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Models and Algorithms for Low-Frequency Oscillations in Power Transmission Systems

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by

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Danksagung

„Wenn sich jemand herzlich bei mir bedankt, so ist mir, als hätte ich ihm einen Pfennig gegeben und er sagte Gotteslohn dafür."

— William Shakespeare

Während meiner Tätigkeit als wissenschaftlicher Mitarbeiter am Lehrstuhl Computergestützte Statistik der Fakultät Statistik an der Technischen Universität Dortmund entstand diese Dissertation.

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Im Umfeld meiner Arbeit im Mathetower habe ich eines meiner liebsten Hobbys entwickelt, das sportliche Freiklettern. Meine Freunde an der Steilwand haben immer eine Hand am Seil und halfen mir meinen Kopf frei zu kriegen. Sie bestärken mich besonders in Situationen, durch die ich über mich hinaus wachse. Ich danke euch allen, die ihr mit mir über Seil verbunden seid.

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Dortmund, Oktober 2018
Dirk Theodor Surmann

Abstract

Energy supply in the European power transmission system undergoes a structural change due to expansion and integration of renewable energy sources on a large scale. Generating renewable energy is more volatile and less predictable because it usually depends on the weather like wind and sun. Furthermore, the increase in power trading as a result of the full integration of national electricity markets into the European transmission system additionally burdens the power network. Higher volatility and increasing power trading consume additional resources of existing transmission lines while construction projects for network extension take a huge amount of time. As a consequence, the available resources within the European network have to be utilised efficiently and carefully. Reducing the security margins of components in power networks leads to higher vulnerability to additional problems.

This thesis focuses on two topics with the aim of supporting power transmission systems stability. Firstly, selecting an optimal subset of nodes within a power network with respect to the particular issue of Low-Frequency Oscillation is addressed. A common application is the optimal placement of measurement devices within a power network. By integrating the modelled oscillations as a preprocessor into the algorithm, the constructed subset includes their characteristics and is optimal to measure this type of oscillation.

Secondly, simulation software is widely applied to power networks generating data or investigating the potential effects of changed device parameters. The state of the art way manually defines test scenarios to investigate effects. Each test scenario challenges the corresponding transmission system by, e. g. changing device parameters, increasing its power consumption, or disconnecting a transmission line. Instead of relying on the manual generation of test scenarios to check the network behaviour for modified or new components, it is advantageous to employ an algorithm for building test scenarios. These mechanisms ensure that the range of operating conditions is covered and at the same time propose challenging test scenarios much better than manually generated test scenarios. Black box optimisation techniques support this process by exploring the possible space for test scenarios using a specialised criterion.

This cumulative dissertation comprises a summary of six papers which deal with modelling of Low-Frequency Oscillations and with the prediction of corresponding values at unobserved nodes within a power transmission system. I will present two published R packages we implemented to simplify the above process. Applying graph kernels in combination with evolutionary algorithms addresses the node selection task. Issues in multimodal optimisation are addressed using contemporary techniques from model-based optimisation to efficiently identify local minima.

Contents

1 Introduction

> *"We are, as it were, dwarfs perched on the shoulders of giants, to see more and farther than they did."*
>
> — Bernard of Chartres

Technical Background

Energy supply in the European power transmission system undergoes a structural change. One factor within the power network is the expansion and integration of renewable energy sources with low emissions on a large scale (European Network of Transmission System Operators for Electricity (ENTSO-E) 2014). For instance, power generation from offshore wind parks, has to be transmitted into the interior of the country to cover the need for electrical power. Furthermore, the generation of renewable energy is more volatile and less predictable compared to classical power plants because it depends on the weather. Another reason is the central aim of the European Union to fully integrate national electricity markets into the European transmission system (Meeus et al. 2011). Increasing power trading ranges from auctioning of yearly cross-border capacities up to the reaction to intraday power generation and consumption across countries (Müller 2015). Higher volatility and power trading require increasing transmission capacities of electrical systems. However, the current network capacity is limited. Its expansion by network construction projects will take decades. For this reason the available European network has to be utilised efficiently to integrate renewable energies and enable a transition to a fully integrated market. This results in smaller operational reserves of the transmission lines and other components of the electrical system leading to different problems such as overloads or line breakdowns. By reducing the security margins of all components to manage higher loads in the electrical system, the electrical system is more vulnerable to additional difficulties. Higher susceptibility can cause a higher risk of cascading blackouts and a more frequent usage of cold reserve to stabilise the power network. Questions and tasks in the field of power engineering were elaborated within subproject 5 'Adaptive Modelling and Realtime Identification' of the research unit FOR-1511 'Protection and Control Systems for Reliable and Secure Operation of Electrical Transmission Systems' funded by the Deutsche Forschungsgemeinschaft (DFG).

Low-Frequency Oscillation

In this thesis, I focus on the so-called Low-Frequency Oscillation (Rogers 2000) and corresponding topics. Aside from the well-known mains frequency of 50 Hz in Europe, the Low-Frequency Oscillation (LFO) describes changes in the mains frequency f. The complex voltage $U^\star$ can be formulated over time t as $U^\star(t) = Ue^{i(\omega t+\varphi)}$ with the angular frequency ω, the voltage magnitude U, and the voltage angle φ. In electrical engineering, magnitude and angle are usually denoted as amplitude and phase, respectively. The constant i represents the imaginary unit $i^2 = -1$. The angular frequency ω is related to the mains frequency f, measured in Hz, by $\omega = 2\pi f$. Stabilising the mains frequency is a central aim of the Transmission System Operators described in the Transmission Code 2007 (Berndt et al. 2007). If f differs more than 10 mHz from the target, a regularisation is carried out to guarantee a stable mains frequency of 50 Hz. Hence, the frequency ω is well controlled. The LFO can be observed in U and φ which depend on time and a mains frequency ω_{LFO} and can be written in general as $U(t; \omega_{LFO})$ and $\varphi(t; \omega_{LFO})$, respectively. Both functions U and φ contain non-linear mechanisms which differ considerably from linear theory (Li et al. 2016). Due to the fact that the mains frequency f (and accordingly ω) are well controlled, the focus of this thesis is on the Low-Frequency Oscillations. I am directly utilising $U(t)$ and $\varphi(t)$ in my analysis instead of extracting it from $U^\star(t)$.

Low-Frequency Oscillations can be interpreted as part of the energy that permanently oscillates through power transmission systems. Compared to the mains frequency of a power network it oscillates with a much lesser frequency, in most cases less than 2 Hz. Li et al. (2016, Ch. 2) describe different reasons which trigger an LFO. They point out the chain structure of transmission systems and interactions of different control devices or power generators, respectively. Among others, these factors may cause resonance mechanisms with a negative damping which can disturb the whole transmission system if it is not compensated by a stronger positive damping. Usually, LFO is divided into a local oscillation mode and an inter-area oscillation mode. The local mode focuses on oscillations between two groups of generators in a local area. Whereas, the inter-area mode represents oscillations between groups of generators in a wide-area transmission system like the European interconnected power network. Groups of generators swing against each other and restrict the available transfer capacity for power transmissions in Europe.

This thesis exclusively deals with inter-area LFOs because they have a wide impact on the European transmission system due to the fact that they last longer in time and are more difficult to damp and control (Li et al. 2016, Ch. 2). As a starting point, we derive a basic meta-model which can be used in further statistical analysis. In contrast to the widely accepted and used power simulations like `DIgSILENT PowerFactory` (DigSILENT GmbH 2013) which are capable of simulating both local and inter-area LFOs in detail, this meta-model aims at simplicity and covers only main characteristics of the inter-area LFO. Besides its simplicity, it should be interpretable by a power system engineer.

Subset Selection within Power Networks

A power network mainly consists of transmission lines and nodes or busbars. Each node can fulfil several tasks. As a power re-routing point each node can operate as a connection between different transmission lines. Generators of all types supplying power for a network can be attached to a node. Further, consumers of power in the form of loads such as cities or industry complexes can be included in a node. These three tasks, connecting transmission lines, containing a generator, or containing a load, can arbitrarily be assigned to a node. Hence, the need for power at a specific load is rarely satisfied by a generator at the same node and is mostly balanced out via generators located at different nodes using the transmission grid. Due to the fact that loads vary during a day, generators balance out the need for power and swing against each other as described above. The collection and provision of information about different electrical conditions turns out to be the central role of nodes in a transmission network. Local information is available at every node and can be combined to an overall picture which is used to identify problems in the network, for instance, overloads of transmission lines or LFO with small or even negative damping. Transmission system operators have to react very fast to these issues (Berndt et al. 2007). However, in the case of inter-area LFOs, it is necessary to comprehend the overall picture to correctly evaluate the behaviour. Applying and analysing data from all nodes can be time-consuming. On larger transmission systems like the European power network which consists of a huge number of nodes and their corresponding transmission lines, efforts in time for computation and simulation scale are at least linear. I discuss the problem to select a subset of nodes, like in experimental design (Montgomery 2012), which fulfils the need for a good overall picture from the transmission network in terms of LFOs.

Test Scenarios in Virtual Transmission Systems

Power simulation software is widely applied to study the variety of operating conditions in transmission systems. The New England Test System (NETS) (Athay; Podmore and Virmani 1997) is one of many virtual power networks to be used in simulation studies. Different types of faults on transmission lines can be simulated as well as the effect of changes in power consumption within these test systems. Furthermore, the impact of generator parameters or additional regularisation devices is investigated. Representatives are the automatic voltage regulator (AVR) and power system stabilisers (PSS) which are used in transmission networks to increase oscillation and transient stability (Dudgeon et al. 2007). One major task in this context is the stability analysis of a power network with respect to a specific subset of operating conditions. State of the art way manually defines a small number of test scenarios for each test system to cover an investigated range of operating conditions. In this case, coverage and range of operating conditions are expressed verbally, i. e., the simulation user has concepts from engineering science instead of mathematical expressions used in experimental designs to define these statements. At the same time, the scenarios are supposed to be challenging for the transmission system with respect to specific objectives projected by the scenario architect. After the successful performance of a, e. g., new regularisation device in all test scenarios, it is assumed to work well in the complete investigated region. In general, evaluation over all manual and other possible scenarios is missing. Especially, their classification is difficult because the quality or analysis targets of manual test scenarios are often not measurable. At this point, the question arises whether the manually defined scenarios actually cover the investigated region and are challenging with respect to particular objectives. This thesis examines the question how to find the most challenging test scenarios which differ among each other regarding a specific objective.

Thesis Overview

Chapter 2 provides a tabular overview of the included published articles and packages for the statistical computing software R (R Core Team 2018). Chapter 3 performs the first step to select nodes in a power network with a descriptive analysis of Low-Frequency Oscillation data of a specific virtual transmission system. Based on the observation of an oscillating power network we model the Low-Frequency Oscillations by homogeneous types of second-order differential equations. Initially, the model is used to describe data at each particular node. A sensitivity analysis investigates the robustness of connected differential equations among multiple nodes of a power network. Chapter 4 completes the selection of node task. We first discuss the prediction of unobserved nodes in a power network from a technical point of view. The chapter finishes with the selection of an optimal subset of nodes within a graph using an evolutionary algorithm. It chooses a subset which stabilises the predictions of a selected response among the corresponding network. Chapter 5 addresses the generation of test scenarios for transmission systems investigated in power simulation software. We propose a methodology to generate test scenarios according to the set of different operating conditions in a power network. The generic approach allows an extended usage of the method in different fields. Finally, in chapter 6 I summarise and discuss possible extensions and further research of the presented algorithms and methods.

2 Publication Overview

Title	Author	Published	Date	Contribution	Cha.
Auswertung von Simulationsdaten zur Analyse von Energienetzen	Surmann	TU Dortmund University	Feb. 11, 2014	I analysed the LFO and proposed the ODE model.	3.2
'Modelling Low Frequency Oscillations in an Electrical System'	Surmann; Ligges and Weihs	Energy Conference (ENERGYCON), 2014 IEEE International	May 2014	I proposed the ODE model and applied it to data with verification.	3.3
ODEnetwork: Network of Differential Equations.	Surmann	`CRAN`	2018	I created an `R` package with an interface to simulate ODE networks.	3.3
Sensitivity Analysis of Ordinary Differential Equation Models	Weber; Theers; Surmann; Ligges and Weihs	TU Dortmund University	May 23, 2018	I supervised students adapting sensitivity analysis to ODE models.	3.4

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Title	Author	Published	Date	Contribution	Cha.
ODEsensitivity: Sensitivity Analysis of Ordinary Differential Equations	Weber; Theers and Surmann	`CRAN`	2018	I supervised students creating an `R` package to support the former task.	3.4
'Predicting Measurements at Unobserved Locations in an Electrical Transmission System'	Surmann; Ligges and Weihs	Computational Statistics	May 24, 2017	I derived a method utilising kernels to predict unobserved nodes in graphs.	4
'Optimal Node Subset with Minimal Graph Kernel Prediction Error in an Electrical Transmission System via Evolutionary Algorithms'	Surmann; Ligges and Weihs	Electric Power Systems Research (under review)	2018	I established an algorithm to optimise a subset of nodes within a network.	4
'Infill Criterion for Multimodal Model-Based Optimisation'	Surmann; Ligges and Weihs	arXiv	Oct. 4, 2018	I defined a new infill criterion to efficiently identify local minima.	5

3 Modelling Oscillations

> *"Conducting data analysis is like drinking a fine wine. It is important to swirl and sniff the wine, to unpack the complex bouquet and to appreciate the experience. Gulping the wine doesn't work."*
>
> — Daniel B. Wright

3.1 Contributed Material

SURMANN, Dirk (Feb. 11, 2014): *Auswertung von Simulationsdaten zur Analyse von Energienetzen*. Technische Universität Dortmund. DOI: 10.17877/DE290R-432

SURMANN, Dirk; LIGGES, Uwe and WEIHS, Claus (May 2014): 'Modelling Low Frequency Oscillations in an Electrical System'. In: *Energy Conference (ENERGYCON), 2014 IEEE International*. Dubrovnik, Croatia: IEEE, pp. 565–571. DOI: 10.1109/ENERGYCON.2014.6850482

SURMANN, Dirk (2018): *ODEnetwork: Network of Differential Equations.* R package Version 1.3.1. URL: https://cran.r-project.org/package=ODEnetwork

WEBER, Frank; THEERS, Stefan; SURMANN, Dirk; LIGGES, Uwe and WEIHS, Claus (May 23, 2018): *Sensitivity Analysis of Ordinary Differential Equation Models*. Technische Universität Dortmund. DOI: 10.17877/DE290R-18874

WEBER, Frank; THEERS, Stefan and SURMANN, Dirk (2018): *ODEsensitivity: Sensitivity Analysis of Ordinary Differential Equations*. R package Version 1.1.1. URL: https://cran.r-project.org/package=ODEsensitivity

3.2 Visualising Results from Power Simulations

Identifying Low-Frequency Oscillation in data is challenging, since it is superimposed by the mains frequency of 50 Hz. Hence, we aim at revealing this information from corresponding data. Phasor measurement units (PMU) provide the required information. However, only very few PMUs are available in the European transmission grid, since data are rather incomplete. For this reason, data used in this thesis are based on the well-established and widely used power simulation system `DIgSILENT PowerFactory` (DIGSILENT GMBH 2013). SURMANN (2014) describes the approach of using power simulation in detail to generate data with an included LFO. The New England Test System (NETS) described by ATHAY; PODMORE and VIRMANI (1997) is used within `DIgSILENT PowerFactory` to investigate LFOs. Usually, a combination of events, such as line take outs, increase of power consumption, or changes in power generation excites the network from its steady state to generate dynamic data. We choose events which do not modify the network topology, for instance, a modification of power consumption of one or multiple loads for a short time. Results are presented as complex voltage over time at each node of the power network where a transient time interval of 20 s after the excitation is skipped because we are interested in the inter-area LFO. Figure 3.1 shows the voltage angle illustrated by the node size at two fixed time points. Between node group A

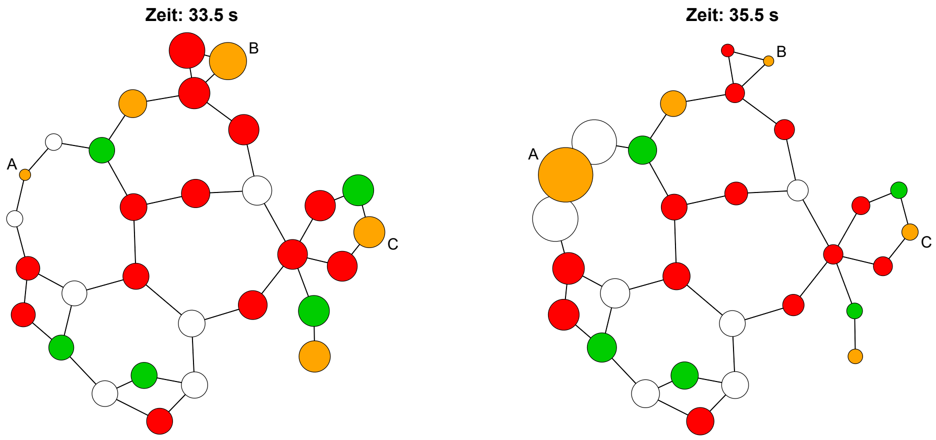

Figure 3.1: Visualisation of oscillating voltage angle in the NETS at 33.5 s on the left side and 35.5 s on the right side. Both figures are taken from Surmann (2014).

and groups B and C we observe an oscillation between the time points 33.5 s and 35.5 s. The most extreme values shown in figure 3.1 have a time lag of roughly 2 s. At 33.5 s node group A reaches its minimum, whereas groups B and C increase and at 35.5 s the opposite is true. Nodes in the centre of the network are independent of the influence of the LFO, visualised by the almost equal size of the corresponding nodes. In general, LFOs interact with all nodes but are only recognised at a few nodes within the transmission grid.

The mains frequency of the LFO is estimated retrospectively, and turns out to be 0.17 Hz within the NETS. It is independent of the excitation method or intensity and depends only on the topology of the given network.

3.3 Modelling Low-Frequency Oscillations

Based on the findings in section 3.2 Surmann; Ligges and Weihs (2014) propose to model LFOs by connected harmonic oscillators. The mechanical representation is a pendulum consisting of a mass m which is linked to a fixed point via a spring with spring constant k and a length r together with a damper with damping constant d. From the physical point of view, a harmonic oscillator converts potential energy into kinetic energy and vice versa. The damper removes energy from the system creating a damping force. We describe the oscillator by Newton's first law of motion which balances the restoring force generated by the spring and the damping force resulting in an accelerated or decelerated mass. The behaviour of an LFO in each node is characterised by a single harmonic oscillator.

Modelling oscillations within a power network by a model of connected harmonic oscillators is a further idea by Surmann; Ligges and Weihs (2014). We realise connections between single oscillators via an additional combination of a spring and a damper. An example with four masses connected in a row is shown in figure 3.2. The model provides a single harmonic

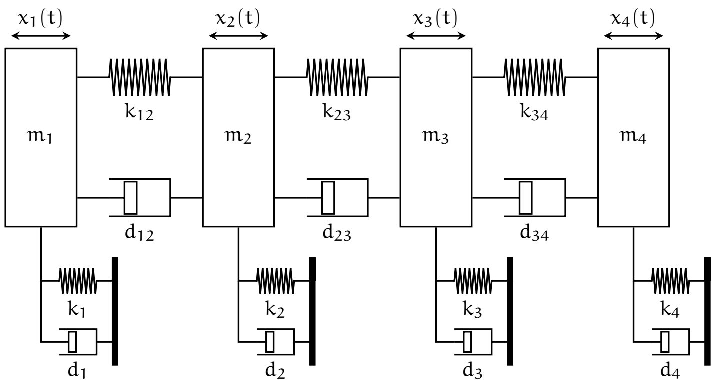

Figure 3.2: Example of four mechanical oscillators connected in a row via additional springs and dampers. Figure is taken from Surmann; Ligges and Weihs (2014).

oscillator for each node inside the transmission grid. The entire network topology, mainly consisting of transmission lines between nodes, is reflected by a combination of springs and dampers between the masses of harmonic oscillators. Mathematically, an ordinary differential equation (ODE) can be summarised in matrix notation as in equation (3.1).

$$0 = \mathbf{M}\ddot{x}(t) + \mathbf{D}\dot{x}(t) + \mathbf{K}x(t) + b \tag{3.1}$$

The vector $x(t) = \big(x_1(t), \dots, x_n(t)\big)^\top \in \mathbb{R}^n$ describes the position of each mass 1 to $n \in \mathbb{N}^+$. Its first and second derivatives with respect to time reflect velocity and acceleration. The matrix $\mathbf{M} = \operatorname{diag}(m_1, \dots, m_n)$ is diagonal with the masses on its main diagonal. All damping and spring constants are summarised in the matrices $\mathbf{D}, \mathbf{K} \in \mathbb{R}^{n \times n}$ with $\mathbf{D} = (d^*_{ij})_{i,j=1,\dots,n}$ and $\mathbf{K} = (k^*_{ij})_{i,j=1,\dots,n}$, respectively. This construction implies $d_{ij} = d_{ji}$ and $k_{ij} = k_{ji}$, thus both matrices are symmetric. The vector $b = \big(b_1, \dots, b_n\big)^\top \in \mathbb{R}^n$ contains the constants of each equation. If $b \neq 0$ equation (3.1) describes an inhomogeneous differential equation. The elements of $\mathbf{D}$, $\mathbf{K}$ and b are derived by rewriting the differential equations for each mass. Equation (3.2) defines the elements of $\mathbf{D}$.

$$d^*_{ij} \coloneqq \begin{cases} -d_{ij} & \text{if } i \neq j \\ d_i + \sum\limits_{j \neq i} d_{ij} & \text{if } i = j \end{cases} \tag{3.2}$$

The damping constant d_i is the connection of the i-th mass to the fixed-point (see figure 3.2). The elements of the spring matrix $\mathbf{K}$ are derived in the same way. Vector b characterises the constant term in the differential equation and is given by the following equation.

$$b_i = -k_i r_i + \sum_{j \neq i} k_{ij} r^*_{ij} \quad \text{with} \quad r^*_{ij} = \begin{cases} r_{ij} & \text{if } i < j \\ r_{ji} = -r_{ij} & \text{if } i > j \end{cases} \tag{3.3}$$

Note that the length from the second mass to the third is r_{23}, whereas $-r_{23}$ is the length in the opposite direction. An alternative model is an electrical RLC circuit consisting of a resistor (R), an inductor (L), and a capacitor (C) leading to an equivalent type of differential equation as shown in equation (3.1). The analytical solution is derived and discussed with regard to the application within a transmission grid. We define a penalty term to ensure a unique solution of the given system of equations.

Fitting a single harmonic oscillator to the LFO data points out the good modelling behaviour of the proposed model across all particular nodes. One purpose is the possibility to interpret the parameters of the harmonic oscillators. Due to the fact that the oscillation frequency can be calculated by the formula $f_i = \frac{1}{2\pi}\sqrt{\frac{k_i}{m}}$, we can directly check the estimated spring constants k_i. The paper emphasises correct estimations of the spring constants, leading to a correct mains frequency of about 0.17 Hz. Furthermore, it is possible to check the damping of each node via the damping constant. Each node in the used test system is positively damped which is central in the discussion by Li et al. (2016). Finally, the estimated value of the spring length r_i can be interpreted as the level of applied voltage magnitude (amplitude) or angle (phase).

In the last part of the paper, we fit a model of connected oscillators to the data and verify it by means of power simulations. The model fits well to the data and estimated parameters can be interpreted in a satisfying way. It is possible to obtain the effects of damping between two nodes i and j via the corresponding damping constant d_{ij}. Each connecting spring constant k_{ij} between nodes i and j can be interpreted as their mutual influence on each other. The spring length r_{ij} reflects the difference between levels of voltage of two nodes. To verify the model of connected oscillators, Surmann; Ligges and Weihs (2014) insert an additional excitation event 80 s after the initial event into both simulations, namely power simulations and the model by the harmonic oscillators described above. In each test scenario with additional excitation events at different and scattered nodes, the similarity between power simulation and model is insufficient over time. Data from the harmonic oscillator model start diverging after the additional event from power simulation in magnitude and frequency and show a deficient fit of the model with connected oscillators.

An encompassing framework for modelling networks of second-order differential equations is available in the `R` package `ODEnetwork` by Surmann (2018). The package provides an easy to use interface to define different networks as well as necessary analysis and plot methods. `ODEnetwork` supports the analytical and numerical solution of ODE systems. It is capable of deciding which methods are suitable for the given problem. Using the numerical solution method allows the package to handle and simulate different types of interventions over time, e. g., changing the position of a mass manually.

3.4 Sensitivity Analysis of Ordinary Differential Equations

The poor fit of the connected harmonic oscillators to the power simulation in section 3.3 raises the demand to check the robustness of the model. Based on a master thesis and student work that I supervised, WEBER; THEERS; SURMANN, et al. (2018) perform a sensitivity analysis to investigate robustness. Major concern of sensitivity analysis is the examination of effects of variations in the input variables $\mathbf{x} = (x_1, \ldots, x_n)^\top$ to a response of a mathematical function f. Identifying relevant model inputs is incorporated as well as learning about the model robustness (CONFALONIERI et al. 2010). The fundamental idea of sensitivity analysis is to generate an adequate variation in the input variables to extract the corresponding influences on the response from the data received. WEBER; THEERS; SURMANN, et al. (2018) describe the statistical preliminaries of MORRIS screening (MORRIS 1991) and SOBOL's sensitivity analysis (SOBOL 1990) in the first part of the paper. MORRIS screening is a local method based on partial derivatives of the response with respect to an input variable x_i. It is called local because the derivatives are computed at a fixed vector $\mathbf{x}_0$ in the input domain. Partial derivatives are called elementary effects and are calculated via a difference quotient for each input variable. A one factor at a time (OFAT) design around $\mathbf{x}_0$ is used to generate corresponding data for this calculation. SOBOL sensitivity analysis follows a different key concept which is based on decomposing the variance similar to an ANOVA. The method is able to estimate interaction sensitivity indices in addition to the elementary effects, and hence allows a better interpretation model. Providing a reliable database for the variance decomposition, SOBOL defines a probability distribution for each input variable along their domain. A Monte Carlo method generates feasible data to calculate the SOBOL sensitivity indices. SALTELLI; CHAN and SCOTT (2010) discuss sensitivity analysis from a more general point of view.

Subsequently, the authors apply both sensitivity methods to the connected model described in section 3.3 for the Low-Frequency Oscillations. The comprehensive code which handles the ordinary differential equations in combination with a sensitivity analysis is provided in the `R` package `ODEsensitivity` by WEBER; THEERS and SURMANN (2018). It is based on the `R` packages `sensitivity` by BERTRAND; ALEXANDRE and GILLES (2018) and `ODEnetwork` by SURMANN (2018). The former package provides all necessary sensitivity methods whereas the latter contains an interface to connected second-order differential equations. WEBER; THEERS; SURMANN, et al. (2018) perform an extensive analysis of a sample with 4 connected harmonic oscillators similar to figure 3.2. MORRIS and SOBOL's methods are calculated and the corresponding sensitivity indices are visualised and interpreted. Results of both methods applied to the LFO model lead to different interpretations. MORRIS' method shows a decreasing influence of spring constants

k_1 and k_3 whereas Sobol's method shows an increase in the corresponding Sobol indices. An expansion of the connected model would increase the issues described by Surmann; Ligges and Weihs (2014) exponentially because the number of connected oscillators increases from 4 to 30 for the New England Test System. The authors conclude to use sensitivity analysis of ordinary differential equations in an explorative way and carefully interpret results. Consequently, we utilise the proposed model to fit data of observed LFOs at each node separately instead of applying the model to data from the transmission grid as a whole. The estimated local parameters from each single node in the power network are interpretable with respect to section 3.3 and reflect the oscillation behaviour in a condensed way.

4 Optimal Subsets within Network Graphs

> *"Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful."*
>
> — George E. P. Box

4.1 Contributed Material

Surmann, Dirk; Ligges, Uwe and Weihs, Claus (May 24, 2017): 'Predicting Measurements at Unobserved Locations in an Electrical Transmission System'. In: *Computational Statistics*. issn: 1613-9658. doi: 10.1007/s00180-017-0734-2

Surmann, Dirk; Ligges, Uwe and Weihs, Claus (2018b): 'Optimal Node Subset with Minimal Graph Kernel Prediction Error in an Electrical Transmission System via Evolutionary Algorithms'. In: *Electric Power Systems Research*. (under Review)

4.2 Measurement Prediction in Power Networks

Phasor measurement units (PMU) are devices capable of measuring 50 Hz waveforms in power transmission systems. Variations in the form of Low-Frequency Oscillations can be extracted from these measurements. Time synchronization ensures the comparability of multiple remote PMUs in the network. It is possible to install PMUs at each node within a power network to compare LFOs and create an overall picture of the inter-area LFO. According to the state of the art technology, only a few PMUs are accessible and spread over the European transmission grid. Surmann; Ligges and Weihs (2017) investigate the arising question how to predict LFOs at unobserved nodes using available measurements.

Based on the data and analysis described in chapter 3, Surmann; Ligges and Weihs (2017) use a single harmonic oscillator at each node to estimate a representative parameter set for a given network. Fitting this model reduces oscillation at each node according to the damping constant d, the spring constant k, and the spring length r. The first parameter can be interpreted as the energy which disperses from the LFO and damps the oscillation. The spring constant describes the oscillation frequency and parameter r represents the applied voltage. Due to the fact that parameters between nodes are not modelled in a joined model although they are highly correlated, we take advantage of the spatial structure of each power transmission system. Firstly, the represented parameter set is modelled across the neighbourhood of a node via a linear model $\mathbf{y} = \mathbf{Z}\boldsymbol{\gamma} + \boldsymbol{\varepsilon}$ with observation vector $\mathbf{y} = (y_1, \ldots, y_n)^\top$ and common error vector $\varepsilon \sim \mathcal{N}\left(0, \sigma^2 \mathbf{I}\right)$. An element z_{ij} of the matrix $\mathbf{Z}$ is 1 if y_i is observed at node j and 0 otherwise. Adapting the penalised least squares criterion to the situation at hand results in smoothed spatial effects across the network. Imposing a penalty on the estimated coefficients smooths them across neighbouring nodes. This reflects the similar behaviour of nodes within regions. The penalised least squares estimator results in $\hat{\boldsymbol{\gamma}} = \left(\mathbf{Z}^\top \mathbf{Z} + \lambda \mathbf{K}\right)^{-1} \mathbf{Z}^\top \mathbf{y}$. It minimises the penalised least squares criterion with parameter λ. The matrix $\mathbf{K}$ represents the neighbourhood structure of the power network. An element on the main diagonal of $\mathbf{K}$ represents the number of neighbours. The off-diagonal elements are -1 for neighbouring nodes, and 0 otherwise.

Secondly, Surmann; Ligges and Weihs (2017) split the observed data vector $\mathbf{y}$ into data at observed nodes $\mathbf{y}_D$ and unobserved nodes $\mathbf{y}_0$. We fit the previous model with a covariance matrix $\text{Cov}\left(\mathbf{y}_D\right) = \boldsymbol{\Sigma}_D$ to the observed data. The best linear unbiased predictor is the conditional expectation E of $\mathbf{y}_0$ given $\mathbf{y}_D$ with its conditional covariance Cov given in equation (4.1) with estimated constant mean $\boldsymbol{\gamma}_0 = \bar{\hat{\boldsymbol{\gamma}}} \in \mathbb{R}$.

$$
\begin{aligned}
\text{E}\left(\mathbf{y}_0 | \mathbf{y}_D\right) &= \boldsymbol{\gamma}_0 + \boldsymbol{\Sigma}_{0D} \boldsymbol{\Sigma}_D^{-1} \left(\mathbf{y}_D - \mathbf{Z}\hat{\boldsymbol{\gamma}}\right) \\
\text{Cov}\left(\mathbf{y}_0 | \mathbf{y}_D\right) &= \boldsymbol{\Sigma}_0 - \boldsymbol{\Sigma}_{0D} \boldsymbol{\Sigma}_D^{-1} \boldsymbol{\Sigma}_{D0}
\end{aligned}
\tag{4.1}
$$

$\boldsymbol{\Sigma}_0$ represents the covariance matrix among unobserved nodes whereas $\boldsymbol{\Sigma}_{D0}$ includes the covariance between observed and unobserved nodes. The covariance matrices are derived from the given neighbourhood structure. Within each power network nodes are connected with each other via transmission lines with a specific electrical impedance. Usually, the impedances are summarised in an adjacency matrix $\mathbf{A}$ where entries corresponding to unconnected nodes are 0. Surmann; Ligges and Weihs (2017) discuss the problem of converting the adjacency matrix to a covariance matrix. Power flows in a transmission grid between two specific nodes according to Kirchhoff's laws. Hence, it is possible to simultaneously use arbitrary sequences of transmission lines and nodes between these two nodes. As expected, the longer an electrical distance between two nodes the less power is transmitted via this sequence. In general, the distance measure between two nodes is anisotropic, i. e. directional dependent, because the electrical impedance varies depending on the path connecting the two nodes. The solution for reflecting this behaviour in calculation is provided by a kernel function κ which summarises all possible sequences between two nodes.

$$
\kappa = \sum_{t=0}^{\infty} \lambda(t) \mathbf{A}^t
\tag{4.2}
$$

Each element of $\mathbf{A}^t$ represents the number of length t sequences between the two corresponding nodes. The function $\lambda(t)$ is introduced by Vishwanathan et al. (2010) as a series of appropriate non-negative coefficients to guarantee convergence in equation (4.2). By defining $\lambda(t) := \frac{\beta^t}{t!}$ (Gärtner; Flach and Wrobel 2003) equation (4.2) becomes the series expansion of the matrix exponential $e^{\beta \mathbf{A}}$ which is positive definite and κ can be interpreted as a covariance matrix. An alternative definition by Gärtner; Flach and Wrobel (2003) uses a geometric kernel $\lambda(t) := \beta^t$ with $|\beta| < \frac{1}{a}$ and a as the minimum number of neighbours among all nodes. The inequality for β with regard to α ensures convergence in equation (4.2) using $\kappa(\lambda)$ as an alternative covariance matrix.

Finally, Surmann; Ligges and Weihs (2017) study the effects of different kernel functions in a simulation study consisting of two virtual transmission systems. The LFO is obtained via a real or imaginary part of the complex voltage and the neighbourhood structure is reflected by two different adjacency matrices. Additionally, the hyper-parameters λ of κ are varied in simulations as well as the proportion of omitted notes. For each simulation we calculate the maximal absolute prediction error $\max(|e_i|)$ among all nodes i of the corresponding transmission system. The maximum prediction error describes the worst node after predicting unobserved nodes within a network. Since one single node with a poor prediction is able to cause an outage of a power network, the maximum characterises the situation at hand in an optimal way. In summary, the simulation study shows no significant difference between the two graph kernels and a slightly better performance when using the networks adjacency matrix with impedances compared to a matrix which dichotomous elements indicate neighbouring nodes. The paper shows a good overall performance of the proposed method to predict nodes in a power network using graph kernels with anisotropic distance function.

4.3 Optimal Subset of Nodes

In section 4.2 the basis for obtaining an optimal subset of nodes within a power transmission system is described. Solving this task is essential to handle PMUs in the power network in order to get an appropriate overall picture of the inter-area LFOs. Due to the fact that only very few PMUs are currently available in the European transmission grid, it is interesting to plan the placement of new PMUs. A suitable PMU placement is important to generate reliable data about inter-area LFOs. On the other hand, one can consider installing PMUs at every node in the transmission system because the devices are considered the most important gauging technology in future power systems (Nuqui 2001). Interrogating all nodes and their PMUs in a transmission system will result in a huge amount of data for power networks of a similar size to the European transmission system. To manage processable parts of data, it is important to request a proper subset of nodes which contains information to create an overall picture about the inter-area LFO.

Surmann; Ligges and Weihs (2018b) optimise the selection of observed nodes employing an evolutionary algorithm as summarised in the literature review by Yuill et al. (2011). In particular, we employ a binary genetic algorithm because the selection task is based solely on dichotomous decisions, whether a node is observed or not. Regarding the nodes of a transmission system as a bit-coded vector supports the application of the binary genetic algorithm.

Each bit-coded vector represents the whole network as one individual within binary genetic algorithms. It denotes which nodes are observed or not as state of the transmission system. We use the maximum prediction error $e_{max} = \max(|e_i|)$ among all nodes i defined in section 4.2 (Surmann; Ligges and Weihs 2017) as fitness function for each individual. As an individual evolves to observe more nodes the prediction error decreases. The best individual would be the observation of all nodes, which is a trivial optimum. Hence, we define a constraint with a fixed ratio of observed nodes and take this into account for all further computations. Binary genetic algorithms consider a group of individuals called population. These algorithms change elements of each individual vector to gain better values of the fitness function. To accomplish this two specific individuals are recombined to two new ones. Subsequently, elements of the new individuals are changed by chance to provide incidental evolution. Due to the fact that we cannot apply gradient descent algorithms to this task, it remains unclear whether changes improve or weaken the individual with respect to the fitness function. Hence, the fitness function has to be calculated for every new individual. Finally, the individuals with the best fitness function form the new population in which optimal individuals evolve. An encompassing overview about evolutionary algorithms is given in Simon (2013).

The extensive simulation study by Surmann; Ligges and Weihs (2018b) reveals a good overall performance and lists the parameter sets of the binary genetic algorithm for the use in different transmission systems. We point out the slightly different parameter sets between the tested power networks and the minor adjustments for further networks. The final application to the virtual test system New England Test System – New York Power System (NETS – NYPS) identifies the optimal individuals in figure 4.1. A circle represents observed nodes

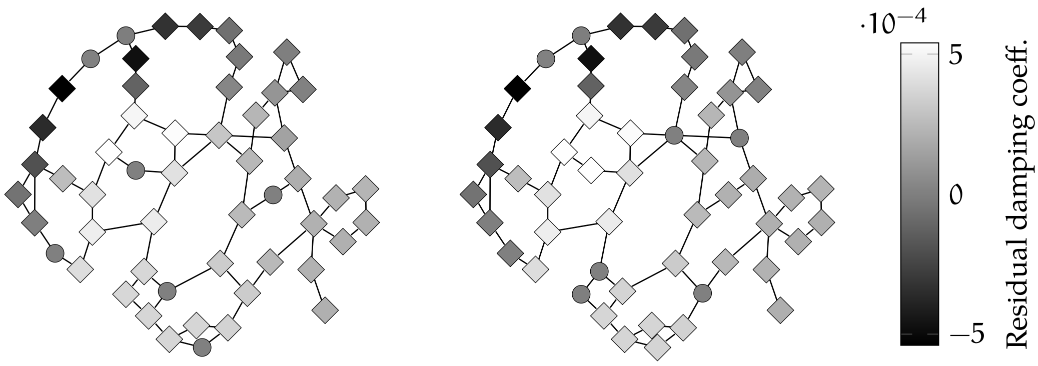

Figure 4.1: Residual damping coefficients of two optimal individuals for 15 % observed nodes in NETS – NYPS from two runs of the binary genetic algorithm. Figure is taken from Surmann; Ligges and Weihs (2018b).

whereas rhombi symbolise unobserved nodes. Both individuals are optimal with respect to an equal fitness function from the binary genetic algorithm. We expect observed nodes within the power network to be distributed rather uniformly without spatial pattern, instead we observe agglomeration of nodes following some spatial pattern. To solve this issue, the genetic algorithm has to be extended, for instance by multi-criteria optimisation.

5 Generating Test Scenarios

> *"Experience without theory is blind, but theory without experience is mere intellectual play."*
>
> — Immanuel Kant

5.1 Contributed Material

Surmann, Dirk; Ligges, Uwe and Weihs, Claus (Oct. 4, 2018a): 'Infill Criterion for Multimodal Model-Based Optimisation'. In: arXiv: 1810.02118 [cs, stat]. url: http://arxiv.org/abs/1810.02118

5.2 Power Simulation Software

Utilising simulation software is a common and widely accepted way (Lin et al. 2012; Li et al. 2016) to generate data of power transmission systems. Apparently, the advantage to work out possible effects of, e. g., new or updated devices within a power network using simulation software is considerably more favourable than applying the change directly to the real transmission system. As power systems become more and more complex, the corresponding simulation software has to reflect this higher complexity. Examples of the increase in complexity are the full integration of national electricity markets (Meeus et al. 2011) and the expansion of renewable energy sources on a large scale (European Network of Transmission System Operators for Electricity (ENTSO-E) 2014). Additionally, more and more devices are installed in power networks to increase their stability (Dudgeon et al. 2007) like an automatic voltage regulator (AVR) and a power system stabiliser (PSS). Furthermore, interactions between larger networks with their higher number of devices challenge the effective application of simulation software.

The state of the art way to analyse the implication of, e. g., a parameter change in an AVR is to manually define a number of test scenarios. A test scenario reflects a hypothetical worst case scenario to examine whether the investigated parameter change handles the defined situation. The scenario architect attempts to prepare tests which cover the investigated parameter region and at the same time challenge the new parameter set. A possible response projected by scenario designers onto the test scenarios could be the time until a test scenario fails to operate a power network. In combination with the parameters as predictors it is interesting to find sets of parameters with low response values. These test scenarios are local minima with regard to functions. However, the functional relation between the predictors and the response is given by the power simulation software. Because of its complexity and time consuming simulation we consider it as an expensive black box function. In this setting model-based optimisation provides techniques to explore the domain of an expensive black box function efficiently.

5.3 Multimodal Model-Based Optimisation

Surmann; Ligges and Weihs (2018a) propose a model-based approach which provides a solid base for generating test scenarios. We try to locate challenging test scenarios for the power simulation software. The response of a model is taken as the value for challenging test scenarios which represent a point in the design space. Hence, it is interesting to detect multiple local minima because they locally correspond to the most challenging available test scenarios. Efficient global optimisation (EGO) by Jones; Schonlau and Welch (1998) aims at finding the global optimum of an expensive black box function. Applying this theory to power simulations is reasonable because from a statistical point of view, a power simulation can be seen as an expensive black box function. In most applications, EGO and the more general model-based optimisation (MBO) approach (Bischl et al. 2017) are stated to detect the global optimum for single- and multi-objective functions. Wessing and Preuss (2017) discuss the identification of multiple minima using EGO and point out the good behaviour of their approach with respect to various artificial test functions. Surmann; Ligges and Weihs (2018a) use MBO with a Kriging based surrogate model and define a new infill criterion to identify local minima considerably better than the expected improvement (EI) criterion used in EGO. We name the criterion gradient enhanced inspection of local minima GEILM($\boldsymbol{x}$) defined by

$$\mathrm{GEILM}(\boldsymbol{x}) = \hat{s}(\boldsymbol{x})\Phi\left(\frac{\hat{y}^\star - \hat{\mu}(\boldsymbol{x})}{s_p}\right) g_\lambda\left(\|\nabla\hat{\mu}(\boldsymbol{x})\|_\infty\right) \tag{5.1}$$

with

$$s_p = \min\left\{ s \in \mathbb{R}^+ \middle| \frac{\hat{y}^\star - \max(\boldsymbol{y})}{s} = \Phi^{-1}(p) \right\} \tag{5.2}$$

where Φ is the distribution function of the standard normal distribution. g_λ is the density of the exponential distribution with parameter λ. $\|\cdot\|_\infty$ describes the supremum norm and is called maximum norm in case of a vector $\boldsymbol{a} = (a_1, \ldots, a_n)^\top$. In this situation it takes the form $\|\boldsymbol{a}\|_\infty = \max\{|a_1|, \ldots, |a_n|\}$. The differential operator, or nabla operator, ∇ is defined in terms of partial derivative operators and denotes the gradient of a scalar field. We choose $\mathrm{SE}(\boldsymbol{x})$ with its exploration nature as a starting point and use the multiplication operator to implement a weighting on $\mathrm{SE}(\boldsymbol{x})$. Summing up the coefficients is only meaningful for infill criteria which deal with $\hat{\mu}(\boldsymbol{x})$ directly instead of a function containing $\hat{\mu}(\boldsymbol{x})$, because $\hat{\mu}(\boldsymbol{x})$ is related to exploitation whereas $\hat{s}(\boldsymbol{x})$ is related to exploration. The weighting via Φ is reused from the expected improvement criterion to add a connection to the expected function value $\hat{\mu}(\mathbf{x})$. Φ weights down $\hat{\mu}(\mathbf{x})$ the more it differs from the current minimum $\hat{y}^\star$ which reflects the higher interest in local minima with lower function values. We adjust the standardisation by a p-quantile standard deviation s_p with $p \in (0, 1)$. s_p is driven by the range of evaluated design points independent of $\hat{s}(\mathbf{x})$. Our approach encourages GEILM($\mathbf{x}$) in exploring the design space with a lower priority for higher expected values $\hat{\mu}(\mathbf{x})$. Due to the fact that the gradient at a point between two local minima has to be significantly different from 0, we add a second weighting via the exponential distribution g_λ. It considers the maximum partial derivative to skip exploration in regions with a steep surrogate function and to ensure the highest weighting for local minima. Hence, design points outside a local optimum (or plateau) get lower priority which further encourages GEILM($\mathbf{x}$) to use the remaining number of runs in promising regions.

Two exemplary design points illustrate the behaviour of GEILM. At the global minimum $\hat{y}^\star$ the total weight on $\hat{s}(\mathbf{x})$ takes its maximum of $\frac{1}{2}\lambda$. In this case Φ is equal to $\frac{1}{2}$ and g_λ to λ because the gradient in an optimum is 0. Hence, GEILM($\mathbf{x}$) is equal to $\frac{1}{2}\lambda\hat{s}(\mathbf{x})$ for the global minimum. If we assume an example point with a high value of the local estimator compared to the global minimum which is not a local minimum, GEILM($\mathbf{x}$) converges to 0. The function Φ converge to 0 for higher values of $\hat{\mu}(\mathbf{x})$ as does the function g_λ because the gradient is different from 0 for points outside local minima. If the surrogate function is unexplored at this point $\hat{s}(\mathbf{x})$ uprates the infill criterion GEILM($\mathbf{x}$).

Subsequent to running MBO with GEILM Surmann; Ligges and Weihs (2018a) discuss the identification of local minima from the fitted Kriging surrogate model. We draw a Latin Hypercube Sample (Stein 1987) and apply a quasi-Newton algorithm with box constraints (Nocedal and Wright 2006) to each sample point. For each agglomeration of sample points, one representative is identified to describe the corresponding local minimum. The approximation set consisting of the representative sample points is finally rated by an adaptation of the peak ratio (PR) defined by Ursem (1999) and the averaged Hausdorff distance (AHD) described by Rockafellar and Wets (2004). Peak ratio is a ratio of the number of points in the approximation set and the correct number of local minima. The AHD describes an average distance between the approximation set and the set of correct local minima.

Finally, Surmann; Ligges and Weihs (2018a) compare the proposed criterion in an exhaustive simulation study to the classical expected improvement criterion and to a Latin Hypercube Sample. We consider 15 artificial test functions with dimension $1 \leqslant p \leqslant 8$ and up to 125 local minima. As an example, we use the Hartmann function (Dixon and Szegö 1978) with dimension 6 and 2 local minima in figure 5.1. On the left side, the peak ratio is plotted against the number of design points grouped by algorithm, whereas the right plot shows the averaged Hausdorff distance. All lines are smoothed by local regression (LOESS) and a 95 % confidence interval under the assumption of normality is highlighted in grey. In the optimal case, PR is expected to be 1 with an AHD of 0. If PR exceeds 1, we conclude an overfitted Kriging

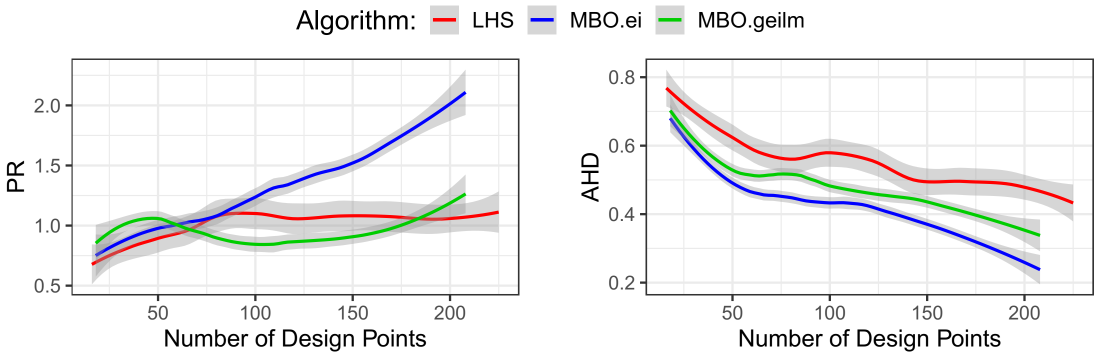

Figure 5.1: Peak ratio (PR) and averaged Hausdorff distance (AHD) over number of design points grouped by algorithm for the exemplary test function Hartmann 6. Figures are taken from Surmann; Ligges and Weihs (2018a).

model. The example at hand shows a good performance of the GEILM criterion with respect to the peak ratio. It outperforms EI in terms of the maximum number of design points because of its divergent behaviour and it outperforms the LHS by its smaller confidence interval. Furthermore, GEILM reaches the expected value of 1 earlier than EI or LHS. Due to the fact that EI detects too many local minima, its AHD is smaller because the misleading minima generate an overall smaller distance to the correct local minima. The meaningful comparison of AHD between LHS and GEILM demonstrates a better performance of the proposed criterion. In summary, designing a criterion especially for identifying multiple local minima is worth the effort and can support the generation of test scenarios that can be examined using a power simulation software.

6 Summary and Outlook

"We absolutely must leave room for doubt or there is no progress and no learning. There is no learning without having to pose a question. And a question requires doubt. People search for certainty. But there is no certainty."

— Richard P. Feynman

In this cumulative dissertation, I presented two methods for constructing optimal subsets and generating improved test scenarios, which both play an important role in applications to power transmission systems. I summarised six papers which deal with modelling of Low-Frequency Oscillations and with the prediction of corresponding values at unobserved nodes within a power transmission system.

The first method works out an optimal subset of nodes based on a physical model defined by differential equations for Low-Frequency Oscillation. An example of a practical application is the optimal placement of phasor measurement units in a power network. The latter presents an algorithm which is able to generate test scenarios in environments of power simulation software. Utilising an objective method within virtual transmission systems supports a sustainable application of computer experiments.

Modelling Low-Frequency Oscillations

The demand for a simple model which is interpretable for a power system engineer leads to the used harmonic differential equations model for the Low-Frequency Oscillations. The characteristic waveform of the LFO is inherently reflected by the chosen model type. The subsequent analysis based on the differential equation model with alternative data from transmission systems or in different domains points out limitations of this model. Hence, it is worthwhile to study additional models to manage these restrictions. Time series analysis would be an evident alternative to the used approach for modelling Low-Frequency Oscillations. Applications in comparable dynamic domains are conceivable which require fast reactions for a large amount of data, such as mobile communications. Particularly, in this field, parameters from a Fourier transformation can be described by the penalised graph kernel model and used in subsequent analysis. Additional studies will show how robustly these models perform on larger networks when they are combined. In this case, the conducted sensitivity analysis may be adapted to identify stable model connections.

Fitting the chosen model to Low-Frequency Oscillations data is currently done offline and retrospectively. In other words, we utilise a fixed existing database with past data to learn the model. The modelling process uses the complete time interval of the available data at once and estimates the corresponding model parameters. An improvement would be the adaptation of the model fit to an online database which changes over time. In this case, new data will be passed directly to the model and affect the succeeding process. Additional pass-through parameters allow to control how fast new events influence the complete algorithm and ensure the stability of the chosen model. This behaviour would reflect the high dynamics in the domain of power transmission systems.

Linking the models among all nodes of a power network is performed by a linear model using a penalised least squares criterion to smooth the estimations across a power transmission system. It includes the fundamental error assumption of a normal distribution. Research in the direction of robust statistics would strengthen the algorithm to be applicable in different domains and with various data. Additionally, it would be worth the effort to improve statistics for the evaluation of a transmission system and data prediction. Currently, the maximum absolute prediction error is used which omits many observations. Further research on the distribution of prediction errors is interesting. Additional statistics which represent the behaviour of a power network failure from a different point of view can also improve the error distribution. A further development is to use these statistics as fitness functions of the binary genetic algorithm. Equal maximum statistics conceal differences in the distribution between two results of optimisation runs and could lead to inexplicable variations between optima. In general, an attractive field of research is to replace the heuristic evolutionary algorithm by deterministic methods. These have the potential to be much more efficient since they avoid time-consuming calculations.

Test Scenarios for Power Simulations

Generating test scenarios for an efficient simulation of power transmission systems is elaborated by proposing a new infill criterion for model-based optimisation. Promising test scenarios challenge the simulated power network and should cover the corresponding domain. The criterion is defined to particularly explore points in the domain with a high probability of being local minima. An extensive and valuable field of research would be the extension to a partly discrete domain. This step is relevant because many parameters describe discrete options or decisions, for instance, disconnecting a transmission line or not. Other examples are transformers which often tend to work on discrete scales.

The proposed algorithm seeks to locate all local minima in the input domain. To assess them with respect to their importance, minima with higher function values get a lower probability, but the infill criterion nevertheless tries to locate them. Due to the fact that a scenario architect is only interested in the n most challenging scenarios, it is worthwhile to include a parameter in the model-based algorithm which controls the number of local minima. An improved infill criterion has to characterise regions which are expected to return higher values than the

n local minima with a very low exploration probability. The identification of local minima of the surrogate function is currently resolved using a gradient descent algorithm of many points spread on the input domain. Defining a mechanism based on cheap functions to identify local minima faster and more reliably could improve the process of generating tests scenarios. Finally, the methods should be thoroughly benchmarked on a more diverse set of test functions. It is fundamental to use higher dimensions and a larger variety of properties of test functions to evaluate the approach and to guarantee an accurate result when proposed test scenarios are evaluated by means of power simulation software.

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Ich erkläre an Eides statt, dass ich die vorliegende Dissertation selbständig verfasst und dabei keine anderen als die angegebenen Hilfsmittel benutzt habe. Sämtliche Stellen der Dissertation, die im Wortlaut oder dem Sinn nach Publikationen oder Vorträgen anderer Autoren entnommen sind, habe ich als solche kenntlich gemacht. Die Dissertation wurde bisher weder gesamt noch in Teilen einer anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Ich habe bisher kein Promotionsverfahren erfolglos beendet und keine Aberkennung eines bereits erworbenen Doktorgrades vorliegen.

Ort, Datum

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