{1}{N}\sum_{s=1}^{N} y(t_s : t_s + \tau)\,, \tag{28}$$

where N is the total number of samples collected with a selected threshold, s is the sample number, t_s is the time instance when the ambient response $y(t)$ crosses the selected threshold, and τ is the length of each sample [2]. The use of the RD technique is presented in Figure 9.

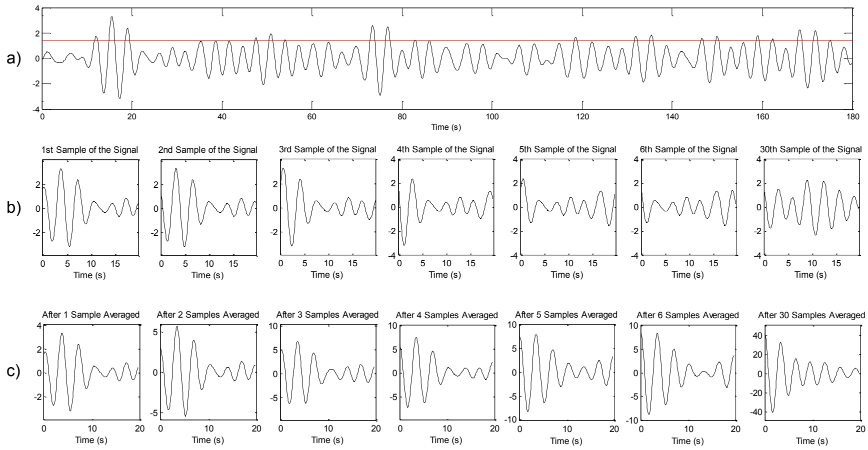

Figure 9. Example of the random decrement technique: a) the ambient response, b) the collected samples, and c) the averaged samples.

ERA in Conjunction with SOBI

The complete ERA algorithm is described in Section 2.2.2. When used in conjunction with the SOBI, the ERA algorithm can be used similarly as described in Section 2.2.2, with following simplifications:

- The impulse responses received from the RD technique contain only one mode since the modes are separated using the SOBI. Thus, in this thesis, the parameters to form the Hankel matrix (17) are selected as follows: $p = 20$ and $r = 40$. (See Section 2.2.3 for more information) However, according to [58], another approach is to build the Hankel matrix using the whole length of the decaying signal provided the signal-to-noise ratio is high.
- The identified state matrix $\widehat{\boldsymbol{A}}$ contains only one mode, and thus, is of dimensions 2×2. Consequently, the model order of the ERA can be limited to 2.

2.3.3 Application to Power System Data and Selection of Method Parameters

Figure 10 shows the application of the SOBI to ambient power system data. Certain steps and properties of the method that are important in its practical application are also discussed below.

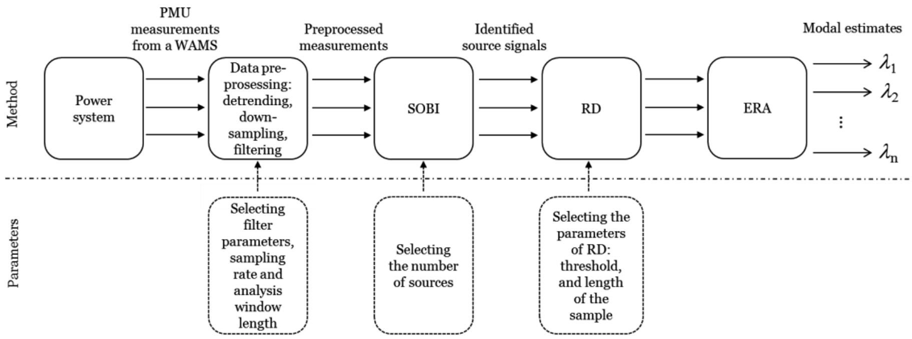

Figure 10. Flow chart of the SOBI-RD-ERA method.

Data Preprocessing
Data preprocessing for the SOBI-RD-ERA method is similar to the MAR method (see Section 2.1.3).

Selecting the Number of Sources
The SOBI algorithm requires the selection of the number of sources to be identified from the ambient data. Usually, the number of sources corresponds to the number of modes to be identified. Thus, the user of the algorithm should select the number of sources to be equal to the number of the modes expected to be present in the analyzed data. If other periodic signals exist in the data, these signals can be also considered source signals.

Selecting the Parameters for the RD Technique
Using the RD technique requires the selection of two parameters: the length of the sample and the threshold value. In this paper, the parameters were selected according to the recommendation of [2]: the length of the sample is 6 oscillation periods of the analyzed mode and the threshold is 1.4 times the standard deviation of the ambient response.

2.4 Bayesian Approach

2.4.1 Introduction

The Bayesian approach has been previously used for ambient modal analysis in the field of civil engineering. Originally, the approach was developed by S. K. Au *et al.* [66]–[69] and it has been found to be highly effective in identifying the oscillatory dynamics of civil and mechanical structures with quantifiable identification precision. Prior to Publication IV and this thesis, however, the Bayesian approach has not been used for identifying electromechanical modes.

Unlike several previously published methods, the Bayesian approach does not use statistical proxies (e.g., correlation function, sample power spectral densities) calculated from the measurement data for modal identification. Rather, the identification information about the parameters are fundamentally expressed using Bayes Theorem in terms of a probability distribution conditional on the data and modeling assumptions.

The Bayesian method identifies the modes based on the Fast Fourier Transform (FFT) information on a selected frequency band. This significantly simplifies the identification model and reduces modeling error in other unmodeled frequency bands, and therefore, improves the robustness of the method. The ambient excitation source and measurement noise differ in order of magnitude and characteristics over different frequency regimes. Using a time domain approach, it might be difficult to have a simple model that accounts for the various frequency characteristics. However, using a frequency domain approach, only the FFTs within the selected band are used for making inference. The frequency characteristics that are irrelevant or difficult to model are ignored by simply excluding the FFTs in their band. In addition, this does not require any band-pass filtering. Since the raw FFT is used and no averaging is involved, distortion effects due to leakage or smearing is significantly reduced compared with conventional methods involving sample spectral estimates [70].

For close modes, the identified mode shape vectors of the Bayesian method are the real ones and they need not be orthogonal. This is in contrast with existing methods, which can only yield the "operational deflection shape" (from eigenvector decomposition) that are necessarily orthogonal.

The Bayesian method also allows the uncertainty of modal parameters (i.e., frequency, damping ratio, modal excitation) to be calculated. This is fundamentally in terms of a posterior distribution that is a function of measured data rather than confidence intervals (in non-Bayesian methods) that are only estimates of "inherent uncertainty" associated with conceptually repeated experiments under small perturbations. The uncertainty information provides a basis for power system operators and analysts to design appropriate configurations for reliable identification and proper interpretation of the modal identification results.

2.4.2 Theoretical Background

Bayesian Approach

Let $\boldsymbol{\theta}$ denote the set of parameters to be identified from a set of measured data $\boldsymbol{D}$. A Bayesian approach to system identification recognizes the fact that it is philosophically impossible to identify the value of $\boldsymbol{\theta}$ exactly because of limited amount of available data, measurement noise, modeling error, etc. Instead, all information that can be extracted from $\boldsymbol{D}$ on $\boldsymbol{\theta}$ is encapsulated in the "posterior" (i.e., given data) probability density function (PDF) $(\boldsymbol{\theta}|\boldsymbol{D})$. Using Bayes' Theorem, the posterior PDF is given by

$$p(\boldsymbol{\theta}|\boldsymbol{D}) = p(\boldsymbol{D}|\boldsymbol{\theta})p(\boldsymbol{\theta})/p(\boldsymbol{D}) \quad (29)$$

Strictly speaking, all the terms in (29) are conditional on modeling assumptions but the latter have been omitted to simplify notations. In (29), for a given model assumed in identification, $p(\boldsymbol{D})$ is a constant, and thus, it does not affect the shape of the PDF; $p(\boldsymbol{\theta})$ is often called the "prior PDF" (i.e., before data is incorporated) and $p(\boldsymbol{D}|\boldsymbol{\theta})$ the "likelihood function", which gives the PDF of the data for a given $\boldsymbol{\theta}$ and must be derived based on modeling assumptions that relate $\boldsymbol{\theta}$ to $\boldsymbol{D}$. The spread of $p(\boldsymbol{\theta})$ reflects one's knowledge on parameters in the absence of data while the spread of $p(\boldsymbol{D}|\boldsymbol{\theta})$ reflects how sensitive the likelihood of data is to parameters. Sensitivity in $p(\boldsymbol{D}|\boldsymbol{\theta})$, which is a joint distribution of data, increases with sample size and so for sufficiently large sample size (which is the case in modal identification) the variation of $p(\boldsymbol{D}|\boldsymbol{\theta})$ dominates that of $p(\boldsymbol{\theta})$. Thus, practically it can be assumed

$$p(\boldsymbol{\theta}|\boldsymbol{D}) \propto p(\boldsymbol{D}|\boldsymbol{\theta}) \quad (30)$$

Ambient Modal Identification

As described in Section 2.2.2, in small signal analysis (i.e. in the vicinity of the current operating point) the oscillatory behavior of each generator in the power system can be described by:

$$\boldsymbol{M}\ddot{\boldsymbol{x}}(t) + \boldsymbol{C}\dot{\mathbf{x}}(t) + \boldsymbol{K}\boldsymbol{x}(t) = \boldsymbol{F}(t) \quad (31)$$

where $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{K}$ are diagonalizable matrices containing the inertia coefficients, damping coefficients and synchronizing power coefficients of each generator, respectively. Here, $\boldsymbol{x}(t)$ is a vector containing the rotor angle deviations of the generators around their equilibrium points and $\boldsymbol{F}$ is the vector of the natural excitation of the system.

As $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{K}$ are diagonalizable, the solution of $\boldsymbol{x}(t)$ can be expressed as a sum of modal contributions:

$$\boldsymbol{x}(t) = \sum_i \boldsymbol{\psi}_i \eta_i(t) \quad (32)$$

where $\boldsymbol{\psi}_i$ $(i = 1,2, \dots)$ are the mode shape vectors of the system satisfying the generalized eigenvalue problem

$$\boldsymbol{K}\boldsymbol{\psi}_i = \omega_i^2 \boldsymbol{M}\boldsymbol{\psi}_i \quad (33)$$

In (32), η_i is the scalar modal response satisfying the uncoupled equation of motion:

$$\ddot{\eta}_i(t) + 2\zeta_i\omega_i\eta_i(t) + \omega_i^2\eta_i(t) = p_i(t) \quad (34)$$

where $\omega_i = 2\pi f_i$; f_i and ζ_i are the natural frequency (Hz) and damping ratio of the mode, respectively, and

$$p_i(t) = \frac{\boldsymbol{\psi}_i^T \boldsymbol{F}(t)}{\boldsymbol{\psi}_i^T \boldsymbol{M} \boldsymbol{\psi}_i} \tag{35}$$

is the modal excitation.

Let $\{\hat{\boldsymbol{y}}_i \in R^n\}_{i=0}^{N-1}$, be a set of discrete time history at n measured degrees of freedom (DOFs) of the system under ambient condition. Given the data, the goal is to identify the system modal properties primarily consisting of the natural frequencies, damping ratios and mode shapes. In the context of the Bayesian approach, it is required to formulate the likelihood function $p(\boldsymbol{D}|\boldsymbol{\theta})$.

Processing the ambient (unfiltered) measurements directly would require a model that explains all the modes in the sampling bandwidth (from zero to the Nyquist frequency). In addition, the measurements can contain frequency components from unknown system dynamics, which the theoretical model cannot explain. Thus, in the Bayesian approach, it is preferable to operate in the frequency domain and use the FFT of time history on a selected frequency band around the modes of interest as data $\boldsymbol{D}$ for Bayesian inference. This significantly reduces the complexity of the model as it only needs to account for the dynamics of the modes in the selected frequency band.

Define the scaled FFT of $\{\hat{\boldsymbol{y}}_j \in R^n\}_{j=0}^{N-1}$ by

$$\hat{\boldsymbol{F}}_k = \sqrt{\frac{\Delta t}{N}} \sum_{j=0}^{N-1} \hat{\boldsymbol{y}}_j e^{-2\mathrm{j}jk/N} \qquad k = 0, \dots, N-1 \tag{36}$$

where Δt is the sampling interval in seconds and $\mathrm{j}^2 = -1$. For $k \le N_\mathrm{q}$, where N_q (index at Nyquist frequency) is the integer part of $N/2$, $\hat{\boldsymbol{F}}_k$ corresponds to frequency $f_k = k/N\Delta t$. The FFT in (36) is scaled by the factor $\sqrt{\Delta t/N}$ so that $E\left[\hat{\boldsymbol{F}}_k \hat{\boldsymbol{F}}_k^{\,*}\right]$ is equal to the power spectral density (PSD) matrix of the data process.

Let $\boldsymbol{D} = \{\hat{\boldsymbol{F}}_k\}$ denote the collection of FFTs within the selected frequency band for the modal identification. To formulate the likelihood function $p(\boldsymbol{D}|\boldsymbol{\theta})$, it is necessary to derive the joint distribution of $\hat{\boldsymbol{F}}_k$ for a given set of modal parameters $\boldsymbol{\theta}$. Not only does $\boldsymbol{\theta}$ need to contain the parameters of interest (e.g., natural frequencies and damping ratios of the electromechanical modes) but also those that together can allow $p(\boldsymbol{D}|\boldsymbol{\theta})$ to be derived explicitly. Within the selected frequency band $\hat{\boldsymbol{F}}_k$ can be modeled as

$$\hat{\boldsymbol{F}}_k = \sum_i \boldsymbol{\varphi}_i \eta_{ik} + \varepsilon_k \tag{37}$$

where the sum is over the modes in the selected frequency band only; η_{ik} denotes the scaled FFT of $\eta_i(t)$; and ε_k is the scaled FFT of the 'prediction error' (e.g., measurement noise). It is assumed that the prediction errors at different channels are independent and identically distributed (i.i.d.) with a constant PSD of $\boldsymbol{S}_e$ within the selected frequency band. Taking the scaled FFT on (34) yields

$$\eta_{ik} = h_{ik} p_{ik} \tag{38}$$

where

$$h_{ik} = (2\pi f_k)^{-2}\left[\left(\beta_{ik}^2 - 1\right) + \mathrm{j}(2\zeta_i \beta_{ik})\right]^{-1} \tag{39}$$

is the transfer function and $\beta_{ik} = f_i/f_k$ is the ratio of the natural frequency f_i to the FFT frequency f_k. In (38), p_{ik} is the scaled FFT of the modal excitation $p_i(t)$, which can be assumed to have a constant PSD matrix of $\boldsymbol{S}$ in the selected frequency band. The above context is sufficient for deriving the joint PDF of $\{\widehat{\boldsymbol{F}}_k\}$, where $\boldsymbol{\theta}$ consists of, for the modes in the selected frequency band, the natural frequencies $\{f_i\}$, damping ratios $\{\zeta_i\}$, the mode shapes (confined to the measured DOFs) $\boldsymbol{\varphi}$, the parameters characterizing the modal excitation PSD matrix $\boldsymbol{S}$ and the prediction error PSD $\boldsymbol{S}_e$.

The likelihood function $p(\boldsymbol{D}|\boldsymbol{\theta}) = p\left(\{\widehat{\boldsymbol{F}}_k\}\,|\boldsymbol{\theta}\right)$ can be derived using asymptotic results of FFTs of stationary processes for long data lengths [71]. Essentially, it can be shown that $\{\widehat{\boldsymbol{F}}_k\}$ at different frequencies (k's) are asymptotically independent. In addition, Re $\widehat{\boldsymbol{F}}_k$ and Im $\widehat{\boldsymbol{F}}_k$ are jointly Gaussian and their covariance matrix can be expressed in terms of $\boldsymbol{\theta}$. Consequently, it can be shown that [66]

$$p(\boldsymbol{D}|\boldsymbol{\theta}) = e^{-L(\boldsymbol{\theta})} \tag{40}$$

where

$$L(\boldsymbol{\theta}) = nN_f \ln \pi + \textstyle\sum_k \ln \det \boldsymbol{E}_k(\boldsymbol{\theta}) + \sum_k \widehat{\boldsymbol{F}}_k{}^* \boldsymbol{E}_k(\boldsymbol{\theta})^{-1} \widehat{\boldsymbol{F}}_k \tag{41}$$

is the "negative log-likelihood function" (NLLF);

$$\boldsymbol{E}_k(\boldsymbol{\theta}) = \boldsymbol{\Phi} \boldsymbol{H}_k \boldsymbol{\Phi}^{\mathrm{T}} + \boldsymbol{S}_e \boldsymbol{I}_n \tag{42}$$

is the theoretical PSD matrix of the measured data;

$$\boldsymbol{\Phi} = [\boldsymbol{\varphi}_1, \dots, \boldsymbol{\varphi}_m] \in R^{n\times m} \tag{43}$$

is the mode shape matrix; $\boldsymbol{I}_n$ denotes the identity matrix of dimension n; $\boldsymbol{H}_k \in C^{m\times m}$ is a transfer matrix whose (i,j)-entry is given by

$$\boldsymbol{H}_k(i,j) = S_{ij} h_{ik} h_{jk}^* \tag{44}$$

and S_{ij} is the (i,j)-entry of the modal excitation PSD matrix $\boldsymbol{S}$.

Computation of Posterior Statistics

The statistical properties of $\boldsymbol{\theta}$ can be extracted from the posterior PDF or equivalently the NLLF in (41), which is essentially a computational problem. For modal identification problems with sufficient data, the posterior PDF has a single peak, say $\widehat{\boldsymbol{\theta}}$. This is the "most probable value" (MPV) as it has the highest probability density according to the posterior PDF. With a second order Taylor expansion of the NLLF around $\widehat{\boldsymbol{\theta}}$, the posterior PDF can be approximated by a Gaussian PDF centered at the MPV. It can be shown that the covariance matrix is then given by the inverse of the Hessian of the NLLF [66].

Computing the MPV by brute-force optimization with the NLLF is not feasible because in practical problems the number of parameters is large. Efficient algorithms have been developed in various cases, including, e.g., well-separated modes [66] and close modes [67]. Essentially, it is found that the MPV of the mode shape vector can be found almost analytically, in such a way that the full set of modal parameters can be found iteratively by optimizing each individual group in turn until convergence. A more thorough review with applications in civil engineering can be found in [68]. Analytical expressions for the Hessian of the NLLF have also been derived so that the covariance matrix of the modal parameters can be calculated efficiently and accurately without resorting to a finite difference method.

Uncertainty Laws

In addition to the modal identification algorithm, closed form expressions have also been derived for the identification uncertainty of the modal parameters under asymptotic situations of long data and low damping [69]. They are collectively called "uncertainty laws". In particular, assuming that the selected bandwidth is $f(1 \pm \kappa\zeta)$ where f is the natural frequency (in Hz), ζ is the damping ratio and κ is a dimensionless bandwidth factor characterizing the usable bandwidth, it can be shown [69] that the posterior coefficient of variation (c.o.v. = standard deviation/mean) of the damping ratio is asymptotically given by

$$\delta \sim [2\pi\zeta B(\kappa) N_c]^{-1/2} \tag{45}$$

where N_c is the data duration expressed as a multiple of the natural period; and

$$B(\kappa) = \frac{2}{\pi}\left[\tan^{-1}\kappa + \frac{\kappa}{\kappa^2+1} - \frac{2\left(\tan^{-1}\kappa\right)^2}{\kappa}\right] \tag{46}$$

is the "data length factor" being a monotonic increasing function of κ, which reflects the effect of widening the usable band on identification precision. This equation can be used for assessing and planning the measurement configuration required to achieve a specified identification accuracy in the modal parameters. For example, with 1 % damping, about 300 natural periods are required to achieve a c.o.v. of 30 % in the damping ratio. Uncertainty laws for other modal parameters are also available [69].

2.4.3 Application to Power System Data and Selection of Method Parameters

Figure 11 shows the application of the Bayesian approach to ambient power system data. Certain steps and properties of the Bayesian approach that are important in its practical application are also discussed below.

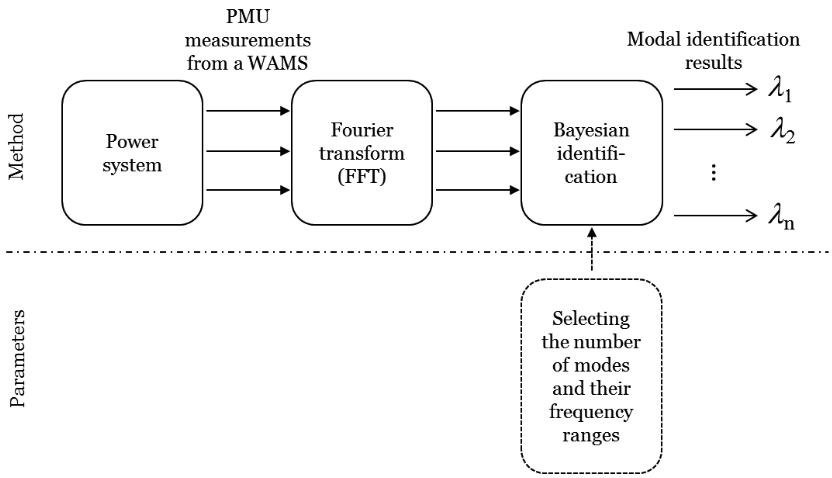

Figure 11. Flow chart of the Bayesian method.

Selecting the Number of Modes and Their Frequency Ranges

The Bayesian approach requires the selection of the number of modes to be identified from the used ambient data set. The number of modes can be selected for example based on *apriori* knowledge of the analyzed system or utilizing spectral analyses of the data (use of spectral analysis to assist modal identification is further discussed in Chapter 4).

To illustrate the selection of the frequency ranges for the identification of the modes, Figure 12 shows the power spectrum of an example PMU measurement collected from the Nordic power system. In the measurement, the mode of interest is around 1 Hz. There are activities of different nature over the whole sampling band up to Nyquist frequency (here 25 Hz). As shown by the figure, the frequency range should be selected such that the mode of interest is well observed there and, if possible, no other significant activities are in the selected range.

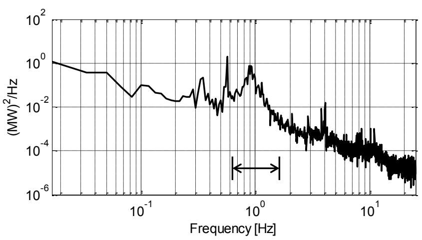

Figure 12. Power spectrum of an example data set collected from the Nordic power system and the selection of the frequency range for modal identification.

3. Validation of the Methods with Simulated and Measured Data

Various test systems and measurement data sets have been used in Publications I–VI to analyze the performance of the ambient modal analysis methods presented in Chapter 2. In this chapter, the functionality of the methods is validated using synthetic data generated with a simple linear test model as well as real measurement data collected from the Nordic power system. The purpose of this chapter, however, is not to present a thorough comparison of the methods.

3.1 Used Data

3.1.1 Synthetic Data Generated with a Linear Model

The performance of the ambient modal analysis methods is first tested here using synthetic data produced with a simple linear simulation model based on transfer functions. The transfer functions were selected such that there were two modes present in the model: 0.3 Hz mode and 0.8 Hz mode. These modes had damping ratios 3 % and 5 %, respectively. Figure 13 presents the model.

As Figure 13 shows, data containing four output signals were created with the model. Gaussian random inputs were used to excite the transfer function modes. The obtained responses of the transfer functions were multiplied by the coefficients presented in Figure 13 and then summed. The goal of this approach was to create data, where the two studied modes are mixed with different observability in different measurements. A sample excerpt of the output data is shown in Figure 14.

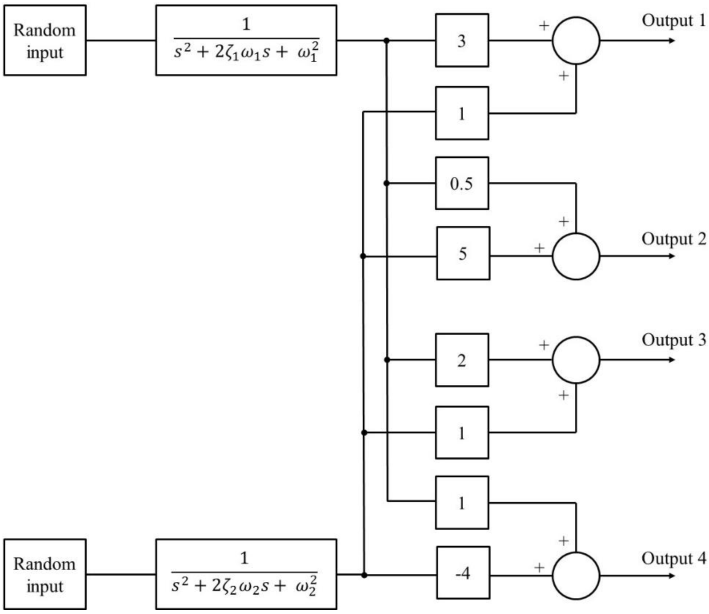

Figure 13. Test model based on transfer functions (ζ_1=0.03, ω_1=1.8850, ζ_2=0.05, ω_2=5.0265).

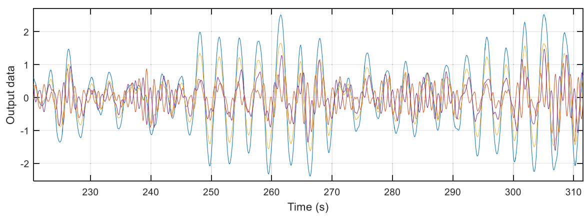

Figure 14. A sample excerpt of the data generated with the model based on transfer functions.

In practical situations, the PMU measurements can contain a certain measurement noise. To analyze the effect of the measurement noise, the synthetic measurements were perturbed with additive white noise. The variance of the noise was adjusted such that the signal-to-noise ratio (SNR) was infinite, 10 and 5. SNR levels of actual PMU measurements are typically higher than 5. The SNR was calculated by:

$$\mathrm{SNR} = \left(\frac{\sigma_{\mathrm{signal}}}{\sigma_{\mathrm{noise}}}\right)^2 , \tag{47}$$

where σ_{signal} and σ_{noise} are the signal and noise standard deviation, respectively.

3.1.2 PMU Measurement Data

In addition to the simulated data, real measured PMU data are used in this thesis to test the performance of the methods. The data were recorded using three PMUs installed in the transmission system of Northern Finland. Figure 15 shows the grid map of the area and the measurement locations.

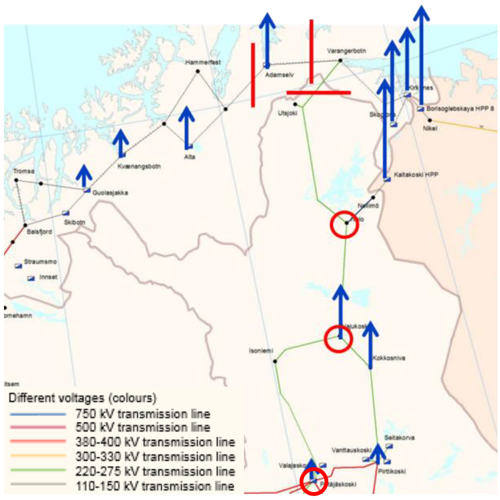

Figure 15. The transmission system in Northern Finland and Northern Norway. The red lines show the possible disconnection points of the grid. The blue arrows illustrate the mode shapes of the 0.8 Hz electromechanical mode when the grid is in ring operation (i.e. not separated in the disconnection points). The red circles show the locations of the PMUs.

The Northern Finland transmission system is characterized by long transmission distances, large amounts of hydro power production, and small consumption. When power transmission is from North to South, the power transfer capacity of the grid is limited by the damping of electromechanical oscillations.

The Northern Finland and Northern Norway transmission system can be operated in different switching conditions, which significantly affect the modal characteristics of the system. Often, the grid is used in ring operation (i.e., there is a direct connection from Northern Finland to the western part of Norway through the grid of Northern Norway). However, the grid is occasionally separated at different locations, which are shown in Figure 15.

Often, the dominant electromechanical mode in the area is observed around the frequency of 0.8 Hz. When exposed to this mode, the generators in Northern Finland and Northern Norway oscillate against the rest of the Nordic system.

The collected measurement data used for testing the performance of the methods contain 24 hours of active power flow from two 220 kV transmission lines situated in Northern Finland. Figure 16 presents a sample excerpt of a measurement.

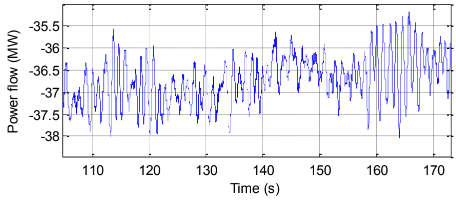

Figure 16. Sample excerpt of a PMU measurement from Northern Finland (active power flow from a 220 kV line).

In addition to the ambient power flow data, the collected measurement data set contains some small transients. These transients were caused by minor changes (i.e., small switching events) in the grid. One of the transients is shown in Figure 17. To obtain reference values for the frequency and damping ratio of the dominant mode, two transients (one in the beginning of the data set and one in the end part of the data set) were analyzed using Prony analysis. The results of the Prony analysis were as follows:

- Transient at 34 minutes (near the beginning of the data set): $f \approx 0.93$ Hz, $\zeta \approx 5\%$
- Transient at 20 hours 7 minutes (near the end of the data set): $f \approx 0.88$ Hz, $\zeta \approx 5\%$

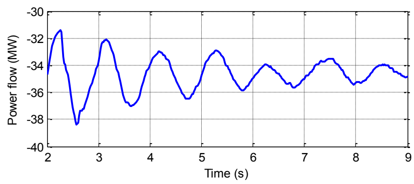

Figure 17. An example transient in the analyzed data set.

3.2 Performance Analysis of the Methods

3.2.1 Modal Analysis of Synthetic Data

The different modal analysis algorithms presented in Chapter 2 were applied to the synthetic measurement data created with the model based on transfer functions (Figure 13). The frequency and damping ratio of the 0.3 and 0.8 Hz modes were analyzed with different analysis window lengths and signal-to-noise ratios. The length of the analysis window was increased by 10 second intervals starting from 1 minute until 15 minutes. Figure 18 shows the results of the analysis.

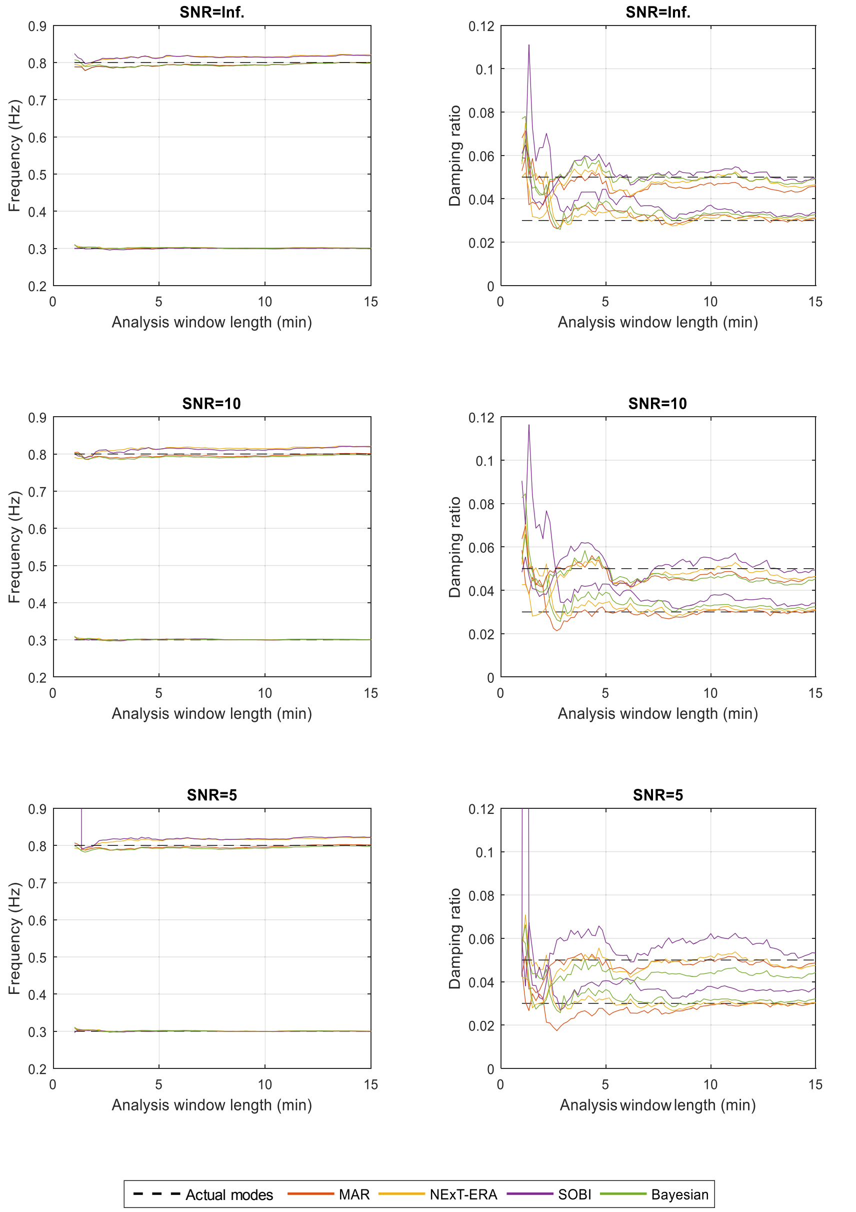

Figure 18. Modal analysis results of the data generated with the linear model with different SNRs.

The results in Figure 18 indicate that the MAR, NExT-ERA, SOBI and Bayesian methods are capable of identifying the frequency and damping ratio of the two modes present in the data generated with the linear model. The identification results for the modal frequency are rather accurate for each method even if the length of the analysis window is short. To achieve more accurate identification results for the damping ratio, slightly longer analysis window lengths (around five minutes) are required in this case.

As more noise is introduced in the measurements, variance of the estimates increases slightly. However, a realistic level of measurement noise does not disturb the modal identification results significantly as long as sufficiently long analysis windows are used. However, Figure 18 only shows the effect of the noise incorporated to the synthetic measurement signals, and the effect of the process noise or the noise from other measurement instrumentation (such as voltage and current transformers) are not shown here and could be a topic of future research.

3.2.2 Modal Analysis of PMU Data

Figure 19 shows the modal identification results for the 24-hour data set (Section 3.1.2) collected from the Nordic power system using the methods presented in Chapter 2. Modal identification is performed at a 1-minute interval, each time using a 10-minute moving analysis window. The goal is to identify the 0.8 Hz mode observed in Northern Finland and Northern Norway.

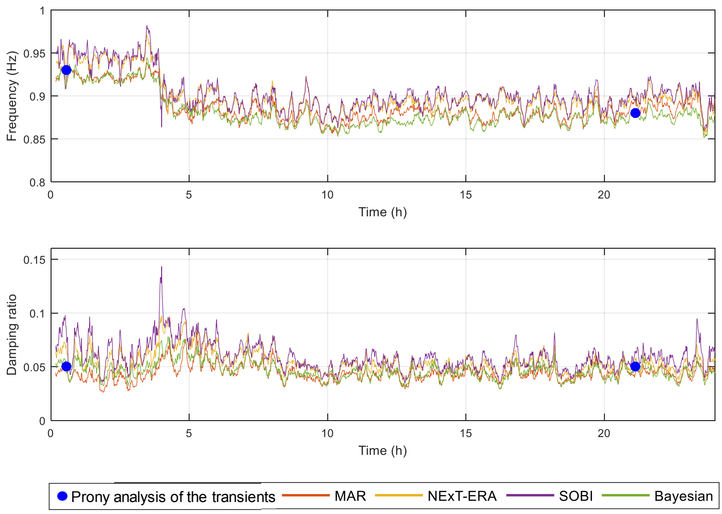

Figure 19. Modal analysis results of the 24-hour data set collected from the grid of Northern Finland and Norway. The blue dots show the results of the Prony analysis of the transients (i.e., reference values for frequency and damping, Section 3.1.2).

The results in Figure 19 indicate that the frequency of the dominant mode remains rather constant during the analyzed period. The damping ratio has slightly higher variations than the frequency. This is rather typical for the transmission system of Northern Finland and Northern Norway. In addition, the results in Figure 19 show that the modal identification results are consistent with the results of the Prony analysis of the transients (presented in Section 3.1.2). This indicates that each method gives rather accurate and consistent results for the analyzed data set.

4. Towards Practical Applications

Experiences in using ambient modal analysis methods for monitoring real power systems have not been widely reported in the literature. However, obtaining practical experiences in using modal identification methods is of high importance for TSOs. This chapter presents observations and practical experiences in using certain ambient modal identification methods for monitoring real power systems.

4.1 Experiences in Using Two Different Modal Analysis Methods for Real-Time Oscillation Monitoring

4.1.1 Used Methods

Publication V shows experiences in using two ambient modal identification methods for the monitoring of electromechanical modes in the Nordic power system: MAR method and a Wavelet based method. The MAR method is described in Section 2.1 and the Wavelet method (proposed by J. Turunen *et al* [2], [26], [27]) is briefly described below.

The Wavelet method [2], [26], [27] is a univariate method. It is based on the Continuous Wavelet Transform (CWT) and Random Decrement Technique (RDT). The method is schematically presented in Figure 20. CWT is an effective method of extracting information of a signal in both the time and frequency domain. The CWT of a signal $y(t)$ is calculated by computing the wavelet coefficients $C(a,b)$ at different scales a and positions b:

$$C(a,b) = \int_{-\infty}^{\infty} y(t) \frac{1}{\sqrt{a}} \Psi^* \left(\frac{t-b}{a}\right) dt \tag{48}$$

where Ψ is a real wavelet function in case of the real CWT and a complex wavelet function in case of the complex CWT.

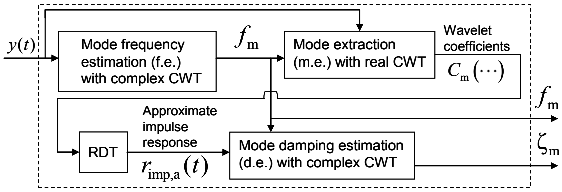

Figure 20. Block diagram of the damping estimation method based on wavelet transform and random decrement. CWT is continuous wavelet transform and RDT is random decrement technique. Input $y(t)$ is the analyzed signal, and outputs f_{m} and ζ_{m} are the estimated mode frequency and damping, respectively. [2]

The CWT is used in the mode frequency estimation and extraction of the mode from the measured signal. The RD technique is then applied to the extracted single-mode ambient response to produce the approximate single-mode impulse response of the system. The damping estimate is finally calculated from the approximate impulse response by first wavelet transforming it and calculating the damping from the decay of the wavelet coefficient. Complete details of the method, including selection of parameters and wavelet types are available in [2].

4.1.2 Analysis of Different Measurement Cases

In this section, two different data sets are used to analyze the performance of the Wavelet and MAR methods. The used data sets are both 24 hours long and they consist of two voltage angle difference measurements collected from Northern Finland (The measurement locations are presented in Figure 15 in Section 3.1.2. However, the measurement cases are different from the measurements used in Section 3.1.2 and 3.2.2.). The first measurement, where the analyzed oscillations are clearly observable, is used as an input to the Wavelet method (univariate), and both measurements are used as inputs to the MAR method (multivariate). The analysis is performed using a 15-minute sliding estimation window that is updated in 1-minute intervals. The analysis approach corresponds to real-time analysis of the data.

Measurement Case 1

In the first measurement case, ambient PMU data from normal operating conditions of the Northern Finland Northern Norway grid are used to analyze the performance of the Wavelet and MAR methods. Figure 21 presents the modal identification results for the data. The dominant electromechanical mode is rather well observable in the analyzed data set and the grid topology remains the same during the analyzed period. The analyzed mode is the 0.8 Hz electromechanical mode, where the generators of Northern Finland and Northern Norway oscillate against the rest of the Nordic system (more information regarding the 0.8 Hz mode is presented in Section 3.1.2).

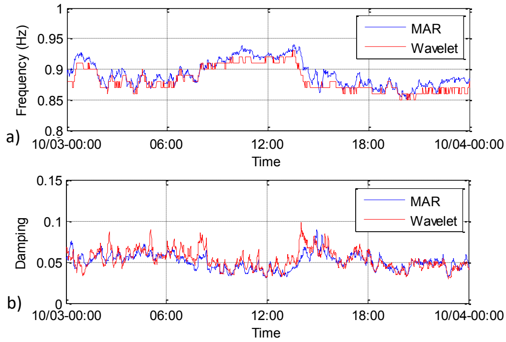

Figure 21. a) Oscillation frequency estimates and b) damping ratio estimates of the Measurement Case 1 (real-time ambient data set) using a sliding analysis window.

As Figure 21 shows, the oscillation frequency and damping ratio estimates of the Wavelet and MAR methods are rather coherent during the analyzed 24-hour period. Both methods indicate that the frequency of the dominant oscillatory mode remains around 0.9 Hz (this is rather typical for the analyzed mode). The damping ratio estimates vary in the range of 3–10 % and there is also a clear correlation between the damping ratio estimates given by the two methods. Thus, both methods yield consistent results in this measurement case, where the analyzed mode is clearly observable.

Measurement Case 2

In the second case, the Wavelet and MAR methods are applied to analyze an ambient PMU data set measured during a period when the system topology changed significantly two times. These changes in the topology and operating conditions have a significant effect on the modal properties of the system. Figure 22 presents the results of the analysis. Similarly as in Measurement Case 1, the analyzed electromechanical mode is the 0.8 Hz mode, but in addition to this mode, there are also certain forced oscillatory modes present in the data.

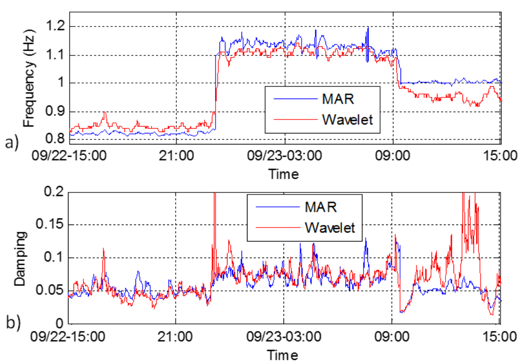

Figure 22. a) Oscillation frequency estimates and b) damping ratio estimates of the Measurement Case 2 (real-time ambient data set with two changes in the grid operating conditions) using a sliding analysis window. The operating conditions of the grid change at around 23:00 and 09:00.

Figure 22 shows that the oscillation frequency estimates given by the Wavelet and MAR methods are rather coherent during the analyzed period. However, there are some differences in the estimates especially in the end part of the analysis. Correspondingly, the damping ratio estimates have a clear correlation at the beginning of the analysis, but the correlation decreases in the end of the analysis. To investigate the reasons for the differences between the estimates given by the two methods, Fourier spectrums were calculated from the beginning, central, and end part of the data set, and they are presented in Figure 23.

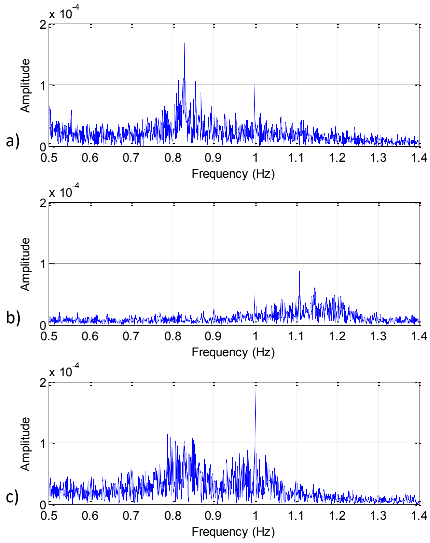

Figure 23. Spectrum of the first angle difference signal (in radians) at the a) beginning of the data set (around 18:00), b) central part of the data set (around 03:00) and c) end of the data set (around 12:00).

As Figure 23 indicates, the electromechanical mode around 0.8–0.9 Hz is dominating the spectrum in the beginning part of the analyzed data set. In the central part, the observability of electromechanical modes becomes poor. Instead, there is a forced mode around 1.1 Hz (the sharp peaks in the spectrum correspond to forced modes). In the end part, there is a strong forced mode at 1 Hz, and poorly observed electromechanical modes.

Figure 23 gives an explanation to the behavior of the modal estimates given by the Wavelet and MAR methods. In the first part of the analyzed data, the electromechanical mode is clearly observable and both methods are able to estimate it accurately. Instead, especially in the end part of the data set, the MAR method mainly estimates the modal properties of the forced mode, whereas the Wavelet method gives estimates at frequencies between the forced mode and the electromechanical mode.

4.2 Using Supporting Methods in the Modal Analysis

4.2.1 Introduction

As shown in Section 4.1.2, real measured quantities from a power system may often include several modes (i.e., inter-area modes, local modes or forced modes) and the modal characteristics of the system may change rather quickly in certain cases. Modal identification methods often try to identify a certain mode continuously even though the mode might occasionally vanish or reappear in the system or its characteristics might change significantly. Under such conditions, the power system operators may have difficulties in interpreting the modal identification results and supporting methods may be needed to help in the interpretation of the results.

Publication V and VI show that spectral analysis methods can be used as diagnostic tools for interpreting the results given by the modal identification methods, and thus, identifying the oscillatory properties of the system and their variation as a function of time. For example, a spectrogram can reveal and visualize when the system has oscillations and clearly show the frequencies of the different modes as presented in Publication VI. Spectrograms can be also used in assessing the accuracy of the modal identification methods and their other properties, for example how quickly the methods detect new oscillatory states. This section presents experiences in using spectrograms as supporting tools to analyze electromechanical modes.

4.2.2 Using Spectrograms Together with Ambient Modal Identification Methods

A spectrogram is an intuitive and visual way of representing oscillations in the signals at different frequencies and time instances. It often includes three-dimensional information with time at x-axis, frequency at y-axis, and amplitude represented by a color. The spectrogram is based on the Short Time Fourier Transform (STFT). More details regarding the use of spectrograms are presented in Publication VI and [5].

This section analyses the dynamic characteristics of the power system in Northern Norway and Northern Finland in two cases, where the operating conditions of the grid are significantly different. Similarly as in Section 4.1.2, voltage angle difference measurements from the locations shown in Figure 15 are used for the analysis. In both cases, spectrograms are used to explain variations in frequency and damping estimates of the modal identification methods.

In this section, the modal estimates are calculated using three methods: Wavelet (described in Section 4.1.1), MAR (Section 2.1) and NExT-ERA (Section 2.2). The presented modal estimates (frequency and damping ratio) are finally computed as median of the estimates given by the three modal identification methods.

Case A

In Case A, the grid of Northern Norway and Northern Finland is in ring operation as explained in Section 3.1.2 and the power flow is from Northern Norway to Northern Finland. As discussed in Section 3.1.2, in such operating conditions, the generators in Northern Norway and Northern Finland typically oscillate against the rest of the Nordic power system at around 0.8 Hz frequency and the 0.8 Hz mode is often rather well observable.

Case A represents an operating situation where the mode frequency decreases slightly and the mode becomes slightly more observable as a function of time. A spectrogram of this case is presented in Figure 24 a), together with the corresponding frequency estimate (median of the Wavelet, MAR and NExT-ERA). Figure 24 b) presents the corresponding damping ratio estimate (median of the Wavelet, MAR and NExT-ERA).

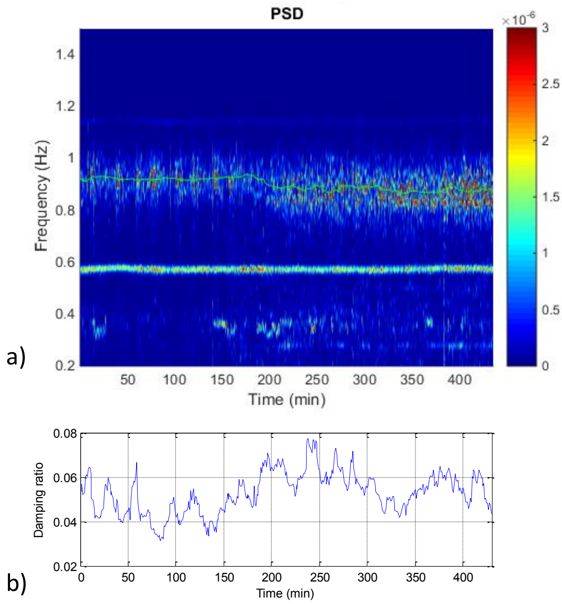

Figure 24. a) Spectrogram for Case A with the median frequency estimate from the three modal identification methods added (the green line). PSD = Power Spectral Density. Unit of the PSD, and thus, the color scale is rad^2/Hz. b) Damping ratio estimate (median of the three methods).

As presented in Figure 24 a, the estimated frequency follows the change in the modal frequency accurately, which indicates that the methods are able to identify the correct system mode. This also gives more certainty in the damping ratio estimation. In addition to the electromechanical system mode at 0.8–0.9 Hz, there is a forced oscillatory mode in the grid at approximately 0.6 Hz. The methods, however, are not disturbed by this mode since it is situated at clearly lower frequencies than the estimated electromechanical mode. Figure 24 b) shows that the identified damping ratio of the electromechanical mode varies in the range of 3–8 %.

Case B

In Case B, the 220 kV grid (see Section 3.1.2 for more details) is initially in ring operation and, as in Case A, the power flow is from Northern Norway to Northern Finland. The ring is opened at a time instant around 360 minutes and the Northern Finland grid is separated from the Northern Norway grid. At around 960 minutes, the ring is reconnected but now the direction of the power flow is from Finland to Norway.

The spectrogram together with the corresponding frequency estimate is presented in Figure 25 a). Furthermore, Figure 25 b) presents the corresponding damping ratio estimate. The frequency and damping ratio estimates are calculated as median of the estimates given by the Wavelet, MAR and NExT-ERA methods (similarly to Case A).

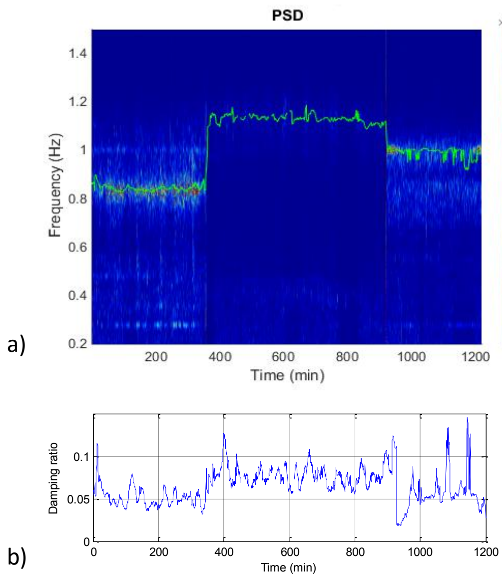

Figure 25. a) Spectrogram for Case B with the median frequency estimate from the three modal identification methods added (the green line). PSD = Power Spectral Density. The unit of the PSD, and thus, the color scale is rad^2/Hz. b) Damping ratio estimate (median of the three methods).

Again, the estimated mode frequency tracks the changes in the oscillation frequency very well. At the beginning (in the ring operation, 0–360 minutes) the estimators discover the 0.8 Hz system mode, after the disconnection (360–960 minutes) they identify weak oscillations at around 1.15 Hz, and after the reconnection into the ring operation (960–1200 minutes) they see the rather strong oscillations at 1 Hz. In general, the spectrogram clearly shows how the oscillations almost vanish from the system when the connection between the grids in Northern Finland and Northern Norway is disconnected and illustrates how the oscillations reappear after reconnecting the ring. Furthermore, Figure 25 b) shows clear variation in the damping ratio of the estimated mode. Thus, the operating conditions of the system have a very significant effect on the damping ratio as well as the frequency of the mode.

5. Summary

5.1 Conclusions

The research work presented in this thesis can be roughly divided in two research directions. The first is the development of new ambient modal identification methods for the monitoring of electromechanical modes. The second direction is the presentation of experiences and comparisons of using different methods including additional tools for analyzing real modes. The main contribution lies in the development of new modal identification methods. The proposed methods are: Multivariate autoregressive model (MAR) method, Natural Excitation Technique – Eigensystem Realization Algorithm (NExT-ERA) method, Second Order Blind Identification (SOBI) based method and Bayesian method. The proposed methods are multivariate (i.e., they use several measurement signals collected from the power system for the modal identification) and they aim to identify the modal characteristics of the studied power system from ambient measurements.

This thesis showed that the proposed methods are functional for real-time monitoring as well as offline analyses of the modes. The performance and characteristics of the methods were studied using different simulated data sets as well as real measured data from the Nordic power system. Each method has certain benefits, and thus, the most suitable method can be selected for a particular application.

Furthermore, the thesis showed that different modal analysis methods often yield similar modal identification results when the identified modes are well observable in the measurements. However, if the observability of the modes is poor, or there are for example forced modes present in the data, different methods may produce conflicting estimates. Also, if the characteristics of the studied system change rapidly, the estimates given by the methods may not be coherent. Thus, in certain cases, the interpretation of the modal analysis results might be difficult.

Due to reasons discussed above, the thesis also highlighted the need of using additional tools, such as spectral analyses, which might significantly help the interpretation of modal identification results. Spectrograms, for example, can illustrate how changes in the system conditions affect the oscillation characteristics and reveal the presence of forced modes. By combining spectral information with damping and frequency information given by modal identification methods, abnormal system conditions can be detected more reliably and the system operators warned of these conditions.

The methods presented in this thesis can be used as building blocks for TSOs to create functional applications for real-time and offline modal analysis of power systems. Modal identification methods can be applied to several different purposes, such as real-time monitoring and offline analyses of the modes, validation of simulation models, identifying components and operating conditions that have an effect on the modal characteristics, detecting power system events, and finding the root causes of certain events and phenomena in the system. In general, real-time monitoring and offline analyses of the modes can improve the situational awareness and enhance the knowledge of the system dynamic characteristics. Consequently, such information may improve the security and reliability of power systems of the future.

5.2 Discussion and Future Work

As shown by the results of this thesis, the presented modal identification methods are functional for identifying electromechanical modes from ambient data. However, before taking the methods to real-time use in power system control centers it is important to test their characteristics with real data collected from the power system. It is recommended to use large data sets (i.e., several months) to investigate the performance of the methods in various different operating conditions. During such tests, it is useful to compare the performance of several methods running in parallel and investigate the different characteristics of the methods. It may be also beneficial to keep multiple instances of a specific method with different parameters running in parallel to find out the effect of different parameters to the method's performance.

Before taking modal identification methods to real-time use, it is also important to organize training sessions for system operators, where different characteristics and limitations of the methods are discussed. It is recommended to use additional tools, such as spectrograms, to help the interpretation and visualization of the modal identification results.

In the future, it is important to create functional applications, where modal identification methods are combined with additional tools. It is paramount that the modal identification results can be presented in a clear context so that the interpretation of the results is easy and the results can be considered reliable. Reliability of the identification results can be improved for example by using several identification methods in parallel. Utilizing the uncertainty information of the modal properties given by certain methods is also beneficial in improving the reliability of the modal identification.

Indeed, if transmission system operators plan to take actions based on the modal identification results, it is highly important that the results are reliable. Thus, the future work should focus on making modal identification methods more reliable in all operating conditions and robust for special situations, such as PMU malfunctions or communication system failures. Furthermore, the future research should investigate, how the uncertainty information of the modal properties can be incorporated in interpretation of the modal identification results, and consequently, the decision-making processes of the power system operators.

The methods presented in the thesis, as well as most existing methods, assume time-invariant properties of the power system during the analysis period. However, as shown in the thesis, the properties of the system might occasionally change rapidly and rather unpredictably. Use of methods that can deal with time-varying models, could be beneficial in such conditions. Thus, the future research should also focus on developing methods that are able to assume time-varying models in modal identification.

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Electromechanical oscillations are constantly present in power systems. The oscillations are excited by changes in the system, such as disturbances and changes in the loads and generation.

The damping of the oscillations is the limiting factor for the transmission capacity of certain transmission corridors. Moreover, in the most severe situations, unstable oscillations may lead to local blackouts or even to the collapse of the entire system. Therefore, it is important to monitor the characteristics of the oscillations.

In this thesis, four new methods for the real-time monitoring and identification of the electromechanical oscillatory modes are presented. In addition, the thesis illustrates tools that can be used to support the modal identification in real power systems. Transmission system operators can use the methods presented in this thesis as building blocks to create applications for the monitoring of electromechanical modes.

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