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Practical modern control design techniques for power systems

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Practical Modern Control Design Techniques for Power Systems

by

Amer Hasanović

Dissertation submitted to the
College of Engineering and Mineral Resources
at West Virginia University
in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy
in
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2004

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genetic algorithms, load frequency control

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Abstract

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Doctor of Philosophy in Electrical Engineering

West Virginia University

Professor Ali Feliachi, Ph.D., Chair

This dissertation is proposing practical control design techniques for electric power systems load frequency control (LFC) and stability enhancement through tuning of power system stabilizers (PSSs).

For the LFC, two novel design techniques are developed. The first one, called GALMI, is for tuning the gains of the traditional controllers to obtain a robust performance similar to the one that will be obtained using a centralized high order controller based on H-infinity design and Linear matrix Inequalities (LMI). The tuning is performed using genetic algorithms (GA). The second approach is a controller design based on model predictive control (MPC). This design is fully decentralized and requires only local area parameters. Furthermore, due to the ability of MPC to handle constraints on controlled variables this design can cope with the nonlinearities in the LFC model.

To enhance power system transient stability margins two methodologies for PSS tuning are also proposed. The first methodology for PSS design is useful for the frequently occurring situation where a single PSS needs to be designed to produce maximum impact on the damping of a power system. In this method an identification is first used to derive low order transfer functions of large-scale power systems and then a GA based optimization of a damping index is used for PSS tuning. The second proposed methodology for PSS design is useful for the situations where several PSS controllers can be tuned together. By coordinating these controllers it is possible to achieve better robustness and damping of interarea modes. Multiobjective optimization is utilized to obtain the controller parameters. The first objective is used to enhance the damping performance of the system. To incorporate robustness explicitly additional optimization objective is added which is based on the infinity norm of the sensitivity transfer function of the system.

Effectiveness of the proposed techniques is demonstrated on a number of case studies including benchmark and actual power systems.

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Chapter 1

Introduction and Literature Survey

1.1 Motivation

Power systems have evolved significantly over the last century, and they now underlie almost every aspect of prosperous societies. During this time the role of electric power has grown steadily in both scope and importance. Quality of life throughout the world is often determined by the level of electric power consumption and electricity is now widely recognized as the major force driving economic prosperity. As the importance of electricity grew so did the complexity of power grids. Operations of infrastructures such as transportation, telecommunications, banking and finance are more and more dependent on reliable power grids. In some regions the demand is already growing faster than the available power capacity making it harder to assure reliable operation. Additionally, today's digital era consumers require electricity of higher quality and reliability. Recent deregulation has introduced many new participants to the power market. Their interaction in the more competitive market has resulted in unpredictable price spikes and more frequent power outages.

According to the Disturbance Analysis Working Group (DAWG) at the North American Electric Reliability Council (NERC) 27 severe power disruptions have been recorded from 1996 to 2001. Many of the outages were intensified by cascading effects. Perhaps the most famous example is the major disturbance that occurred in the Western Interconnection (Western Systems Coordinating Council, WSCC), August 10, 1996 resulting in the Interconnection separating into four electrical islands. Conditions prior to the disturbance were marked by high summer temperatures of about 100 degrees Fahrenheit in most of the Region, by heavy exports from the Pacific Northwest into California and from Canada into the Pacific Northwest, and by the loss of several 500 kV lines in

Oregon. Faults at the Oregon at the Keeler-Allston 500 kV line precipitated the overloading and opening of parallel lines, this further led to voltage drops and undesirable removal from service of key hydro units, and subsequent increasing oscillations, which then resulted in the formation of four islands, causing the widespread uncontrolled outage of generation and interrupting electric service to about 7.5 million customers. The overall cost was estimated between \$1.5 billion to \$2 billion. The studies have shown that the well-timed load shedding control action could have prevented the system separation.

It is expected that the power systems in the future are going to be operated under even more stressful conditions which could provide the environment for more frequent occurrence of power outages. This becomes even more apparent considering the consequences of the most recent blackout which happened in the Mid-west and Northeast United States and eastern Canada on August 14, 2003. This was the biggest power outage in the US history which left more than 50 million people without electricity and paralyzed major metropolitan areas including New York City, Albany, Hartford, Toronto, Ottawa, Detroit, Cleveland and Ontario.

Hence, there is a clear requirement to provide better safety margins by enhancing the power system control mechanisms. This represents a very challenging problem considering the physical properties of power systems:

- Power systems are massively large scale systems with spatial scales that span countries or even continents.
- Millions of distributed components tightly interconnected within power systems are interacting in nonlinear fashion. These relationships and interdependencies are too complex for conventional mathematical theories and control methods.
- The time scale within power systems can range from milliseconds for one phenomena to hours and even years for another. Table 1.1 shows the time scale for various power grid control and operation tasks.

In general, a typical control function for today's power systems consists of a load-trajectory following function working on top of a faster stabilization function.

The load-following function is a slower quasi-dynamic function where a trajectory is planned and then updated. In this manner, the generation is made to follow the load and supply the transmission losses in the global sense. The system tries to follow the changes that occur in generation, load, or system topology, mainly by reacting to frequency changes via preset feedback

mechanisms in real time. The regulation requirement in MW is allocated among the generating units that are under control. Setpoints of controlled units is calculated with respect to security and economy criteria.

Table 1.1: Time scale for various control actions within the power grid, adopted from [3]

Action or Operation	Timeframe
Wave effects (fast dynamics, such as lightning causing surges or overvoltages)	Microseconds to milliseconds
Switching overvoltages	Milliseconds
Fault protection	100 milliseconds or a few cycles
Electromagnetic effects in machine windings	Milliseconds to seconds
Stability	60 cycles or 1 second
Stability	Augmentation Seconds
Electromechanical effects of oscillations in motors and generators	Milliseconds to minutes
Tie-line load frequency control	1 to 10 seconds; ongoing
Economic load dispatch	10 seconds to 1 hour; ongoing
Thermodynamic changes from boiler control action (slow dynamics)	Seconds to hours
System structure monitoring (what is energized Steady state; and what is not)	on-going
System state measurement and estimation Steady state;	on-going
System security monitoring Steady state;	on-going
Load management, load forecasting, and generation scheduling	1 hour to 1 day or more, ongoing
Maintenance scheduling Months to 1 year,	ongoing
Expansion planning	Years, ongoing
Power plant site selection, design, construction, environmental impact, etc.	10 years or longer

Working within a smaller time scale are the devices designated to cope with the consequences of severe disturbances such as line tripping, loss of generation and/or significant loads. Stabilization of the system is the key function of devices at this level. One such device is power system stabilizer (PSS) which is designed for suppressing low-frequency oscillations in power systems.

The proposed research aims to address the issues related to the control design problems for the load-following and stabilization functions. The following sections give a brief overview of these problems and present a survey of related publications.

1.2 Literature survey

1.2.1 Load frequency control

Traditionally, the responsibility of overseeing and directing the control of the generation and transmission resources within a power system belongs to the control centers. Typical power systems usually consist of a number of control areas interconnected through the tie lines. Each control center within its control area provides the automatic generation control (AGC) service. AGC is comprised of two functions: economic dispatch and load frequency control (LFC). As part

of the economic dispatch, setpoints for dispatchable generating units are calculated taking into consideration physical and economic constraints of the system. Frequency and power interchange between areas are kept at the scheduled values as part of the LFC function of the AGC mechanism. Figure. 1.1 graphically depicts the LFC mechanism.

Figure 1.1: Load-Frequency and Voltage Regulator control loops of a Synchronous Generator

The LFC function is implemented in the form of a closed-loop control system. First, the area control error (ACE) signal is calculate according to the eq. (1.1). Then, the ACE signal is fed into the LFC controller. Through the governor, the LFC controller adjusts the turbine valve position changing the amount of steam flowing through the turbine. This further affects the generator power output directly influencing the regulation of the ACE signal.

$$ACE = \beta \cdot \Delta f + \Delta P_{tie} \quad (1.1)$$

where:

Δf - frequency deviation (Hz)

ΔP_{tie} - power interchange deviation (MW)

β - frequency bias coefficient (MW/Hz)

Performance of the LFC controller should be such that it is robust over a range of operating condition and in compliance with the criteria set by NERC. Additionally, it should reduce excessive maneuvering of governor system so that the mechanical wear and tear of equipment would be

minimized. Traditionally, LFC architecture most frequently used by the industry is based on proportional-integral (PI) controllers which are tuned online using trial-and-error approaches. This approach can be quite cumbersome and inefficient. Hence, over the years a number of research papers have dealt with the issues of LFC design. These research efforts in general fall into two categories.

In the first category are the papers [4, 5, 6] with the main objective of deriving methods for picking parameters of PI controllers, which are more analytical in nature. Additionally, they all formulate the PI tuning problem as an optimization problem. Also, these papers share similar time domain simulation based performance index functions. In [6] a Genetic Algorithms (GAs) based optimization procedure and in [4, 5] a Newton based procedure is utilized to obtain the controller parameters. Practical application of the proposed methods is limited by the fact that they require physical parameters from all control areas within a power system to perform the optimization. These parameters are unlikely to be shared among the control centers. Another drawback of these methods is that they rely on lengthy simulations to compute the optimization performance index.

In the second category are the papers which are proposing completely new controller structures for the LFC problem. A number of decentralized load frequency controllers based on the concepts of optimal and robust control were developed in [7, 8, 9, 10, 11]. However, most of them are complex high-order dynamic controllers that require state measurements, which is not practical for industry practices. Additionally, proposed controllers could yield unsatisfactory performance since the effects of nonlinearities such as generation rate constraints (GRC) were not considered. During the last decade Model Predictive Control (MPC) emerged as a viable control strategy and proved its usefulness in process industry (oil refining and glass industry). MPC represents a model based multivariable control architecture where in each sampling interval, an optimization procedure is performed in order to calculate optimal control adjustments. It is especially useful for environments with multiple contingencies since it can handle changing conditions, such as requirements modifications, switching-off or failure of sensors and actuators. Moreover it can deal with constraint type of requirements, i.e. it can keep both manipulated as well as controlled variables in certain pre-defined ranges. The ability to incorporate economic objectives as part of control requirements, makes it a good candidate for LFC control. In [12, 13], a distributed MPC architecture based on information sharing between multiple controllers, was proposed for LFC. Although, a successful control performance was demonstrated, only a simple swing equation based model of a two-area power system was used to test the controllers' performance. Additionally, the proposed strategy does not consider the net power interchange error and assumes the availability

of generator rotor angle measurements which is not practical for implementation.

1.2.2 Transient stability

Transient stability analysis examines the dynamic behavior of power system electrical networks, electrical loads, and the electro-mechanical equations of motion of the interconnected generators for as much as several seconds following a disturbance. Under normal operating conditions, an electrical power system is near equilibrium, with only minor deviations from true steady-state conditions caused by small, nearly continuous, changes in the loads.

When a severe disturbance, such as a short circuit, occurs in the power network, there are significant, nearly instantaneous, changes in the loads at some generators in the system. Depending on the level of disturbance, lightly damped electro-mechanical modes of oscillation could be aggravated. During the oscillations triggered by these modes, kinetic energy of rotating masses is exchanged between synchronous generators while electric power flows through the network. The power swings further produce oscillations in voltages and currents. Sufficiently large oscillations can stress or damage equipment and disrupt monitoring devices. Additionally, oscillations can cause voltages to exceed limits causing protective devices to trip and forcing equipment outages. Hence, oscillations play significant role in the cascading outages that produce system separations and blackouts. Two types of oscillations are of particular interest [14]:

- *Local oscillations* are associated with the swinging of units at a generating station with respect to the rest of the power system. The term *local* is used because the oscillations are localized at one station, typically with a frequency of $1 - 2 \text{ Hz}$.
- *Interarea oscillations* are associated with the swinging of many machines in one part of the system against machines in the other parts. They are a complex phenomenon with potentially many contributing causes which can span entire interconnections. Typical frequency of such oscillations is between $0.1 - 1 \text{ Hz}$. Interarea modes in general exhibit low damping. If damping is negative even a small perturbation may excite a growing oscillation.

Power system controls significantly affect the damping of electro-mechanical modes. Generation control and particularly the generator voltage regulation can potentially be a source of negative damping. For weak tie lines and high power transfers, an oscillation in real power also causes an oscillation in voltage magnitudes and interaction with the generator voltage regulation. High gain in the generator voltage regulation can lead to poor or negative damping of the oscillation.

This problem led to the deployment of power system stabilizers (PSS) to modify the voltage regulation to damp these oscillations sufficiently. The basic function of a PSS is to add damping to the generator rotor oscillations by controlling its excitation using auxiliary stabilizing signal(s) [14]. The device acts as an add-on device to the Automatic Voltage Regulator (AVR). The PSS usually uses shaft speed, active power output or bus frequency as input. The stabilizer itself mainly consists of two lead-lag filters as shown in Figure 1.2.

Figure 1.2: Block diagram of a conventional power system stabilizer.

These are used to compensate for the phase lag introduced by the AVR and the field circuit of the generator, and are tuned so that speed oscillations give a damping torque on the rotor. Other filter sections are usually added to reduce the impact on torsional dynamics of the generator. K_s is the stabilizer gain, while T_w and $T_1 - T_4$ are the parameters of washout and lead-lag filters respectively. The PSS output is added to the difference between reference (V_{ref}) and actual value (V_{act}) of the terminal voltage. The PSS is often required to improve damping a specific mode of oscillation. While this mode receives special attention, it is desirable to design the phase compensation so that the PSS contributes to damping over a wide range of frequency covering both existing interarea and local modes of oscillation. Ideally, the stabilizer gain should be set at a value corresponding to maximum damping. However, the gain is often limited by other considerations.

A vast amount of valuable work is dedicated to the design and tuning procedures of PSS. The early PSS designs were based on a single-machine-infinite-bus power system model. In [15], useful concepts of synchronizing and damping torque coefficients for PSS design were pioneered. In [16], application of damping torque coefficients was extended to multimachine power systems including FACTS devices. Coordination among different controllers was achieved by analyzing the stabilizer contribution diagram which was constructed for every mode under consideration. The described procedure was not automated and became very complex when subjected to all rotor and exciter modes. The method was improved in [17] by application of linear programming to minimize the weighted sum of stabilizer gain increments, subjected to specified damping criteria for the modes

of interest and to lower and upper limits on stabilizer gains. However, the improved method could only determine the gain parameter while the time constants for stabilizers (i.e. phase compensation) still had to be set manually. Various constrained optimization techniques were also applied to the PSS design. In [18], an application of nonlinear constrained optimization to PSS tuning was described. The modal performance index was based on the energy contained under the envelopes of sinusoidal output signal responses, starting from given initial conditions. Potential drawback of this method lies in the limited search space of nonlinear solvers. Therefore, solution obtained by this method depends on initial parameter guess used to initialize the nonlinear optimization. In [19], PSS tuning by means of genetic algorithms was described. This work investigated the use of genetic algorithms for simultaneous stabilization of multimachine power systems over a wide range of operating conditions via power system stabilizers with fixed parameters. Techniques that can take into consideration plant uncertainties and have potential to handle plants linearized around a number of operating conditions, such as LMI, H_∞ and μ designs, have been reviewed in [20, 21, 22].

Most of the methods above linearize a detailed power system dynamic model about an operating point and then apply control theory to the linearized model. This can be a serious obstacle when applying these techniques on large scale power systems. It is often the case that the programs used to perform large scale transient stability analysis do not possess the capability to produce linearized power system models or, when that capability is available, the number of states that can be linearized is limited. Additionally, majority of the techniques require eigenvalue computations of power system state matrices. Typical power systems are represented by large state matrices, often exceeding 10000 states. Therefore, specialized large-scale eigenanalysis programs are required. Also, repeated computation of eigenvalues of systems of such size is time consuming.

To overcome these limitations identification methods that generate low order linear systems from time domain data obtained from standard transient stability analysis (TSA) packages could be utilized. In that context Prony signal analysis has been extensively studied by the power system community. The first application of Prony analysis to power system oscillations was reported in [23] where modal content of field measured data was analyzed. Using Prony analysis for the single-input-single-output transfer function identification for control design was reported in [24, 25, 26]. The extension of Prony analysis to multi-output systems was demonstrated in [27]. Also, obtaining transmission network equivalents via Prony analysis for EMTP simulations was described in [28]. Other identification techniques, not based on Prony analysis, have been analyzed in [29, 30, 31].

Chapter 2

Overview

Chapter 1 described the main challenges facing the modern power systems. The proposed research aims to address these issues by proposing both novel controllers and new design methodologies to acquire parameters for controllers which are already in operation. This dissertation focuses on the LFC and transient stability control.

2.1 Novel techniques for LFC design

This section gives an overview of the two proposed techniques for the LFC problem.

2.1.1 Robust PI tuning

As it was described in section 1.2.1 overwhelming majority of control centers are using PI controllers to perform load frequency control functions. Considering the investment needed to change these controllers and the conservative nature of power system utilities it is highly unlikely that these controllers will be substituted in the near future. Additionally, there is a limited number of analytical techniques that describe the way to tune these controllers when only partial system model is available with full data information available only from a local control area. Hence, the first proposed technique casts the PI controller tuning problem into a robust control design framework. Within this framework interconnections among areas are treated as disturbances. The PI tuning is then performed by solving the H_∞ optimization problem where a peak gain of a transfer functions from the disturbance to the controlled variable is minimized. This optimization problem is shown to be nonlinear and nonconvex when a fixed order controller structure is assumed. Therefore, the standard tools for solving robust control problems such as Linear Matrix Inequalities (LMI) cannot

be applied directly. To be able to obtain the solution for the optimization problem a hybrid solver is proposed. The solver is based on combination of Genetic Algorithm and LMI techniques. Hence, it is appropriately called GALMI. As part of the research related to the GALMI technique the following research tasks are performed:

1. To be able to apply GALMI a suitable model for the control area is formulated.
2. GALMI solver is implemented in MATLAB environment.
3. Using a three-area benchmark power system, GALMI-obtained PI controllers are tested and results are compared with the full order H_∞ controllers.

2.1.2 MPC based AGC

When designing PI controllers for LFC problem a purely linear model is assumed. In reality, many nonlinear effects exist, specifically limits and rate constraints on some variables, that need to be adequately represented. PI controllers have shown they are often capable of dealing with these nonlinearities.

However, formulating the PI controller design to explicitly include the nonlinear effects is very difficult. One control design technique that explicitly incorporates the constraints on variables is Model Predictive Control (MPC). Furthermore, since the MPC design is based on online optimization different performance indices can be specified for optimization. Therefore, for the second part of the LFC related research an MPC based strategy for automatic generation control is proposed. The following research tasks are performed:

1. To be able to apply MPC design a suitable model for the control area is formulated.
2. MPC toolbox in MATLAB is used to implement the MPC strategy.
3. Using a three-area benchmark power system, model predicative controllers are tested and results are compared with the full order H_∞ controllers. Impact of generation rate constraint (GRC) are also investigated.

2.2 Novel techniques for PSS tuning

Modern power systems are experiencing operational challenges due to unforeseen transaction and power flow patterns, created largely by FERC-ordered Transmission Access and lack of

new transmission resources. Often, the systems are operated near contingency thermal and stability limits. Therefore, transmission planners and operators are forced to look for ways to improve thermal and stability margins and to make more efficient use of the existing assets.

One such operating challenge involves oscillatory stability performance. North American power systems are increasingly experiencing oscillatory stability problems, which often translate to operational constraints. In addressing oscillatory stability problems, either new power system stabilizers (PSS) are applied to the existing generators or the existing PSS equipment is tuned for optimum control performance. These sections give an overview of two proposed methodologies for PSS tuning.

2.2.1 PSS design thorough low order transfer function identification

The utility companies most frequently apply the single-machine-infinite-bus (SMIB) framework when tuning a PSS for a specific plant in their power systems. Within this framework the plant is modeled in full details while the rest of the system is substituted by a fixed voltage bus (i.e. infinite bus). The PSS parameters are then obtained by applying phase-compensation technique in the frequency domain using linearized version of the SMIB model. This design technique has shown in practice that it produces parameters which provide robust performance over a range of operating conditions. However, some modes of oscillation which are present in the model of the entire system cannot be retained or reproduced in the SMIB framework. The assumption made during the control design is that these modes usually appear in the range of frequencies between 0.1 Hz and 1 Hz. Therefore, this method could potentially fail to provide the optimal damping for these modes of oscillations.

To overcome these limitations a technique, which combines a low-order identification of the generator in different operating conditions with a control design based on optimization of overall damping, is proposed. The identification technique is based on the Prony method. It is performed on the entire power system model. To overcome the limitation of the standard Prony method to provide estimates of transfer functions for controller design, the technique is utilizing a two step procedure. First, modal content of the model is extracted by applying the standard Prony method on the impulse response power system data. Then, a nonlinear optimization based on genetic algorithm (GA) is performed to fit the transfer function to the second set of data obtained from a TSA package by exciting the power system model via a Pseudo Random Binary Signal (PRBS) [30]. Only the zeros of the transfer function are optimized while the modes of the transfer function are

kept fixed to those values obtained in the first step. This identification technique is coupled with a controller design which can produce robust PSS settings for large scale power systems. Controller robustness is achieved by simultaneously improving the damping of low order transfer functions that represent a power system in different operating conditions. For this part of the dissertation the following research tasks are performed:

1. To be able to probe power systems with PRBS and pulse signals all necessary software modifications are performed in:
 - Power Analysis Toolbox (PAT) a simulation package developed by Advanced Power and Electricity Research Center (APEREC) at West Virginia University.
 - Power System Simulator for Engineering (PSS/E) an industry grade simulation software developed by Power Technologies, Inc.
2. Functions for low order model identification from the data obtained by pulse and PRBS probings are implemented in MATLAB
3. Identification technique is tested and a number of low order generator models are obtained for the following systems:
 - Two-Area-Four-Generator IEEE benchmark system
 - Fifty-Generator IEEE benchmark system
 - An actual 23300-bus American Electric Power/Eastern Interconnection (AEP/EI) power system model
4. Damping optimization technique is used on identified models to tune PSS controllers for the above systems. Controllers are then tested via nonlinear simulations.

2.2.2 Robust simultaneous tuning of multiple PSSs through multiobjective optimization

The PSS design methodology through low order transfer function identification in previous section is suitable for frequently occurring situations in practice where a single PSS needs to be tuned or re-tuned for optimal performance. However, in some situations multiple PSSs have to be tuned simultaneously in order to provide the damping of interarea modes of oscillation. In [32] a technique for simultaneous tuning of multiple PSS controllers was presented. The main focus of

this technique is providing optimal performance while implicitly including robustness criterion by observing simultaneously the system damping in multiple operating conditions. Therefore, since only the performance index is explicitly optimized the results obtained with this technique, although optimal for the analyzed operating conditions, could fail to produce robust performance under other operating points.

To address the issues of robustness and performance simultaneously a multiobjective optimization technique is proposed. The first objective is the performance objective formulated via a damping based index. The second objective is the H_∞ norm of a MIMO system which is a standard formulation used in robust control. The solution of the optimization is going to be a Pareto-like trade-off curve between the two objectives. Since, simultaneous optimization of two objective functions is required and both optimization problems are known to be nonlinear when a fixed controller structure is assumed, conventional tools for optimization cannot be utilized. Hence, to solve the optimization problem the use of evolutionary solver known as a Micro-Genetic Algorithm (MGA) [1] is proposed. For this part of the dissertation the following research tasks are performed:

1. To be able to perform multiobjective optimizations, available C++ based libraries for evolutionary optimizations are interfaced with MATLAB environment
2. Simultaneous tuning for multiple PSSs by means of multiobjective optimization is performed for the following systems:
 - Two-Area-Four-Generator IEEE benchmark system
 - Fifty-Generator IEEE benchmark system

Controllers are tested using a number of contingencies to test there performance and robustness.

Chapter 3

Function optimization

3.1 Introduction

When performing control designs different aspects, such as performance, robustness and control law, have to be considered. Performance specifications describe how the system behaves in the closed-loop. Several criteria might be of interest such as stability, damping or controller effort. Robust performance specifications describe how the closed-loop system would behave if some parts of the system were changed or perturbed. The perturbations could be due to any of the following:

- the system under control may have been inaccurately modeled or identified.
- the operating point of nonlinear system changes, and linear representation could be inadequate for the new operating point.
- potential sensor failures.

Control law specifications describe properties of the controller itself, i.e. the controller structure.

Assuming that the controller structure is known, robustness and performance objectives can often be given in the form of one or more objective functions. The controller parameters could then be determined by solving the optimization problem. This chapter gives an overview of the function optimization problem in its most general case and focuses specifically on Genetic Algorithms (GA) as one technique capable of efficiently handling this problem.

3.2 Multiobjective optimization problem formulation

A general multiobjective optimization problem can be expressed by the following equations:

$$\begin{aligned} \min F(x) &= \begin{bmatrix} f_1(x) & f_2(x) & \dots & f_n(x) \end{bmatrix} \\ \text{s.t. } x &\in S \end{aligned} \tag{3.1}$$

$$x = \begin{bmatrix} x_1 & x_2 & \dots & x_m \end{bmatrix}^T \tag{3.2}$$

where $\begin{bmatrix} f_1(x) & f_2(x) & \dots & f_n(x) \end{bmatrix}$ are n objective functions, $\begin{bmatrix} x_1 & x_2 & \dots & x_m \end{bmatrix}^T$ are the m optimization parameters that can be continuous and discrete and $S \in R^m$ is the parameter space. Parameter space in general case is defined as a set of nonlinear constraint functions on optimization parameters. Function F maps the parameter space onto the attribute space denoted by $Y \in R^n$, $F : S \rightarrow Y$.

In most cases, the objective functions are in conflict, so the reduction of one objective function leads to the increase in another. The result of the multi-objective optimization is known as a Pareto-optimal solution. A Pareto-optimal solution has the property that it is not possible to reduce any of the objective functions without increasing at least one of the other objective functions. A point $p^* \in S$ is defined as being Pareto-optimal if and only if there exists no other point $p \in S$ such that:

1. $f_i(p) \leq f_i(p^*), \forall i = 1, \dots, n$ and
2. $f_i(p) < f_i(p^*)$, for at least one i

The Pareto-optimal set is illustrated in Figure 3.1 for the case with two objective functions and two parameters, i.e. $n = 2$ and $m = 2$. A point lying in the interior of the attainable set Y is sub-optimal, since both f_1 and f_2 can be reduced simultaneously. A point lying on P the boundary of the set (the Pareto-optimal set) requires f_1 to be increased if f_2 is to be decreased and vice versa. If the final solution is selected from the set of Pareto optimal solutions, there would not exist any solutions that are better in all attributes. Hence, the final solution should be a member of Pareto optimal set.

Methods for obtaining the solution of the optimization problem can be divided into derivative and non-derivative methods. Non-derivative methods, also known as black box methods, are easier to implement for general engineering design problems since they do not require any derivatives

Figure 3.1: Sample two dimensional problem with two objective functions

of the objective function in order to calculate the optimum. They can easily handle continuous and discrete parameters. Another advantage of these methods is that they are more likely to find a global optima, and not get stuck in a local optima point as gradient methods might do. Furthermore, they do not impose any restrictions on objective and constraints functions. In this dissertation Genetic Algorithms based techniques are used to perform both single- and multi-objective optimization. The following sections give a more detailed theoretical background on genetic algorithms.

3.3 Genetic Algorithms

3.3.1 Introduction

Genetic Algorithms (GAs) represent a heuristic search technique based on the evolutionary ideas of natural selection and genetics. GAs are usually used to solve optimization problems by exploitation of a random search. When searching a large state-space, or n -dimensional surface, a genetic algorithm may offer significant benefits over the classical optimization techniques such as linear programming or nonlinear constrained optimization. Although randomized, using the historical information they direct the search into the region of better performance within the search space. GA based optimization techniques are designed to mimic processes in natural systems necessary for evolution. Since in nature, competition among individuals for resources results in the fittest individuals dominating over the weaker ones.

Individuals in GAs are usually in the form of character strings that are analogous to the

chromosome found in DNA. Each individual represents a possible solution within a search space. A number of individuals constitute a *population*. The individuals in the population are then made to go through a process of evolution, in order to produce a new *generation* of individuals that is closer to the optimal solution. The process of evolution is based on the following principles:

- Individuals in a population compete for resources and mates.
- The most successful individuals in each generation will have a chance to produce more offspring than those individuals that perform poorly.
- Genes from ‘good’ individuals propagate throughout the population so that two good parents will sometimes produce offspring that are better than either parent. Thus each successive generation will become more suited to their environment.

3.3.2 Implementation Details

A population of individuals is maintained within search space for a GA, each representing a possible solution to a given problem. Each individual is coded as a finite length vector of characters. A *fitness value* is assigned to each solution representing the ability of an individual to ‘compete’. The goal is to produce an individual with the fitness value close to the optimal. By combining information from the chromosomes, selective ‘breeding’ of individuals is utilized to produce ‘offspring’ better than the parents. Continuous improvement of average fitness value from generation to generation is achieved by using the *genetic operators*. The basic genetic operators are:

- *selection* — Used to achieve the survival of the fittest.
- *crossover* — Used for mating between individuals.
- *mutation* — Used to introduce random modifications.

The genetic operators are used in the GAs optimization procedure according to the flowchart given in Figure 3.2.

Selection

The selection mechanism favors the individuals with high fitness values. It allows these individuals better chance for reproduction into the next generation while reducing the reproduction

ability of least fitted members of population. Fitness of an individual is usually determined by an objective function.

Figure 3.2: Genetic Algorithms flowchart

Crossover

The crossover operator divides a population into the pairs of individuals and performs recombination of their genes with a certain probability. If *one-point* crossover is performed, as shown in Figure 3.3, one position in the individual genetic code is chosen. All gene entries after that position are exchanged among individuals. The newly formed offspring created from this mating are put into the next generation. Recombination can be done at many points, so that multiple portions of good individuals are recombined, this process is likely to create even better

individuals.

Figure 3.3: One-point crossover example

Mutation

When using mutation operator a portion of the new individuals will have some of their bits flipped with a predefined probability. In Figure 3.4 mutation operator is applied to the shaded genes of the parent. The purpose of mutation is to maintain diversity within the population and prevent premature convergence. The usage of this operator allows the search of some regions of the search space which would be otherwise unreachable.

Figure 3.4: Mutation example

The described operators are basic operators used when the individuals are encoded using binary alphabet. Operators for real valued coding scheme, i.e. an alphabet of floats, were developed by Michalewicz [33]. The following operators are defined: uniform mutation, non-uniform mutation, multi-non-uniform mutation, boundary mutation, simple crossover, arithmetic crossover and heuristic crossover.

- *Uniform mutation* randomly selects one individual and sets it equal to a uniform random number.
- *Boundary mutation* randomly selects one individual and sets it equal to either its lower or upper bound.

- *Non-uniform mutation* randomly selects one variable and sets it equal to a non-uniform random number.
- *Multi-non-uniform mutation* operator applies the non-uniform operator to all of the individuals in the current generation.
- *Real-valued simple crossover* is identical to the binary version.
- *Arithmetic crossover* produces two complementary linear combinations of the parents.
- *Heuristic crossover* produces a linear extrapolation of the two individuals.

In this dissertation a MATLAB implementation of Genetic Algorithm called GAOT [34] was used for single-objective function optimization in sections 4.1 and 5.1. This implementation is using real-valued alphabet parameter encoding. In both cases optimization was set to terminate after the prespecified number of generations was reached. The best individual of the final generation is considered to be the solution.

3.4 Micro-GA

The term micro-genetic algorithm (micro-GA) stands for a genetic algorithm with a small-population size. It was initially introduced in [35], where it was demonstrated that the population size of 3 was enough to achieve convergence regardless of the problem size. This was achieved by the process of reinitialization where a small initial population is generated randomly, then after it achieves nominal convergence a new population is generated by copying the best individuals from the old population and reinitializing the rest of the population randomly.

This approach was extended to a multiobjective optimization in [1] where a two memory micro-GA method was proposed. The population memory is introduced as a source of diversity and is further divided into a replaceable and a non-replaceable portion. External memory is used to store the Pareto solutions. The method works in the similar way as the classical GA. Initial population is generated randomly and fed into the population memory. At the beginning of each cycle with a certain probability initial population is taken from the both portions of the population memory.

As shown in Figure 3.5 the micro-GA then undergoes conventional genetic operators: tournament selection, two-point crossover, uniform mutation, and elitism. After which the non-dominated vectors are chosen and stored in the external memory providing that they dominate

vectors which are already stored in the external memory. This will also clear the external memory from all previously stored contents. Similar process is also done in the replaceable memory so that over time, the replaceable part of the population memory will tend to have more nondominated vectors. Further details about the micro-GA can be found in [1]. The authors also provided their micro-GA solver in the form of a C++ source code. This solver was used in section 5.2 to perform multiobjective optimization based PSS tuning. To interface this solver with the MATLAB environment a C++ mex function given in Appendix D was developed.

Figure 3.5: Micro GA block diagram adopted from [1]

Chapter 4

LFC design

4.1 GALMI method for robust PI controller tuning

This section describes GALMI technique and is organized as follows. A dynamic model of each control area for load frequency control problem when formulated for GALMI design is presented in section 4.1.1. Then, the algorithm of the proposed robust control design using the GALMI technique is illustrated in section 4.1.2 and section 4.1. Two types of robust load frequency controllers, which are based on the conventional H_∞ control and GALMI tuned PI control, are tested on a three-area power system with three scenarios of load disturbances, and their robust performance is compared in section 4.1.4 using nonlinear simulation.

4.1.1 Dynamic model

A large power system consists of a number of interconnected control areas, each of which has several generating units. In this section, a dynamic model of a generic control area i including n generating units is shown in Fig. 4.1. The units in each area are assumed to be coherent. To obtain the area frequency (Δf_i), generators are lumped. The state space model is given in eq. (4.1) and eq. (4.2). Also its controlled variables ($z_{i\infty}$) for H_∞ control design is defined as eq. (4.3).

$$\dot{x}_i = A_i x_i + B_{iu} u_i + B_{iw} w_i \quad (4.1)$$

$$y_i = C_i x_i \quad (4.2)$$

$$z_{i\infty} = C_{i\infty} x_i + D_{i\infty} u_i \quad (4.3)$$

Figure 4.1: Dynamic model of control area i .

or

$$z_{i\infty} = \begin{bmatrix} \beta_{1i}\Delta f_i & \beta_{2i} \int ACE_i & \beta_{3i}\Delta P_{Ci} \end{bmatrix}^T \quad (4.4)$$

$$w_i = \begin{bmatrix} \eta_i & \Delta P_{Di} \end{bmatrix}^T \quad (4.5)$$

where

$$x_i^T = \begin{bmatrix} x_{ia}^T & x_{i1}^T & x_{i2}^T & \dots & x_{in}^T \end{bmatrix}, \quad u_i = \Delta P_{Ci}$$

$$y_i^T = \begin{bmatrix} ACE_i & \int ACE_i \end{bmatrix}, \quad \eta_i = \sum_{\substack{j=1 \\ j \neq i}}^N T_{ij} \Delta f_j$$

$$x_{ia}^T = \begin{bmatrix} \Delta f_i & \Delta P_{tie_i} & \int ACE_i \end{bmatrix}$$

$$x_{i1}^T = \begin{bmatrix} \Delta P_{T1} & \Delta P_{V1} \end{bmatrix}$$

$$x_{in}^T = \begin{bmatrix} \Delta P_{Tn} & \Delta P_{Vn} \end{bmatrix}$$

$$A_i = \begin{bmatrix} AREA_i & MP_i \\ DROOP_i & TG_i \end{bmatrix}, \quad C_i = \begin{bmatrix} C_i^* & 0 \end{bmatrix}$$

$$B_{iu} = \begin{bmatrix} 0 \\ B_{iu}^* \end{bmatrix}, \quad B_{iw} = \begin{bmatrix} B_{iw}^* \\ 0 \end{bmatrix}, \quad C_{i\infty} = \begin{bmatrix} C_{i\infty}^* & 0 \end{bmatrix}$$

$$\begin{aligned}
AREA_i &= \begin{bmatrix} -\frac{D_i}{T_{Pi}} & \frac{-1}{T_{Pi}} & 0 \\ 2\pi \sum_{\substack{j=1 \\ j \neq i}}^N T_{ij} & 0 & 0 \\ B_i & 1 & 0 \end{bmatrix}, \quad C_i^* = \begin{bmatrix} B_i & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\
MP_i &= \underbrace{\begin{bmatrix} \left(\begin{smallmatrix} \frac{1}{T_{Pi}} & 0 \\ 0 & 0 \end{smallmatrix} \right) & \cdots & \left(\begin{smallmatrix} \frac{1}{T_{Pi}} & 0 \\ 0 & 0 \end{smallmatrix} \right) \\ \left(\begin{smallmatrix} \frac{1}{T_{Pi}} & 0 \\ 0 & 0 \end{smallmatrix} \right) & \cdots & \left(\begin{smallmatrix} \frac{1}{T_{Pi}} & 0 \\ 0 & 0 \end{smallmatrix} \right) \end{bmatrix}}_{n \text{ blocks}} \\
TG_i &= \begin{bmatrix} \begin{pmatrix} \frac{-1}{T_{T1}} & \frac{1}{T_{T1}} \\ 0 & \frac{-1}{T_{H1}} \end{pmatrix} & & 0 \\ & \ddots & \\ 0 & & \begin{pmatrix} \frac{-1}{T_{Tn}} & \frac{1}{T_{Tn}} \\ 0 & \frac{-1}{T_{Hn}} \end{pmatrix} \end{bmatrix} \\
DROOP_i &= \begin{bmatrix} \begin{pmatrix} 0 & 0 & 0 \\ \frac{-1}{R_1 T_{H1}} & 0 & 0 \end{pmatrix} \\ \vdots \\ \begin{pmatrix} 0 & 0 & 0 \\ \frac{-1}{R_n T_{Hn}} & 0 & 0 \end{pmatrix} \end{bmatrix} \\
B_{iu}^* &= \begin{bmatrix} \alpha_1 \begin{pmatrix} 0 \\ \frac{1}{T_{H1}} \end{pmatrix} \\ \vdots \\ \alpha_n \begin{pmatrix} 0 \\ \frac{1}{T_{Hn}} \end{pmatrix} \end{bmatrix}, \quad B_{iw}^* = \begin{bmatrix} 0 & \frac{-1}{T_{Pi}} \\ -2\pi & 0 \\ 0 & 0 \end{bmatrix} \\
C_{i\infty}^* &= \begin{bmatrix} \beta_{1i} & 0 & 0 \\ 0 & 0 & \beta_{2i} \\ 0 & 0 & 0 \end{bmatrix} \quad D_{i\infty} = \begin{bmatrix} 0 \\ 0 \\ \beta_{3i} \end{bmatrix}
\end{aligned}$$

where

P_T : turbine power
 P_V : governor valve
 P_C : governor load setpoint
 P_D : power demand
 f : area frequency
 P_{tie} : net tie-line flow
 η : area interface
 T_P : area aggregate inertia
 D : area load governing characteristic
 Δ : deviation from nominal values
 T_{ij} : Tie-line synchronizing coefficient between area i & j
 T_T : turbine time constant
 T_H : governor time constant
 R : droop characteristic
 B : frequency bias
 α : ramp rate factor
 N : number of control areas

In section 4.1, two types of robust LFC controllers are introduced. The first one is based on standard robust H_∞ design using LMI technique. The second controller is a GALMI tuned PI controller to achieve similar robust performance as the first one. The optimization objective for both is to minimize the effects of disturbances given in eq. (4.5) on the controlled variables as defined in eq. (4.4). This objective is :

$$\min \gamma_i = \|T_{z_{i\infty}w_i}\|_\infty \quad (4.6)$$

where $\|T_{z_{i\infty}w_i}\|_\infty$ is the infinity norm of the transfer function from w_i to $z_{i\infty}$.

Specifically, the design objectives are:

1. To regulate frequency deviation and area control error
2. To reduce excess maneuvering and unit wear and tear caused by equipment excursions.

The β_{1i} , β_{2i} , and β_{3i} in eq. (4.4) are weighting coefficients chosen by the designer. In this dissertation, they are 0.5, 1, and 500 respectively. The large coefficient “500” for example is chosen to limit control effort associated with overshoot and number of reversals of the governor load setpoint signal.

4.1.2 Robust H_∞ Control Design via LMI

Over the past two decades, robust control theory has been useful and applied to control system designs that require robustness against possible disturbances such as parameter uncertain-

ties, system modeling errors, plant and measurement noises, and external disturbances.

One major objective of robust control is to synthesize a controller that would guarantee internal stability of the system when bounded perturbations are present. This subsection describes the H_∞ control design via LMI approach, which is less complex than standard frequency-domain approaches that require substantial mathematical and computational effort.

Figure 4.2: Close-loop system via robust H_∞ control.

Fig. 4.2 shows a classical block diagram of the robust H_∞ control problem. The objective is to design a control law u based on the measured variables y such that the effects of the disturbance w on the controlled variables z_∞ as expressed by the infinity norm of its transfer function $\|T_{z_\infty w}\|_\infty$ does not exceed a given value, γ , defined as guaranteed robust performance. In order to synthesize an H_∞ controller via LMI approach, state space realizations of the system $P(s)$ and controller $K_\infty(s)$ are needed. They are given by eq. (4.7) and eq. (4.8) respectively.

State Space System Model

$$\begin{aligned}
 \dot{x} &= Ax + B_1 w + B_2 u \\
 z_\infty &= C_\infty x + D_{\infty 1} w + D_{\infty 2} u \\
 y &= C_y x + D_{y1} w
 \end{aligned} \tag{4.7}$$

(A, B_2) is stabilizable, and (A, C_y) is detectable.

State Space Controller Model

$$\begin{aligned}
 \dot{\zeta}_\infty &= A_{k\infty} \zeta_\infty + B_{k\infty} y \\
 u &= C_{k\infty} \zeta_\infty + D_{k\infty} y
 \end{aligned} \tag{4.8}$$

Combining the above equations results in the following closed-loop system:

$$\begin{aligned}
 \dot{x}_{cl} &= A_{cl} x_{cl} + B_{cl} w \\
 z_\infty &= C_{cl1} x_{cl} + D_{cl1} w
 \end{aligned} \tag{4.9}$$

where

$$\begin{aligned}
 x_{cl} &= \begin{bmatrix} x \\ \zeta_\infty \end{bmatrix}, \quad A_{cl} = \begin{bmatrix} A + B_2 C_{k\infty} C_y & B_2 C_{k\infty} \\ B_{k\infty} C_y & A_{k\infty} \end{bmatrix} \\
 B_{cl} &= \begin{bmatrix} B_1 + B_2 C_{k\infty} D_{y1} \\ B_{k\infty} D_{y1} \end{bmatrix} \\
 C_{cl1} &= \begin{bmatrix} C_\infty + D_{\infty 2} D_{k\infty} C_y & D_{\infty 2} C_{k\infty} \end{bmatrix} \\
 D_{cl1} &= D_{\infty 1} + D_{\infty 2} D_{k\infty} D_{y1}
 \end{aligned}$$

The following lemma relates H_∞ control design to LMI.

Lemma 4.1 *The closed-loop RMS gain or H_∞ norm of the transfer function from w to z_∞ , $\|T_{z_\infty w}\|_\infty$, does not exceed γ , if and only if there exists a symmetric matrix X_∞ such that*

$$\begin{bmatrix} A_{cl} X_\infty + X_\infty A_{cl}^T & B_{cl} & X_\infty C_{cl1}^T \\ B_{cl}^T & -I & D_{cl1}^T \\ C_{cl1} X_\infty & D_{cl1} & -\gamma^2 I \end{bmatrix} < 0 \quad (4.10)$$

$$X_\infty > 0 \quad (4.11)$$

An optimal H_∞ control design can be achieved by minimizing the guaranteed robust performance index, γ , subject to the constraints given by the matrix inequalities eq. (4.10) and eq. (4.11). The MATLAB's LMI control toolbox provides the function "hinflmi" to solve an H_∞ control problem directly. This function returns the controller parameters, $K_\infty(s)$, as shown in eq. (4.8) with the optimal robust performance index γ^* . The obtained controller is a dynamic type, whose order is the size of the system and hence very large in general.

Some control applications require predefined controller structures such as proportional-integral (PI), or output feedback controllers, which are different than the above full-order dynamic controller shown in eq. (4.8). This might modify the current H_∞ control design into a nonconvex optimization problem, which cannot be directly solved by LMI techniques. As a result, genetic algorithms, a powerful search technique, is utilized as an additional tool for solving such a hard optimization problem.

4.1.3 Novel Robust Control Design via GALMI

In practice, the LFC controller structure is traditionally a proportional-integral (PI) type controller using the ACE as its input as shown in eq. (4.12). In this section, the robust control design algorithm for such a load frequency controller using GALMI technique is presented. The objective of the proposed design is to tune the PI controller parameters to achieve the same robust performance as the conventional H_∞ design.

$$u_i = \Delta P_{Ci} = K_{Pi}ACE_i + K_{Ii} \int ACE_i \quad (4.12)$$

$$u_i = [K_{Pi} \ K_{Ii}] \begin{bmatrix} ACE_i \\ \int ACE_i \end{bmatrix} \quad (4.13)$$

$$u_i = K_i y_i \quad (4.14)$$

From the above equations, the desired controller is only a simple static output feedback controller, and it is much less complex than the one obtained from the conventional H_∞ control design shown in eq. (5.2). To determine the control parameter vector (K_i), eq. (4.2) is first substituted into eq. (4.14), which results in eq. (4.15). Next, eq. (4.15) is substituted into eq. (4.1) and eq. (4.3), and the closed-loop system is finally obtained as eq. (4.16).

$$u_i = K_i C_i x_i \quad (4.15)$$

$$\dot{x}_i = A_{cl} x_i + B_{cl} w_i \quad (4.16)$$

$$z_{i\infty} = C_{cl1} x_i + D_{cl1} w_i$$

where

$$A_{cl} = A_i + B_{iu} K_i C_i, \quad B_{cl} = B_{iw}$$

$$C_{cl1} = C_{i\infty} + D_{i\infty} K_i C_i, \quad D_{cl1} = [0]$$

Subsequently, K_i is searched for in order to minimize the performance index, γ , subject to robust control constraints given by matrix inequalities eq. (4.10) and eq. (4.11). The successfully obtained control vector (K_i) also guarantees the system stability, which is the small-signal stability of the control areas in this case.

However, a solution of the consequent nonconvex constrained optimization problem cannot be achieved by using LMI techniques alone. Therefore, the proposed genetic algorithm (GA)

Figure 4.3: Robust control design via GALMI technique.

optimization technique is utilized to search off-line for the control parameters (K_i) of the PI load frequency controller at the upper level, whereas the LMI control toolbox is used at the lower level to solve the linear matrix inequalities given as constraints for robust H_∞ control design. The off-line hybrid optimization algorithm that describes the GALMI technique is shown in Fig 4.3.

The proposed algorithm gives the constant optimal robust control parameters (K_i^*), when the minimum robust performance index (γ^*) is achieved. According to Fig. 4.3, NUM is the number of generations the GA procedure is required to evolve when searching for the best K_i^* . This number is prespecified and should be large enough to ensure that the global minimum of γ is found. The described control design is applied in the next section to design load frequency controllers for a three-area power system.

4.1.4 Case study

The test system, shown in Fig. 4.4, consists of three control areas, and its parameters are tabulated in Table 4.1.

Figure 4.4: A three-area power system.

Table 4.1: Generating unit parameters

Parameters	Genco								
MVA_{base} (1000 MW)	1	2	3	4	5	6	7	8	9
Rate (MW)	1000	800	1000	1100	900	1200	850	1000	1020
D (pu/Hz)	0.0150	0.0140	0.0150	0.0160	0.0140	0.0140	0.0150	0.0160	0.0150
T_P (pu.sec)	0.1667	0.1200	0.2000	0.2017	0.1500	0.1960	0.1247	0.1667	0.1870
T_T (sec)	0.4	0.36	0.42	0.44	0.32	0.40	0.30	0.40	0.4100
T_H (sec)	0.08	0.06	0.07	0.06	0.06	0.08	0.07	0.07	0.08
R (Hz/pu)	3.00	3.00	3.30	2.7273	2.6667	2.50	2.8235	3.00	2.9412
B (pu/Hz)	0.3483	0.3473	0.3180	0.3827	0.3890	0.4140	0.3692	0.3493	0.3550
α	0.4	0.4	0.2	0.6	0	0.4	0	0.5	0.5
Ramp rate (MW/min)	8	8	4	12	0	8	0	10	10

Each area has three generating units that are owned by different generation companies (Gencos). Two types of robust decentralized load frequency controllers, 1) robust H_∞ control designed according to the procedure described in section II, and 2) robust GALMI tuned PI control designed based on the proposed GALMI algorithm presented in section IV, are implemented in each area. The obtained robust performance indices (γ) of both designs are almost identical as shown in Table 4.2.

The results show no degradation on the GALMI tuned PI control design. But its structure is much simpler than the robust H_∞ design, whose order is the number of system states (or the size of A_i) that increases with the modeling details and the number of units, and it can be very

Table 4.2: Robust performance index

Control Design	γ_{area1}	γ_{area2}	γ_{area3}	Control Structure
GALMI	500.0090	500.0085	500.0086	PI
H_∞	500.0152	500.1470	500.0183	9 th order

large. In this section, the performance of the robust PI controllers is compared with that of the dynamic H_∞ controllers for three scenarios of load disturbances.

For Scenario 1, random load changes, shown in Fig. 4.5(a), representing expected load fluctuations, are applied to the three control areas. The area control error (ACE), frequency deviation (Δf), and governor load setpoint (ΔP_C) closed-loop responses are shown in Fig. 4.5(b)-4.6(b).

From the results, both controllers ramp generated power to match the load fluctuations effectively. The performance of the GALMI tuned PI controllers is almost identical to that of full order H_∞ controllers. In addition, Fig. 4.7 shows the raise/lower signals allocated to all generating units in area 1 conforming to their offered ramp rates.

For Scenario 2, a large disturbance, a step increase in demand, is applied to each area: $\Delta P_{D1} = 100$ MW, $\Delta P_{D2} = 80$ MW, and $\Delta P_{D3} = 50$ MW. The purpose of this scenario is to test the robustness of the proposed controllers against large disturbances. In fact, these large step changes in demand rarely occur since a party which causes a serious mismatch between actual and forecast load is likely to be penalized.

Fig. 4.8 and 4.9 show the responses of areas 1 and 2. The ACE and frequency deviation (Δf) are effectively damped to zero with very small oscillations by the GALMI tuned PI controllers. The control input (ΔP_C) is also smoothly increased to the expected value without overshoot and oscillations. These controllers perform as well as the robust H_∞ controllers. Above step changes in power demand are considered significant because of the large overshoot (0.1 Hz) in the frequency deviations.

For Scenario 3, large step increases in demand are applied to areas 2 and 3: $\Delta P_{D2} = 100$ MW, and $\Delta P_{D3} = 50$ MW. To make the scenario drastic, it is assumed that LFC reset controllers of areas 2 and 3 are out of service. As a result, the frequency deviation of all areas cannot be driven to zero, which causes the area interface (η), treated as a system disturbance, to remain nonzero all the time. The purpose of the scenario is to investigate the response of the system to such a severe condition, when only area 1 proposed LFC controller is kept active.

The responses of area 1, given in Fig. 4.10, show that the ACE is driven to zero successfully,

(a) Load changes for Scenario 1

(b) Area 1

Figure 4.5: System response for Scenario 1. Solid (GALMI), Dash-dotted (H_∞)

(a) Area 2

(b) Area 3

Figure 4.6: System response for Scenario 1. Solid (GALMI), Dash-dotted (H_∞)

Figure 4.7: Raise/lower signals of units in area1. Solid (GALMI), Dash-dotted (H_∞) Figure 4.8: Area 1 response for Scenario 2. Solid (GALMI), Dash-dotted (H_∞)

Figure 4.9: Area 2 response for Scenario 2. Solid (GALMI), Dash-dotted (H_∞)

Figure 4.10: Area 1 response for Scenario 3. Solid (GALMI), Dash-dotted (H_∞)

Figure 4.11: Area 3 response for Scenario 3. Solid (GALMI), Dash-dotted (H_∞)

and the governor load setpoint has very small oscillations during transient and goes back to zero in a very short time. The response of the governor load setpoint of GALMI tuned PI controller is slightly degraded compared with that of the H_∞ controller. This is because the H_∞ controller is a high order dynamic controller where its order is as large as the number of states of the system. For this example the H_∞ controller is of 9^{th} order, but the GALMI controller is a simple PI controller. Incidentally, the responses of ACE and frequency deviation of the H_∞ and GALMI tuned PI controllers are almost the same. In addition, the responses of area 3 are shown in Fig. 4.11. Without the LFC controller, the ACE cannot be driven back to zero.

4.2 Model Predictive Control strategy for LFC

This section describes a fully decentralized MPC control architecture for LFC, where only ACE signal is used as the input to the controller. The chapter is organized as follows. Technical background on MPC is given in section 4.2.1. Next, a dynamic model of each control area when formulated for the proposed MPC design is presented in section 4.2.2. In section 4.2.3, using a nonlinear simulation of a three-area power system with three scenarios of load disturbances, the MPC controllers are tested and their performance is compared to that of H_∞ controllers.

4.2.1 Model Predictive Control

The underlying idea behind the Model Predictive Control is to first obtain a process model around a certain operating point, where the output signals, y , are expressed in terms of past and future control signals, u . Then, the future control strategy is calculated by optimizing the forecast from the obtained process model according to some pre-specified criterion. The typical MPC scheme is given in Fig. 4.12.

Figure 4.12: Schematic representation of a model based process control system

There are a number of formulations of the MPC strategy based on the same underlying idea that differ either, in the way the process model is obtained, i.e. step response model or finite impulse response model, or in the formulation of the objective function. However, they all use a model of the process explicitly to obtain the control signal by minimizing an objective function. The following steps represent the core of model predictive control and at least some of these steps are included in each different variant of MPC:

1. At present time t , calculate or predict the output $\hat{y}(t+k|t)$ from the process, over a prediction horizon M . These outputs will depend on future control signals $\bar{u}(t+j)$, $j = 0, \dots, N$, and past outputs and control signals, which are known. The output prediction is obtained by using a process model.
2. Choose a criterion based on the variable $\hat{y}$ and the states $\hat{x}$ and optimize it with respect to $\bar{u}(t+j)$, $j = 0, \dots, N$ under the chosen constraints. The current state of the plant is used as the initial state for the prediction.

3. Apply the first control signal $u(t)$ obtained from the optimization procedure.
4. At time $t + 1$ go to the first step and repeat.

There are several tuning parameters in the MPC algorithm [36], and they should be chosen with care to get the desired result. They are:

- M. M is the prediction horizon for the outputs y . M should be chosen so that it covers the settling time for the system, thus making it possible to look beyond to the more stable behavior. The value of M will directly influence the calculation time of the optimization problem.
- N. N is the prediction horizon for the control signals u . It is often a smaller number than M , since it more or less decides the size of the optimizing problem.

Additionally, the crucial part of the MPC control design is to pick the criterion to be optimized. It is up to the designer of the control system to chose reasonable, sensible criterion, the one that can be fulfilled by the system.

In this dissertation routines from the MPC Toolbox [37] were used in order to implement an MPC strategy within MATLAB environment. The MPC toolbox assumes that the model that describes the controlled process can be expressed with the following set of equations.

$$\begin{aligned} x(k+1) &= Ax(k) + B_u u(k) + B_v v(k) + B_d d(k) \\ y(k) &= Cx(k) + D_v v(k) + D_d d(k) \end{aligned} \quad (4.17)$$

where $x(k)$ represents the state of the system, $u(k)$ are manipulated variables or control inputs, $v(k)$ is a vector of measured disturbances, $d(k)$ are unmeasured disturbances, and $y(k)$ is the output vector.

The unmeasured disturbance $d(k)$ is modelled as the output of the following Linear Time Invariant (LTI) system:

$$x_d(k+1) = Fx_d(k) + Gn(k) \quad (4.18)$$

$$d(k) = Hx_d(k) + Kn(k) \quad (4.19)$$

System eq. (4.18) is driven by the random Gaussian noise $n(k)$, which has zero mean and unit covariance matrix.

The MPC controller selects the input $u(k)$ by solving the following optimization problem

$$\min_{\Delta u(k|k), \dots, \Delta u(m-1+k|k)} \sum_{i=0}^{p-1} \left[\|\omega_i^u [u(k+i|k) - u_{\text{target}}(k)]\|^2 + \|\omega_i^{\Delta u} [\Delta u(k+i|k)]\|^2 + \right] + \rho_\varepsilon \varepsilon^2$$

$$\text{subj.to} \begin{cases} u_i^{\min} \leq u(k+i|k) \leq u_i^{\max} \\ \Delta u_i^{\min} \leq \Delta u(k+i|k) \leq \Delta u_i^{\max} & i = 1, \dots, p-1 \\ -\varepsilon + y_i^{\min} \leq y(k+i|k) \leq y_i^{\max} + \varepsilon \\ \Delta u(k+j|k) = 0 & j = m, \dots, p \\ \varepsilon > 0 \end{cases}$$

with respect to the sequence of input increments $\Delta u(k|k), \dots, \Delta u(m-1+k|k)$ and the slack variable ε . Input and input-variation constraints are treated as hard constraints, output constraints are considered as soft. This is done by introducing the slack variable ε that prevents the MPC controller to get stuck because of infeasibility of the optimization problem. In the above equation, $u_{\text{target}}(k)$ is a set-point for the input vector; w_i^y , w_i^u and $w_i^{\Delta u}$ are nonnegative weighting coefficients; $u_i^{\min}$, $u_i^{\max}$, $\Delta u_i^{\min}$, $\Delta u_i^{\max}$, $y_i^{\min}$ and $y_i^{\max}$ are lower/upper bounds to be enforced; $*(k+i|k)$ denotes the value predicted for time $k+i$ based on the information available at time k ; $r(k)$ is the current sample of the output reference.

4.2.2 Dynamic model

A large power system consists of a number of interconnected control areas, each of which has several generating units. In this section, a dynamic model of a generic control area i including n generating units is shown in Fig. 4.2. The units in each area are assumed to be coherent. To obtain the area frequency (Δf_i), generators are lumped. The state space model is given in eq. (4.20).

$$\dot{x}_i = A_i x_i + B_{iu} u_i + B_{id} d_i \quad (4.20)$$

$$y_i = C_i x_i \quad (4.21)$$

where

$$\begin{aligned}
x_i^T &= \begin{bmatrix} x_{ia}^T & x_{i1}^T & x_{i2}^T & \dots & x_{in}^T \end{bmatrix}, & u_i &= \Delta P_{Ci} \\
y_i &= \begin{bmatrix} ACE_i \end{bmatrix}, & \eta_i &= \sum_{\substack{j=1 \\ j \neq i}}^N T_{ij} \Delta f_j \\
x_{ia}^T &= \begin{bmatrix} \Delta f_i & \Delta P_{tie_i} \end{bmatrix}, & d_i &= \begin{bmatrix} \eta_i & \Delta P_{Di} \end{bmatrix} \\
x_{i1}^T &= \begin{bmatrix} \Delta P_{T1} & \Delta P_{V1} \end{bmatrix} \\
x_{in}^T &= \begin{bmatrix} \Delta P_{Tn} & \Delta P_{Vn} \end{bmatrix} \\
A_i &= \begin{bmatrix} AREA_i & MP_i \\ DROOP_i & TG_i \end{bmatrix}, & C_i &= \begin{bmatrix} \hat{C}_i & 0 \end{bmatrix} \\
B_{iu} &= \begin{bmatrix} 0 \\ \hat{B}_{iu} \end{bmatrix}, & B_{id} &= \begin{bmatrix} \hat{B}_{id} \\ 0 \end{bmatrix} \\
AREA_i &= \begin{bmatrix} -\frac{D_i}{T_{Pi}} & \frac{-1}{T_{Pi}} \\ 2\pi \sum_{\substack{j=1 \\ j \neq i}}^N T_{ij} & 0 \end{bmatrix}, & \hat{C}_i &= \begin{bmatrix} B_i & 1 \end{bmatrix} \\
MP_i &= \underbrace{\begin{bmatrix} \begin{pmatrix} \frac{1}{T_{Pi}} & 0 \\ 0 & 0 \end{pmatrix} & \dots & \begin{pmatrix} \frac{1}{T_{Pi}} & 0 \\ 0 & 0 \end{pmatrix} \end{bmatrix}}_{n \text{ blocks}} \\
TG_i &= \begin{bmatrix} \begin{pmatrix} \frac{-1}{T_{T1}} & \frac{1}{T_{T1}} \\ 0 & \frac{-1}{T_{H1}} \end{pmatrix} & & 0 \\ & \ddots & \\ 0 & & \begin{pmatrix} \frac{-1}{T_{Tn}} & \frac{1}{T_{Tn}} \\ 0 & \frac{-1}{T_{Hn}} \end{pmatrix} \end{bmatrix} \\
DROOP_i &= \begin{bmatrix} \begin{pmatrix} 0 & 0 \\ \frac{-1}{R_1 T_{H1}} & 0 \end{pmatrix} \\ \vdots \\ \begin{pmatrix} 0 & 0 \\ \frac{-1}{R_n T_{Hn}} & 0 \end{pmatrix} \end{bmatrix} \\
\hat{B}_{iu} &= \begin{bmatrix} \alpha_1 \begin{pmatrix} 0 \\ \frac{1}{T_{H1}} \end{pmatrix} \\ \vdots \\ \alpha_n \begin{pmatrix} 0 \\ \frac{1}{T_{Hn}} \end{pmatrix} \end{bmatrix}, & \hat{B}_{iw} &= \begin{bmatrix} 0 & \frac{-1}{T_{Pi}} \\ -2\pi & 0 \end{bmatrix}
\end{aligned}$$

In this dissertation the area model described by eq. (4.20), is first discretized with a chosen sampling rate, and then used as a process model eq. (4.17) for the MPC controller design. Since completely decentralized design is sought, vector d_i , consisting of area interconnections η_i and area power demand change ΔP_{Di} , is treated as an unmeasured disturbance for the i -th area (see eq. (4.17)). Therefore, the obtained discrete versions of A_i , B_{iu} and B_{id} from eq. (4.20) correspond to A , B_u and B_d from eq. (4.17), while B_v is omitted since no disturbance is measured. As the result of the optimization procedure given in eq. (5.6), the MPC controller produces a governor setpoint signal ΔP_C , using only the local *ACE* measurement. The weighting coefficients w_i^y , w_i^u and $w_i^{\Delta u}$ are obtained by a trial and error procedure.

4.2.3 Case study

The test system, shown in Fig. 4.4, consists of three control areas, and its parameters are tabulated in table 4.1. Each area has three generating units that are owned by different generation companies (Gencos). Two types of robust decentralized load frequency controllers, 1) MPC controller designed based on the algorithm presented in sections 4.2.1 and 4.2.2, and 2) robust H_∞ control designed according to the procedure described in 4.1.2, are implemented in each area. Controllers performance is tested in three scenarios.

For Scenario 1, random load changes, shown in Fig. 4.13(a), representing expected load fluctuations, are applied to the three control areas. This scenario tests the controllers' ability to cope with the usual load changes that are happening constantly in power systems. The area control error (ACE), frequency deviation (Δf), and governor setpoint (ΔP_C) closed-loop responses for area 1, 2 and 3 are shown in Fig. 4.13(b), Fig. 4.14(a) and Fig. 4.14(b) respectively. From the results, both controllers ramp generated power to match the load fluctuations effectively. The performance of the MPC controllers is almost identical to that of H_∞ controllers. Therefore, both control designs handle this type of contingency in a similar manner.

For Scenario 2, a large disturbance, a step increase in demand, is applied to each area: $\Delta P_{D1} = 100$ MW, $\Delta P_{D2} = 80$ MW, and $\Delta P_{D3} = 50$ MW. In this scenario generating rate constraint was not imposed on the system. The purpose of this scenario is to test the robustness of the proposed controllers against large disturbances. In fact, these large step changes in demand rarely occur since a party which causes a serious mismatch between actual and forecasted load is likely to be penalized.

Fig. 4.15, Fig. 4.16 and Fig. 4.17 show the responses of areas 1, 2 and 3. The ACE

(a) Load changes for Scenario 1

(b) Area 1

Figure 4.13: System response for Scenario 1. Solid (MPC), Dash-dotted (H_∞)

(a) Area 2

(b) Area 3

Figure 4.14: System response for Scenario 1. Solid (MPC), Dash-dotted (H_∞)

Figure 4.15: Area 1 response for Scenario 2. Solid (MPC), Dash-dotted (H_∞)

Figure 4.16: Area 2 response for Scenario 2. Solid (MPC), Dash-dotted (H_∞)

Figure 4.17: Area 3 response for Scenario 2. Solid (MPC), Dash-dotted (H_∞)

and frequency deviation (Δf) are successfully damped to zero with very small oscillations by both types controllers. The control input (ΔP_C) is also smoothly increased to the expected value without overshoot and oscillations. From the system responses, it can be observed, that under this scenario, the MPC controllers perform slightly better than H_∞ controllers.

In Scenario 3, the same load disturbance as in Scenario 2 was applied in each area. Additionally, a generating rate constraint of 20 MW/min was imposed on each area. The purpose of this scenario is to test the robustness of the proposed controllers under large disturbances while at the same time handling the GRC. The responses from each area are given in Fig. 4.18, Fig. 4.19 and Fig. 4.20.

A longer time period of 2000 seconds was simulated in order to fully observe the effects of GRC on control performance. The superior performance of MPC controllers can be observed. The responses show that the MPC controllers successfully bring the system back to the stable operating point in less than 350 seconds without any oscillations or overshoot, while at the same time, the system controlled by H_∞ controllers is experiencing severe oscillations and does not achieve the equilibrium point even after 2000 seconds of simulation. For this scenario MPC design outperforms the H_∞ , due to the fact that the MPC incorporates hard constraints on the rate of change of command inputs u as a part of the optimization procedure (see eq. (5.6)).

Figure 4.18: Area 1 response for Scenario 3. Solid (MPC), Dash-dotted (H_∞) Figure 4.19: Area 2 response for Scenario 3. Solid (MPC), Dash-dotted (H_∞)

Figure 4.20: Area 3 response for Scenario 3. Solid (MPC), Dash-dotted (H_∞)

Chapter 5

PSS design

5.1 PSS design through low order model identification

The chapter describes a novel technique for PSS tuning and is organized as follows. Technical background on transfer function identification and controller design method is given in section 5.1.1 and section 5.1.2. Case studies with descriptions of the three test systems are presented in section 5.1.3.

5.1.1 Low Order Model Identification

The essential part of the proposed model identification procedure is the Prony algorithm. The Prony method is a procedure for fitting a signal $y(t)$ to a weighted sum of exponential terms of the form:

$$\hat{y}(t) = \sum_{i=1}^n R_i e^{\lambda_i t} \quad (5.1)$$

where R_i is the residue associated with the mode λ_i . The residues and modes are identified by fitting, in a least squares sense, $\hat{y}$ to the system output y . The strategy for obtaining the Prony solution for residues and modes is summarized in [23]. To acquire a low order model of power system suitable for the PSS design the following procedure is proposed:

- *Step 1* – In the TSA package the large-scale system is first perturbed with a pulse probing signal and then with a pseudo random binary probing signal. Both probing signals are applied into the exciter at the PSS signal input point. The duration and amplitude of the pulse should be set at the appropriate values to ensure that the system operates in the linear region. The PRBS probing signal is processed following the guidelines given in [30]. The

system responses to the pulse and PRBS excitation are obtained for all PSSs to be designed. During the simulations, potential controller input signals (e.g. speed deviation, electrical power or accelerating power) are recorded.

Using measurements obtained in this step the next two steps are carried out in MATLAB to acquire low order transfer functions suitable for controller design.

- *Step 2* – Standard Prony analysis is performed on the impulse response power system data to identify the modal content of the system. As suggested in [23, 27] extra high order model is needed to ensure accuracy of the identified modes. Transfer function obtained in this fashion has a number of redundant modes. These modes are eliminated from the model by analyzing corresponding residues. First, the residue vector is normalized and sorted in descending order. Then, starting from the top of the vector, the residues and their corresponding modes are added to the reduced model until a certain threshold value (e.g. 90%) of the residue vector norm is retained in the reduced model. In this way only a small number of important eigenvalues with high observability and controllability indices are retained in the reduced model. The low order model identified in this step is transformed into the canonical state space model of the form:

$$\begin{aligned} \dot{x} &= \Lambda x + \Gamma u \\ y &= \Omega x \end{aligned} \tag{5.2}$$

where: $\Lambda = \text{diag} \{ \lambda_i, i = 1, \dots, n \}$

- *Step 3* – The system given by eq. (5.2) is excited using the same probing PRBS signal as applied on the large-scale system in the first step of the procedure. Nonlinear optimization, by means of the GAs, is then performed to fit, in a least square sense, the PRBS response of the low order system to the PRBS response of the large-scale system. During the optimization matrix Λ is kept unchanged with the identified modes placed on the main diagonal. The GA algorithm is set to search for the optimal values of Γ and Ω vector entries. The bounds of the search space is within $\pm 400\%$ of their initial values identified by the Prony analysis. The optimization is terminated after the specified number of iterations is executed.

5.1.2 Controller Design

This section describes the procedure for controller tuning. For each operating condition, the power system models are obtained by utilizing the described identification technique. Hence,

a low order single-input-single-output (SISO) model is obtained for each generator with PSS controller capabilities in every operating condition under consideration. The problem of selecting the parameters of a PSS controller that would assure optimal damping performance over the considered set of operating points is solved via a GAs optimization procedure with an eigenvalue-based performance index.

Model and Controller Structure

Eq. (5.2) describe a low order transfer function identified around a certain operating point.

Controller equations in the state-space can be written as:

$$\begin{aligned}\dot{x}_k &= A_k x_k + B_k y \\ u &= C_k x_k + D_k y\end{aligned}\tag{5.3}$$

where x_k is the state vector of the controller.

Combining eq. (5.3) with eq. (5.2) a closed loop system given in eq. (5.4) is obtained.

$$\begin{bmatrix} \dot{x} \\ \dot{x}_k \end{bmatrix} = \underbrace{\begin{bmatrix} \Delta + \Gamma D_k \Omega & \Gamma C_k \\ B_k C & A_k \end{bmatrix}}_{A_{cl}} \begin{bmatrix} x \\ x_k \end{bmatrix}\tag{5.4}$$

where A_{cl} is the closed loop matrix of the system.

Let $\lambda_j = \alpha_j \pm i\beta_j$ be the j -th eigenvalue (mode) of the closed loop matrix A_{cl} . Its damping ratio (ξ_j) is defined:

$$\xi_j = -\frac{\alpha_j}{\sqrt{\alpha_j^2 + \beta_j^2}}\tag{5.5}$$

Objective Function

The goal of GA based optimization procedure is to improve the damping *for all modes over all operating conditions under consideration*, by exploring the search space of admissible controller parameters.

Two types of power system stabilizers were considered in this dissertation: 1) a single input PSS shown in Fig. 5.1 for case studies in sections 5.1.3 and 5.1.3, 2) a dual input PSS shown in Fig. 5.2 for case study in section 5.1.3. Any other PSS model that can be represented in a transfer function form can be used. The system is identified in the open loop between points V_{Cin} and V_{Cout} (Fig. 5.1 and Fig. 5.2). Parameters determined by the GA procedure were PSS gain K_s ,

and lead/leg time constants T_1 , T_2 , T_3 , and T_4 . Washout time constants were kept fixed during the optimization.

Figure 5.1: Single input PSS

Figure 5.2: Dual input PSS

Let Ξ_p be a vector of damping coefficients ξ_j , $j = 1, \dots, n$ for the p -th operating condition. Where n is the total number of modes of the closed loop matrix A_{cl} . Then, the optimization problem to be solved by the GA is written in the following form:

$$\max_{K_S, T_1, T_2, T_3, T_4} F = \sum_{p=1}^m \left(\sum_{j=1}^n \Xi_p(j) \right) \quad (5.6)$$

subject to

$$\begin{aligned} K_{Smin} &\leq K_S \leq K_{Smax} \\ T_{1min} &\leq T_1 \leq T_{1max} \\ T_{2min} &\leq T_2 \leq T_{2max} \\ T_{3min} &\leq T_3 \leq T_{3max} \\ T_{4min} &\leq T_4 \leq T_{4max} \end{aligned} \quad (5.7)$$

where m is the total number of operating conditions under consideration.

5.1.3 Case Studies

Two Area System

This two-area power system, introduced in [38] as a benchmark system for inter-area oscillations studies, consists of two generators in each area, connected via a 220 km tie line. All generators are equipped with simple exciters and have the same parameters which are given in Appendix B. The one-line diagram of the test system is given in Fig. 5.3.

Figure 5.3: The Two-Area system single line diagram

With 400 MW power flow from Area 1 to Area 2, the most critical contingency for this test system is the loss of a line between buses 3 and 101. Without the supplementary controllers installed, a poorly damped mode of frequency 0.62 Hz is excited following this disturbance. The effects of installing power system stabilizers at generators 1 and 3 on the overall system damping were analyzed.

To design the PSS the low order systems were first identified for the following two system configurations:

- *Operating Condition 1* – Two lines between bus 3 and bus 101
- *Operating Condition 2* – A single line between bus 3 and bus 101

Steps 1-3 described in section 5.1.1 were applied to this system. Following *Step 3*, 12 dominant modes were retained, compared to 40 modes for the full linearized system. Responses to the PRBS excitation of the identified model for generator 3 and the full-scale power system are shown in Fig 5.4. It can be seen that the two responses are practically identical. Additionally, as shown in Fig 5.5 the actual and the low order system exhibit similar characteristics in the frequency domain. Similar results were obtained for generator 1.

Figure 5.4: Comparison between identified and actual systems in time domain

Figure 5.5: Comparison between identified and actual systems in frequency domain

Hence, the identified low order models are suitable for the design of power system stabilizers at generators 1 and 3. The tuning is performed according to the procedure described in section 5.1.2. Setting $T_1 = T_3$ and $T_2 = T_4$ during the optimization the following controller transfer functions were obtained:

$$G_1(s) = \frac{111s}{(1+10s)} \frac{(1+1.7s)^2}{(1+0.58s)^2} \quad (5.8)$$

$$G_3(s) = \frac{223s}{(1+10s)} \frac{(1+0.26s)^2}{(1+0.03s)^2} \quad (5.9)$$

Fig. 5.6 shows the dominant modes of the linearized system in *Operating Condition 1* and *Operating Condition 2* in the open loop and when closed with the two designed PSSs.

Figure 5.6: Dominant modes of the full system in two operating conditions

The controllers are tested using the following simulation scenarios.

- Scenario 1 At time $t = 100$ ms, a three-phase fault is applied at the line between buses 3 and 101, the near end of the line is opened at $t = 190$ ms and the line is completely removed at $t = 200$ ms.
- Scenario 2 Same as Scenario 1 in terms of the type, location and duration of the fault. To test the impact of a dynamic load on the system stability a double cage induction motor was

connected to the bus 13 through a transformer. The power consumption of the motor was set to $90MW$ while equivalent amount of power was reduced at bus 14. Parameters for the motor are given in Appendix B.

Fig. 5.7 shows the Scenario 1 response of relative angle between the two areas for the system with and without damping controllers.

Figure 5.7: Three-Phase fault angle difference response Scenario 1

Figure 5.8 and Figure 5.9 present the simulation results for Scenario 2 for the system with and without damping controllers. It can be observed that the uncontrolled system exhibits severe oscillations in both scenarios, while the system controlled with the designed PSS controllers is well damped and recovers within 6 seconds.

Fifty Machine System

The second system studied is a fifty machine system [39]. This is a mid-sized benchmark system that retains the dynamic behavior of large-scale power systems. The system consists of 50 generators, 44 modeled as classical machines and six generators represented in the form of a subtransient machine model. The single line diagram of the studied area is given in Fig. 5.10 while the machine and exciter parameters are given in Appendix B.

The ability of the system to withstand a loss of the important line between bus 6 and bus 7 after a three phase fault at bus 6 is investigated. Therefore, the system is analyzed in two

Figure 5.8: Three-Phase fault angle difference response Scenario 2

Figure 5.9: Three-Phase voltage at bus 13 response Scenario 2

Figure 5.10: The Fifty-Machine system single line diagram

operating conditions with the following configurations:

- *Operating Condition 1* – System as shown in Fig. 5.10.
- *Operating Condition 2* – System with the line 6-7 out of service.

The original system configuration without damping controllers has two poorly damped modes with frequencies of 1.4 Hz and 1.8 Hz. Supplementary damping for the system is provided via two PSSs installed at generators 1 and 2. In *Step 2* of the identification procedure the Prony algorithm identified initial transfer functions for the two generators. Generator 1 model was identified to contain 7 modes in the first operating condition and 11 modes in the second operating condition. The total number of retained modes for generator 2, was 7 and 9 in the first and second operating conditions, respectively. The full linearized model of the 50 machine system contained 118 modes. In *Step 3* of the identification procedure the identified models were optimized using the described GA optimization procedure. The final low order models were tested in the time domain using the PRBS excitation and also in the frequency domain by observing the Bode diagrams. The results of these tests for generator 1 in the first operating mode are shown in Fig 5.11(a) and Fig 5.11(b). Again, it can be observed that the low order model provides a good match to the

(a) *Time Domain* (b) *Frequency Domain*

Figure 5.11: Comparison between identified and actual systems

actual system in both figures.

Figure 5.12: Dominant modes of the full system in two operating conditions

In order to improve the damping of the system, using the identified low order models, two PSSs are tuned according to the procedure described in section 5.1.2. Setting $T_1 = T_3$ and $T_2 = T_4$ during the optimization the following controller transfer functions were obtained:

$$G_1(s) = \frac{33s}{(1 + 10s)} \frac{(1 + 1.7s)^2}{(1 + 0.59s)^2} \quad (5.10)$$

$$G_2(s) = \frac{29s}{(1 + 10s)} \frac{(1 + 1.67s)^2}{(1 + 0.57s)^2} \quad (5.11)$$

Fig. 5.12 shows the dominant modes of the linearized system in *Operating Condition 1* and *Operating Condition 2* in the open loop and when closed with the two designed PSSs.

The controllers are tested by nonlinear simulation for the following scenario. At time $t = 500$ ms, a three-phase fault is applied on the line between buses 6 and 7 and the line is completely removed at $t = 600$ ms. Fig. 5.13 shows the relative angle difference between generators 3 and 1 obtained by simulating the system with and without PSS controllers. It can be observed that the controlled system is well damped and recovers within 10 seconds of simulation.

Figure 5.13: Angle difference between generators at bus 93 and bus 111 for a three phase fault at bus 6

AEP/EI power system

A 23300-bus power system model of the Eastern Interconnection was used for this application. The model contained 3875 generators and tens of thousands of state variables. The proposed technique was tested on AEP's Rockport plant to derive PSS parameters.

Fig. 5.14 shows the configuration of AEP's Rockport plant located in Southern Indiana, and transmission system arrangement in its vicinity. The plant consists of two identical 1300 MW coal-fired units that were placed in service in 1984 and 1989, respectively. The Rockport station has two 765 kV outlets terminated at the Jefferson and Sullivan stations.

With only two transmission outlets, the stability margins at the Rockport plant are very narrow. For this reason, the Plant was designed with momentary fast turbine valving implemented on both units to enhance the plant stability. Still, the stability performance under several operating conditions, involving loss of the nearby transmission equipment, was marginal, requiring plant curtailments. Over the years, several enhancements were made to improve the plant's steady-state, transient and oscillatory stability performance. This involved extensive testing and re-tuning of the excitation control system (ECS) equipment in 1989 [40], application of special controls such as Quick Rapid Switching on the Rockport-Sullivan line, Rapid Unit Runback on both Rockport units, and Emergency Unit Tripping on both units, all three implemented in 1990 [41]. However, the stability studies done in the late 1990's indicated that further improvements were desirable to meet the changing system needs and to minimize the plant curtailments.

Figure 5.14: Rockport plant configuration

Further ECS enhancements, including PSS application, were made in 2002, following an analysis of a disturbance involving a 2500 MW generation trip out of Rockport plant. (A description of this disturbance will appear in NERC's "2002 System Disturbance" document to be published in 2003-2004.) The existing PSS was designed using the industry standard tuning procedure.

As it can be seen from the above, an ongoing objective of AEP is to maximize the Rockport output under the most critical operating conditions, while maintaining satisfactory stability margins. Hence, AEP is continuously looking for better ways to optimize Rockport ECS-PSS settings. Considering the multitude of the special controls at this location, as well as the significant interaction of the Rockport machines with the rest of the system, the design of the ECS-PSS controls represents a challenging problem. The technique proposed in this paper is a well-suited candidate for Rockport PSS design because of its ability to extract crucial information from the entire Eastern Interconnection grid while simultaneously considering multiple operating conditions.

The three most critical contingencies at Rockport plant are:

- *Contingency 1.* No prior outage, 3-ph line opening of Rockport Jefferson 765 kV line
- *Contingency 2.* Breed-Casey 345 kV line on prior outage, 3-ph line opening of Rockport Jefferson 765 kV line
- *Contingency 3.* Rockport Jefferson 765 kV line on prior outage, 3 phase fault on Breed-Casey 345 kV line

Large-scale system responses to the impulse and PRBS signals were obtained in the PSS/E package for the following five operating conditions:

1. All facilities in service
2. Rockport-Jefferson line out of service
3. Rockport-Jefferson and Breed-Casey lines out of service.
4. Same as 2, under different loading conditions.
5. Same as 3, under different loading conditions.

Steps 2 and 3 of the identification procedure, discussed in section 5.1.1, were carried out in MATLAB to produce five low order models of sizes ranging from 10 to 16 modes. These models were then used for controller design by applying the proposed GA based controller design technique

(a) Contingency 1

(b) Contingency 2

Figure 5.15: Rockport transient simulation results

(a) Contingency 3

(b) Contingency 3 - 50 MW increase in plant's output

Figure 5.16: Rockport transient simulation results

to search for a set of PSS parameters that would provide the optimal damping under the described operating conditions. PSS controller design was performed in MATLAB. Table. 5.1 shows the dominant modes of identified system in the open loop and when closed with the designed controller in two operating conditions.

Table 5.1: Dominant modes of the identified system in operating conditions 2 and 5

	Open Loop			Closed Loop		
	Eigenvalue	Damping (%)	Frequency (rad/sec)	Eigenvalue	Damping (%)	Frequency (rad/sec)
Operating Condition 2	$-0.018 \pm 3.79i$	0.49	3.79	$-0.12 \pm 3.83i$	3.03	3.83
	$-0.84 \pm 10.27i$	8.15	10.30	$-0.85 \pm 10.47i$	8.10	10.51
Operating Condition 5	$-0.033 \pm 4.29i$	0.77	4.29	$-0.068 \pm 4.31i$	1.58	4.31
	$-0.33 \pm 5.51i$	6.06	5.52	$-0.39 \pm 5.49i$	7.13	5.51
	$-0.78 \pm 10.20i$	7.60	10.23	$-0.75 \pm 10.27i$	7.25	10.30

The obtained controller was tested on the large-scale system by simulating *Contingencies 1-3*. Simulations were carried out in the PSS/E package. Fig. 5.15 compares the results of transient simulations for the system without PSS, with existing PSS, and the proposed PSS. It can be observed that both PSSs improved the damping of the system. Fig. 5.15(a) and Fig. 5.15(b) show that for contingencies 1 and 3 the existing and proposed PSSs perform in a similar fashion. However, for the second contingency, the proposed controller offers slight improvement over the existing PSS (see Fig. 5.16(a)). Furthermore, the new PSS controller improves transient stability margin by 50 MW. (see Fig. 5.16(b)).

5.2 Robust PSS design through multiobjective optimization

Previous section describes the design which is suitable for situations where a single PSS needs to be tuned or re-tuned for optimal performance. This design is mainly focused on performance specifications since the objective function used during the optimization is formulated via the damping coefficients. Robustness performance is implicitly aggregated in the performance objective by observing the damping coefficients in multiple operating conditions simultaneously. Hence, the designer first has to determine troublesome operating conditions and then perform the control design around low order transfer functions identified in these operating points.

In some situations, especially when interarea modes of oscillations are present in a power system, multiple PSSs have to be coordinated in order to provide the best possible damping. Considering the number of possible contingencies in this case, it becomes more complicated to determine which operating points to include in the control design. It is possible to formulate

robust performance specifications around the nominal operating point in the frequency domain by minimizing a certain norm of the system [2]. However, this introduces an additional objective function. Hence, if performance and robustness specifications are to be met simultaneously a multiobjective optimization is necessary.

To address the issues of robustness and performance simultaneously PSS tuning via a multiobjective optimization technique is proposed in the following sections. First the objective functions are derived and then the proposed technique is tested by tuning multiple PSSs simultaneously for the two example power systems.

5.2.1 Robustness objective

Classical robust specifications are usually formulated in the frequency domain and are given in the form of constraints on the way of how the Nyquist diagram of the nominal open loop approaches the critical point $+1$ (or -1 if the feedback signal is taken with a negative sign). Typical examples are gain and phase margins which represent a measure of relative stability of the system.

Definition 5.1 *The gain margin is the smallest positive number k_m by which the Nyquist plot of the nominal open loop $L^{nom}(j\omega)$ must be multiplied so that it passes through the point $+1$. We have:*

$$k_m = \frac{1}{\|L^{nom}(j\omega_r)\|}$$

where ω_r is the angular frequency for which the Nyquist plot intersects the real axis furthest from the origin.

Definition 5.2 *The phase margin is the extra phase Φ_m that must be added to make the Nyquist plot of the nominal open loop system pass through the point $+1$. The phase margin Φ_m is the angle between the real axis and $L^{nom}(j\omega_m)$, where ω_m is the angular frequency where the Nyquist plot intersects the unit circle closest to the point $+1$.*

In classical feedback system design, robustness is often specified by establishing minimum values for the gain and phase margins. Practical requirements are $k_m > 2$ for the gain margin and $30^\circ < \Phi_m < 60^\circ$ for the phase margin. However, gain and phase margins do not necessarily adequately characterize the robustness. It is possible for a system to have large phase and gain margins and have a loop gain close to $+1$ at some frequency ω_0 . The risk of this happening is greater for higher order systems. Figure 5.17 shows an example of an open loop system which has

comfortable gain and phase margins but Nyquist plot approaches uncomfortably the critical point [2].

Figure 5.17: System with high gain and phase margins but small loop margin (adopted from [2])

Better measurement of robustness which does not share this problem with gain and phase margins is called *loop margin*. The loop margin M is the minimal distance in the complex plane between the Nyquist plot of the open loop system L^{nom} and the critical point $+1$. Hence, we have

$$M = \min_{\omega} \text{dist} (+1, L(j\omega)) \quad (5.12)$$

If the nominal open system $L^{nom}(s)$ is perturbed by a stable transfer function $\Delta(s)$ we get a perturbed system $L(s) = L^{nom}(s) + \Delta(s)$. The closed loop perturbed system is stable for all Δ such that:

$$\|\Delta\|_{\infty} < \frac{1}{M}$$

Therefore, by maximizing the loop margin M it is possible to have an additive perturbation with a larger magnitude for all frequencies while keeping the closed loop system stable. From eq. (5.12)

we can further write:

$$\begin{aligned}
 M &= \min_{\omega} \text{dist} (+1, P(j\omega)K(j\omega)) \\
 &= \min_{\omega} |1 - P(j\omega)K(j\omega)| \\
 &= \frac{1}{\max_{\omega} \left| \frac{1}{1 - P(j\omega)K(j\omega)} \right|} \\
 &= \frac{1}{\|H_{WZ}\|_{\infty}}
 \end{aligned} \tag{5.13}$$

In general case $\|H(s)\|_{\infty}$ is defined as:

$$\|H(s)\|_{\infty} = \begin{cases} \max_{\omega} |H(j\omega)|, & \text{SISO case} \\ \max_{\omega} \sigma_{\max}(H(j\omega)), & \text{MIMO case} \end{cases} \tag{5.14}$$

where $\sigma_{\max}(\cdot)$ denotes the largest singular value of a matrix.

Figure 5.18: System block diagram

From eq. (5.13) we can observe that a loop margin is inversely proportional to the peaking of the transfer function H_{WZ} at some frequency. Hence, $\|H_{WZ}\|_{\infty}$ can be used as a robustness objective when casting the controller design in the form of function optimization. Signals W and Z are shown in the block diagram of the system Figure 5.18. Transfer function between these signals is often called the sensitivity transfer function.

5.2.2 Multiobjective optimization controller design formulation

In order to formulate the multiobjective optimization goals the following assumptions are used:

- A linear representation of an open loop power system is obtained around the nominal operating point. The input points used for linearization are the auxiliary input points for each exciter where PSSs are connected. The output points used for linearization are the PSS input signals such as generator speed and/or active power output. The obtained linear model is denoted by P in Figure 5.18.
- The following transfer function model is assumed for the i -th PSS:

$$G_i(s) = \frac{K_i s}{1 + sT_{wi}} \frac{(1 + sT_{1i})^2}{(1 + sT_{2i})^2}, \quad i = 1, \dots, m_c \quad (5.15)$$

where the gain K_i and time constants T_{wi} , T_{1i} and T_{2i} are the unknown design parameters, while m_c is the total number of PSSs to be designed simultaneously. All PSS controller transfer functions are aggregated in a single controller block denoted by K in Figure 5.18.

The optimization problem can then be formulated as:

$$\begin{aligned} \min_x F(x) &= \begin{bmatrix} f_1(x) & f_2(x) \end{bmatrix} \\ \text{s.t.} & \end{aligned} \quad (5.16)$$

$$\text{Real}(\lambda_l) < 0, \quad l = 1, \dots, n_m$$

$$K_{i_{min}} \leq K_i \leq K_{i_{max}}$$

$$T_{w_{min}i} \leq T_{wi} \leq T_{w_{max}i}$$

$$T_{1_{min}i} \leq T_{1i} \leq T_{1_{max}i}$$

$$T_{2_{min}i} \leq T_{2i} \leq T_{2_{max}i}$$

where $x = \begin{bmatrix} K_1 & \dots & K_{m_c} & T_{w1} & \dots & T_{wm_c} & T_{11} & \dots & T_{1m_c} & T_{21} & \dots & T_{2m_c} \end{bmatrix}^T$, λ_l is the l -th mode of the closed-loop system and n_m is the total number of modes of the closed-loop system.

Objective vector field $F(x)$ is defined in the following way:

- Function $f_1(x)$ is defined with the following equation:

$$f_1(x) = \|H_{WZ}\|_\infty \quad (5.17)$$

where H_{WZ} is the sensitivity transfer function of the system given in Figure 5.18.

- Function $f_2(x)$ can be defined as

$$f_2(x) = - \min_{j=1, \dots, n_m} \xi_j \quad (5.18)$$

where ξ_j is the damping coefficient of the j -th mode of the closed-loop system, while n_m is the total number of modes

or

$$f_2(x) = - \sum_j \xi_j \quad (5.19)$$

where ξ_j is the damping coefficient of the j -th mode of the closed-loop system such that the corresponding frequency ω_j of that mode satisfies the inequality $\omega_{min} < \omega_j < \omega_{max}$.

Function $f_1(x)$ is the robustness objective while $f_2(x)$ is the performance objective. Performance objective specified via eq. (5.19) is better suited for cases where there is a substantial number of poorly damped modes in the system. Minus sign in eq. (5.18) and eq. (5.19) is added since the real goal of the optimization is to maximize damping of the closed-loop system. Optimization problem can be formulated as specified in eq. (5.16) for any power system and then solved using the multiobjective optimization algorithm described in section 3.4.

5.2.3 Case studies

To test the proposed controller design technique, a C++ based micro-GA solver developed by the authors of [1] was interfaced with the MATLAB environment. The developed C++ mex interface function is provided in Appendix D. Using the described multiobjective optimization tuning procedure, multiple PSS controllers were designed simultaneously for the two-area and 50 machine power systems which were introduced in section 5.1.3. The following sections present the obtained results.

Two Area System

The two-area system was linearized in the operating condition described with the nominal power flow of 400 MW from Area 1 to Area 2 and the system configuration as shown in Figure 5.3. The system was linearized using the PAT's linearization feature with the Simulink block diagram shown in Appendix C. Two controllers installed at generators 1 and 3 were then tuned to provide optimal performance and robustness objectives described via eq. (5.18) and eq. (5.17) respectively. For each PSS the following design parameters were tuned K , T_w , T_1 and T_2 . The optimization returned the solution set shown in Figure 5.19. This solution is the approximation of the Pareto trade-off curve between the two objectives.

Figure 5.19: Pareto solution set for the two-area system

Figure 5.20: Contingency 1 simulation result

Figure 5.21: Contingency 2 simulation result

The following equations describe one solution from the Pareto set, with the corresponding function values $f_1 = 1.804$ and $f_2 = -0.28$.

$$G_1(s) = \frac{27.53s}{(1 + 9.54s)} \frac{(1 + 1.32s)^2}{(1 + 0.36s)^2} \quad (5.20)$$

$$G_3(s) = \frac{25.48s}{(1 + 5.00s)} \frac{(1 + 1.41s)^2}{(1 + 0.53s)^2} \quad (5.21)$$

The above solution was chosen for nonlinear simulation testing. The following contingencies were simulated:

1. The first contingency is the application of a three phase fault on line 3-101 at time $t = 0.1s$, while power (400MW) is flowing from area 1 to area 2. The fault was removed at $t = 0.2s$.
2. The second contingency is the same in terms of the type, location and duration of the fault. The power was reversed to flow from area 2 to area 1.

Figure 5.20 and Figure 5.21 show the relative angle difference between generators 1 and 3 obtained after nonlinear simulations of the first and second contingency respectively. In both contingencies, the system is well damped and stabilized in less than 8 seconds. Hence, it can be concluded that the designed PSSs are robust and provide sufficient damping.

Fifty Machine System

The fifty machine system was linearized in the operating condition described with the nominal loading conditions and the system configuration as shown in Figure 5.10.

Figure 5.22: Pareto solution set for the fifty machine system

PAT block diagram used for linearization and nonlinear simulation is given Appendix C. Eq. (5.19) was used as robustness objective since this system has a large number of oscillatory modes due to the machines modeled as classical generators. As it was the case with the previous test system, performance criterion was specified via eq. (5.17). Four controllers installed at generators 1, 2, 5 and 6 were then simultaneously tuned specifying K , T_w , T_1 and T_2 as design parameters. Hence, in total 16 parameters were determined by the optimization algorithm. Figure 5.22 shows the trade-off curve between the two objectives obtained after the optimization.

The following equations describe one solution from the Pareto set, with the corresponding function values $f_1 = 0.399$ and $f_2 = -13.725$.

$$G_1(s) = \frac{25.91s}{(1 + 2.64s)} \frac{(1 + 0.59s)^2}{(1 + 0.39s)^2} \quad (5.22)$$

$$G_2(s) = \frac{14.87s}{(1 + 7.98s)} \frac{(1 + 1.01s)^2}{(1 + 0.35s)^2} \quad (5.23)$$

$$G_5(s) = \frac{28.14s}{(1 + 2.10s)} \frac{(1 + 0.38s)^2}{(1 + 0.28s)^2} \quad (5.24)$$

$$G_6(s) = \frac{6.24s}{(1 + 2.11s)} \frac{(1 + 0.99s)^2}{(1 + 0.40s)^2} \quad (5.25)$$

The above solution was chosen for nonlinear simulation testing. In [42] several critical contingencies together with their critical clearing times were identified. Five of those contingencies were used here to test the proposed controllers:

1. The first contingency is the application of a three phase fault on line 6-7 at time $t = 0.1s$. The fault was removed at $t = 0.2s$. Figure 5.23 shows this contingency simulation result with and without the controllers.
2. The second contingency is the application of a three phase fault on line 6-9 at time $t = 0.1s$. The fault was removed at $t = 0.17s$. Figure 5.24 shows this contingency simulation result with and without the controllers.
3. The third contingency is the application of a three phase fault on line 66-111 at time $t = 0.1s$. The fault was removed at $t = 0.25s$. Figure 5.25 shows this contingency simulation result with and without the controllers.
4. The fourth contingency is the application of a three phase fault on line 100-72 at time $t = 0.1s$. The fault was removed at $t = 0.32s$. Figure 5.26 shows this contingency simulation result with and without the controllers.
5. The fifth contingency is the application of a three phase fault on line 112-69 at time $t = 0.1s$. The fault was removed at $t = 0.32s$. Figure 5.27 shows this contingency simulation result with and without the controllers.

The simulation results reveal that the system is stable and well damped in all tested contingencies after applying the proposed controllers. Hence, it can be concluded that the proposed design met the objectives in terms of robustness and performance criteria.

Figure 5.23: Contingency 1 Angle difference between generators at bus 104 and bus 111

Figure 5.24: Contingency 2 Angle difference between generators at bus 104 and bus 111

Figure 5.25: Contingency 3 Angle difference between generators at bus 104 and bus 111

Figure 5.26: Contingency 4 Angle difference between generators at bus 104 and bus 111

Figure 5.27: Contingency 5 Angle difference between generators at bus 104 and bus 111

Chapter 6

Summary and conclusion

This dissertation introduces four new design techniques for different levels of power system controls with the primary focus set on LFC and transient stability control. The first technique for LFC, called GALMI, is designed for tuning of controllers of proportional-integral (PI) type traditionally used in the industry. Main idea is to obtain the robust controller performance by treating the interconnections with the other areas in the power system as disturbances. More specifically, instead of solving the H_∞ control problem to obtain a robust high-order dynamic controller, the proposed GALMI technique, coordinates genetic algorithms with the LMI control toolbox optimization in order to obtain the control parameters, K_P and K_I , of a traditional PI controller that satisfy the robust H_∞ constraints. The proposed technique represents a fully decentralized systematic design since only the local ACE signal is used for control. Furthermore, to perform the proposed design no information from other areas in the power system is required. A three-area power system is used as the test system with the three scenarios of load disturbances. The simulation results show that the responses of GALMI tuned PI load frequency controllers are almost the same as those of the robust H_∞ controllers, which have effective control performance and robustness against possible disturbances. In the second part of the dissertation dedicated to LFC novel controller design based on model predictive control is proposed. This design is also fully decentralized and requires only local area parameters. Furthermore, due to the ability of MPC to handle constraints on controlled variables this design can cope with the nonlinearities introduced in the LFC model. This capability was fully demonstrated in the example test scenario of a three-area power system which includes generation rate constraints. For this scenario the proposed MPC controller outperformed a full order H_∞ controller.

To enhance power system transient stability margins two methodologies for PSS tuning

are proposed in this dissertation. The first methodology for PSS design is useful for the frequently occurring situation where a single PSS needs to be designed to produce maximum impact on the damping of a power system. In this method an identification is first used to derive low order transfer functions of large-scale power systems and then a GA based optimization of a damping index is used for tuning of PSS. Robustness is implicitly included in the design by formulating the damping index so that it includes a range of operating conditions. The initial low order model is identified using the standard Prony method. To enhance its accuracy for closed loop controller design a GA based optimization of transfer function zeros is proposed. An interface with a standard production grade transient stability analysis package, PSS/E, was developed to allow identification of realistic large-scale power systems. The technique presented in this dissertation is used to identify transfer functions for PSS design. However, it can be easily adapted for other damping controllers. The problem of selecting the parameters of a PSS controller that would assure optimal damping performance for multiple operating conditions is solved via a GA optimization procedure with an eigenvalue-based performance index. The effectiveness of the proposed methodologies was demonstrated on the three power systems: (1) a Two-area-four-machine system, (2) a Fifty-machine system and (3) an AEP/EI power system. The first two systems are well known benchmark systems extensively studied in the literature. The third system is the actual Eastern Interconnection system with the detailed representation of the AEP's network, commonly used for transmission planning and operational studies by transmission entities in the Eastern Interconnection. Simulation results presented in the case studies show that the proposed design is robust and its objectives are met for the investigated systems. It has also been shown for 23300-bus power system that the proposed design outperforms the design used by the industry standard for one of the contingencies presented since a 50 MW increase is achieved. However, the technique can be improved by adding additional constraints during the optimization to eliminate the solutions which are impractical for implementation. This would require implementation with another GA solver since the GAOT toolbox used in this dissertation does not have the capability to handle additional constraints. Another point which requires further attention is the method for elimination of redundant modes in the initial low order model. It would be beneficial to investigate other indices for elimination of redundant modes such as the energy of the system based index proposed in [29].

The second proposed methodology for PSS design is useful for the situations where several PSS controllers can be tuned together. By coordinating these controllers it is possible to achieve better robustness and damping of interarea modes. Multiobjective optimization is utilized to obtain the controller parameters. The first objective is used to enhance damping performance of the system

and is similar to the one used in the first proposed methodology for PSS design. To incorporate robustness explicitly additional optimization objective is added which is based on the ∞ norm of the sensitivity transfer function of the system. To be able to perform multiobjective optimization a MATLAB interface with the microGA solver was developed. Based on the simulation results obtained for the two benchmark system it can be concluded that the proposed design meets the objectives in terms of damping and robustness performance. However, since the technique requires repetitive computation of eigenvalues of the linearized power system it could be time consuming to apply it directly on a very large scale systems. This problem can be circumvented in two ways, first if the linear representation of large scale power system is available, model reduction, such as the one proposed in [43], can be performed to obtain smaller representation of the original model, second, if the linear representation of the large scale power system cannot be obtained a system identification techniques capable of capturing low order MIMO systems from the time domain data, such as N4SID, can be utilized. Future work could than be geared toward investigating possible degradations in performance when the reduced-size models are used. For the second test system Figure 5.22 reveals grouping of the solutions along the first objective function axis. Hence, only a small part of the Pareto solution set was obtained. This can be attributed to the current implementation of microGA solver since similar results were obtained running the optimization multiple times. Therefore, another way to possibly enhance the proposed design is to utilize another multi-objective solver. However, most of the currently available solvers are in the early stages of development and it is safe to assume that in the near future they will have the ability to produce more reliable and robust results.

The following section provides the list of journal and conference papers produced with this dissertation. The paper from the list titled “Model Predictive Control Design for Load Frequency Control Problem” received the 2002 IEEE Power Engineering Society Student Prize Paper Award in Honor of T. Burke Hayes.

6.1 Accomplishments and list of publications

1. Amer Hasanović, A. Feliachi, Azra Hasanović, N.B. Bhatt and A.G. DeGross, “Practical Robust PSS Design Through Identification of Low Order Transfer Functions,” *Approved for publication*, IEEE Transactions on Power Systems

Abstract

This paper presents a low order identification technique, which is based on standard Prony

analysis. The technique has the ability to extract crucial dynamic characteristics from a system of any size (e.g. a large-scale power system), which then can be used for developing a robust controller. In this paper the proposed identification technique is coupled with a robust controller design technique based on genetic algorithm to simultaneously tune Power System Stabilizers (PSSs) for multiple operating conditions. To illustrate the proposed identification and controller design techniques three case studies are presented, including a two-area benchmark system, a fifty-machine test system and a large-scale (23300 bus) Eastern Interconnection power system. To allow the proposed tools to be applied to the large-scale power system, the authors developed an interface with a standard production grade transient stability analysis software package PSS/E.

2. K. Schoder, Amer Hasanović, A. Feliachi and Azra Hasanović, "PAT: A Power Analysis Toolbox for MATLAB/Simulink," IEEE Transactions on Power Systems, vol. 18, pp. 42-46, Feb. 2003.

Abstract

A power system simulation environment in MATLAB/Simulink is presented in this paper. The developed Power Analysis Toolbox (PAT) is a very flexible and modular tool for load flow, transient and small signal analysis of electric power systems. Standard power system component models and a wide range of FACTS devices are included. Its data structure and block library have been tested to confirm its applicability to small to medium sized power systems. Its advantages over an existing commercial package are given.

3. D. Reerkpreedapong, A. Hasanović and A. Feliachi, "Robust Load Frequency Control Using Genetic Algorithms and Linear Matrix Inequalities," IEEE Transactions on Power Systems vol. 18, pp. 855-861, May. 2003.

Abstract

In this paper, two robust decentralized control design methodologies for load frequency control (LFC) are proposed. The first one is based on H_∞ control design using linear matrix inequalities (LMI) technique in order to obtain robustness against uncertainties. The second controller has a simpler structure, which is more appealing from an implementation point of view, and it is tuned by a proposed novel robust control design algorithm to achieve the same robust performance as the first one. More specifically, Genetic Algorithms (GAs) optimization is used to tune the control parameters of the proportional-integral (PI) controller subject to the H_∞ constraints in terms of LMI. Hence, the second control design is called GALMI.

Both proposed controllers are tested on a three-area power system with three scenarios of load disturbances to demonstrate their robust performances.

4. N. Atić and A. Hasanović, “Model Predictive Control Design for Load Frequency Control Problem,” First Prize 2002 IEEE Power Eng. Society Student Paper Contest, Toronto, Canada, 2003

Abstract

This paper presents a decentralized Model Predictive Control (MPC) design for the Load Frequency Control (LFC) problem. The Area Control Error (ACE) signal was used as the only input to the controller to achieve the decentralized scheme. A part of the ACE signal, which refers to changes in interarea tieline power flow, and local changes in power demand are treated as an unmeasured disturbance for the controller design. Simulation is performed on a three-area power system model with three different load disturbance scenarios. The results are presented and compared to those obtained using PI controllers.

5. A. Hasanović and A. Feliachi, “Low Order Transfer Function Identification and Robust PSS Control Design,” Proc. IEEE Power Eng. Society General Meeting, Toronto, Canada, 2003.

Abstract

This paper presents a low order identification technique suitable for power system damping controller design, which is based on standard Prony analysis. The proposed identification technique when combined with a robust controller design, can be used to tune Power System Stabilizers (PSSs) for a number of operating conditions. Technical background of the method is presented first, and then a benchmark power system model is used to illustrate the proposed identification and controller design techniques.

6. A. Hasanović and A. Feliachi, “Genetic algorithm based inter-area oscillation damping controller design using MATLAB,” Proc. IEEE Power Eng. Society Summer Meeting, Chicago, IL, 2002.

Abstract

This paper presents a tuning procedure for Power System Stabilizers (PSS) and FACTS damping controllers in a multi-machine power system using a Genetic Algorithm optimization implemented in MATLAB environment. To demonstrate the efficiency and robustness of the described procedure, simultaneous tuning of PSS and SVC controllers is demonstrated on two-area-four-machine system as well as New England/New York sixteen machine power

system. Different control strategies, based on local and remote measurements, are analyzed and subjected to optimization.

7. A. Hasanović, N. Atić, D. Reerkpreedapong and A. Feliachi, “Load Frequency Control Using Model Predictive Control,” Proc. IEEE North American Power Symposium, Tempe, AZ, 2002. *Abstract*

In this paper a Model Predictive Control (MPC) design is proposed for the LFC problem. The MPC controller is implemented in a completely decentralized fashion, using only Area Control Error (ACE) signal as the controller input. To achieve decentralization, interfaces between interconnected power system control areas are treated as disturbances. MPC controllers’ performance is tested on a three-area power system with three different load disturbance scenarios. Simulation results are presented and compared with those obtained using a robust H_∞ controller.

8. N. Atić, D. Reerkpreedapong, A. Hasanović and A. Feliachi, “NERC Compliant Decentralized Load Frequency Control Design Using Model Predictive Control,” Proc. IEEE Power Eng. Society General Meeting, Toronto, Canada, 2003.

Abstract

This paper presents a decentralized Model Predictive Control (MPC) design for the Load Frequency Control (LFC) problem. The proposed algorithm has two objectives, (1) to assure compliance with control performance standards CPS_1 and CPS_2 set by NERC, and (2) to reduce wear and tear of generating units. A nonlinear simulation of a test system with multiple generation and distribution companies including regulation and load following services is performed to illustrate the proposed control scheme.

Appendix A

Mathematical models

A.1 Differential-Algebraic Equations model

The complete differential-algebraic equation set of any power system has the form:

$$\begin{aligned}\dot{x} &= f(x, V) \\ YV &= I(x, V)\end{aligned}$$

where:

- x - state vector of all devices in the system
- V - bus voltage vector of the system
- I - current injection vector into the system
- Y - network admittance matrix, including constant impedance loads and the modifications due to the faults

Initially $\dot{x} = 0$ and $YV_0 = f(x_0, V_0)$. Note that both $f(x, V)$ and $I(x, V)$ are highly nonlinear functions and can be computed if the operating condition (x, V) is given. $I(x, V)$ is a current injection vector, which includes currents from all dynamic and nonlinear static devices, and Y is the network admittance matrix, which includes constant impedance loads.

A.1.1 Synchronous machine models

Subsynchronous machine model

State equations

$$\begin{aligned}
 \dot{E}'_q &= \left(E_f - (x_d - x'_d) I_d - E'_q \right) \frac{1}{T'_{d0}} \\
 \dot{E}'_d &= \left((x_q - x'_q) I_q - E'_d \right) \frac{1}{T'_{q0}} \\
 \dot{E}''_q &= \left(E'_q - (x'_d - x''_d) I_d - E''_q \right) \frac{1}{T''_{d0}} \\
 \dot{E}''_d &= \left(E'_d + (x'_q - x''_q) I_q - E''_d \right) \frac{1}{T''_{q0}} \\
 \dot{\omega} &= (T_m - T_e) \frac{1}{2H} \\
 \dot{\delta} &= (\omega - \omega_0) 2\pi f
 \end{aligned}$$

Stator equations

$$\begin{aligned}
 E''_q - V_q &= R_a I_q + x''_d I_d \\
 E''_d - V_d &= R_a I_d - x''_q I_q
 \end{aligned}$$

Classical machine model

The classical machine model assumes that the magnitude E' of the voltage behind transient impedance remains constant. The angle of the voltage is determined from the following equations:

State equations

$$\begin{aligned}
 \dot{\omega} &= (T_m - V_{re} I_{re} - V_{im} I_{im}) \frac{1}{2H} \\
 \dot{\delta} &= (\omega - \omega_0) 2\pi f
 \end{aligned}$$

Network interface

$$\begin{aligned}
 V_{re} &= E' \cos \delta + x'_d I_{re} \\
 V_{im} &= E' \sin \delta - x'_d I_{im}
 \end{aligned}$$

A.1.2 Network interface

In Park's equations the terminal voltages and currents are transformed, from the actual voltages and currents, to a reference frame fixed in the machine rotor. The equations below demonstrate this transformation:

$$\begin{bmatrix} V_q \\ V_d \end{bmatrix} = \begin{bmatrix} \cos \delta & -\sin \delta \\ \sin \delta & \cos \delta \end{bmatrix} \begin{bmatrix} V_{re} \\ V_{im} \end{bmatrix}$$

and inverse transformation is given as

$$\begin{bmatrix} V_{re} \\ V_{im} \end{bmatrix} = \begin{bmatrix} \cos \delta & \sin \delta \\ -\sin \delta & \cos \delta \end{bmatrix} \begin{bmatrix} V_q \\ V_d \end{bmatrix}$$

A.1.3 Exciter model

Figure A.1: Simple exciter model

A.1.4 Turbine and governor model

Figure A.2: Turbine and governor model

Appendix B

Power system model parameters

B.1 Two Area system

Data file for the Two-area system

```
%
% Two Area Test Case
% (two area - four machines)
%
% bus data format
% bus:
% col1 number
% col2 voltage magnitude(pu)
% col3 voltage angle(degree)
% col4 p-gen(pu)
% col5 q-gen(pu),
% col6 p-load(pu)
% col7 q-load(pu)
% col8 G shunt(pu)
% col9 B shunt(pu)
% col10 bus-type
%         bus-type - 1, swing bus
%                   - 2, generator bus (PV bus)
%                   - 3, load bus (PQ bus)
% col11 q-gen-max(pu)
% col12 q-gen-min(pu)
% col13 v-rated (kV)
% col14 v_max pu
% col15 v_min pu

% Contingency 1 - Power flows from area 1 to area 2
bus = [...
    1  1.03    0.0  7.00    1.85  0.00  0.00    0.00  0.00  1  99.0 -99.0  22.0  1.1 .9;
    2  1.01    0.0  7.00    2.35  0.00  0.00    0.00  0.00  2  99.0 -99.0  22.0  1.1 .9;
    3  0.9781  0.0  0.00    2.00  0.00  0.00    0.00  0.00  3  0.0   0.0  500.0  1.5 .5;
    4  0.95    0.0  0.00    0.00  9.76  1.00    0.00  0.00  3  0.0   0.0  115.0  1.05 .95;
   10  1.0103  0.0  0.00    0.00  0.00  0.00    0.00  0.00  3  0.0   0.0  230.0  1.5 .5;
   11  1.03    0.0  7.19    1.76  0.00  0.00    0.00  0.00  2  99.0 -99.0  22.0  1.1 .9;
   12  1.01    0.0  7.00    2.02  0.00  0.00    0.00  0.00  2  99.0 -99.0  22.0  1.1 .9;
   13  0.9899  0.0  0.00    3.50  0.00  0.00    0.00  0.00  3  0.0   0.0  500.0  1.5 .5;
   14  0.95    0.0  0.00    0.00  17.67 1.00    0.00  0.00  3  0.0   0.0  115.0  1.05 .95;
```



```

    20  0.9876  0.0  0.00  0.00  0.00  0.00  0.00  0.00  0.00  3  0.0  0.0  230.0  1.5  .5;
    101  1.0    0.0  0.00  0.00  0.00  0.00  0.00  0.00  1.60  3  99.  -99.  500.0  1.5  .5;
    110  1.0125 0.0  0.00  0.00  0.00  0.00  0.00  0.00  0.00  3  0.0  0.0  230.0  1.5  .5;
    120  0.9938 0.0  0.00  0.00  0.00  0.00  0.00  0.00  0.00  3  0.0  0.0  230.0  1.5  .5 ];
% Contingency 2 - Power flows from area 2 to area 1
bus = [...
    1  1.03    0.0  7.00    1.85  0.00  0.00    0.00  0.00  1  99.0 -99.0  22.0  1.1  .9;
    2  1.01    0.0  7.00    2.35  0.00  0.00    0.00  0.00  2  99.0 -99.0  22.0  1.1  .9;
    3  0.9781  0.0  0.00    2.00  0.00  0.00    0.00  0.00  3  0.0  0.0  500.0  1.5  .5;
    4  0.95    0.0  0.00    0.00  17.67 1.00    0.00  0.00  3  0.0  0.0  115.0  1.05 .95;
   10  1.0103  0.0  0.00    0.00  0.00  0.00    0.00  0.00  3  0.0  0.0  230.0  1.5  .5;
   11  1.03    0.0  7.19    1.76  0.00  0.00    0.00  0.00  2  99.0 -99.0  22.0  1.1  .9;
   12  1.01    0.0  7.00    2.02  0.00  0.00    0.00  0.00  2  99.0 -99.0  22.0  1.1  .9;
   13  0.9899  0.0  0.00    3.50  0.00  0.00    0.00  0.00  3  0.0  0.0  500.0  1.5  .5;
   14  0.95    0.0  0.00    0.00  9.67  1.00    0.00  0.00  3  0.0  0.0  115.0  1.05 .95;
   20  0.9876  0.0  0.00    0.00  0.00  0.00    0.00  0.00  3  0.0  0.0  230.0  1.5  .5;
  101  1.0    0.0  0.00    0.00  0.00  0.00    0.00  1.60  3  99.  -99.  500.0  1.5  .5;
  110  1.0125 0.0  0.00    0.00  0.00  0.00    0.00  0.00  3  0.0  0.0  230.0  1.5  .5;
  120  0.9938 0.0  0.00    0.00  0.00  0.00    0.00  0.00  3  0.0  0.0  230.0  1.5  .5 ];

% line data format: from bus, to bus, resistance(pu), reactance(pu),
%                   line charging(pu), tap ratio, tap phase, tapmax, tapmin, tapsize

% Operating condition 1 - Two lines between busses 3 and 101
line = [...
    1  10  0.0    0.0167  0.00    1.0  0. 0.  0. 0.;
    2  20  0.0    0.0167  0.00    1.0  0. 0.  0. 0.;
   10  20  0.0025  0.025   0.0437  1.0  0. 0.  0. 0.;
   20  3  0.001   0.0100  0.0175  1.0  0. 0.  0. 0.;
    3  4  0.0    0.005   0.00    1.0  0. 1.2 0.8 0.05;
    3  101 0.011  0.110   0.1925  1.0  0. 0.  0. 0.;
    3  101 0.011  0.110   0.1925  1.0  0. 0.  0. 0.;
  101  13  0.011  0.11    0.1925  1.0  0. 0.  0. 0.;
  101  13  0.011  0.11    0.1925  1.0  0. 0.  0. 0.;
   13  14  0.0    0.005   0.00    1.0  0. 1.2 0.8 0.05;
   13  120 0.001  0.01    0.0175  1.0  0. 0.  0. 0.;
  120  110 0.0025  0.025   0.0437  1.0  0. 0.  0. 0.;
   11  110 0.0    0.0167  0.0     1.0  0. 0.  0. 0.;
   12  120 0.0    0.0167  0.0     1.0  0. 0.  0. 0.];

% Operating condition 2 - A single line between busses 3 and 101
line = [...
    1  10  0.0    0.0167  0.00    1.0  0. 0.  0. 0.;
    2  20  0.0    0.0167  0.00    1.0  0. 0.  0. 0.;
   10  20  0.0025  0.025   0.0437  1.0  0. 0.  0. 0.;
   20  3  0.001   0.0100  0.0175  1.0  0. 0.  0. 0.;
    3  4  0.0    0.005   0.00    1.0  0. 1.2 0.8 0.05;
    3  101 0.011  0.110   0.1925  1.0  0. 0.  0. 0.;
  101  13  0.011  0.11    0.1925  1.0  0. 0.  0. 0.;
  101  13  0.011  0.11    0.1925  1.0  0. 0.  0. 0.;
   13  14  0.0    0.005   0.00    1.0  0. 1.2 0.8 0.05;
   13  120 0.001  0.01    0.0175  1.0  0. 0.  0. 0.;
  120  110 0.0025  0.025   0.0437  1.0  0. 0.  0. 0.;
   11  110 0.0    0.0167  0.0     1.0  0. 0.  0. 0.;
   12  120 0.0    0.0167  0.0     1.0  0. 0.  0. 0.];

% Machine data format
% Machine data format
%      1. machine number,
%      2. bus number,
%      3. base mva,
%      4. leakage reactance x_l(pu),
%      5. resistance r_a(pu),
%      6. d-axis synchronous reactance x_d(pu),

```

```

%      7. d-axis transient reactance x'_d(pu),
%      8. d-axis subtransient reactance x''_d(pu),
%      9. d-axis open-circuit time constant T'_{do}(sec),
%     10. d-axis open-circuit subtransient time constant
%          T''_{do}(sec),
%     11. q-axis synchronous reactance x_q(pu),
%     12. q-axis transient reactance x'_q(pu),
%     13. q-axis subtransient reactance x''_q(pu),
%     14. q-axis open-circuit time constant T'_{qo}(sec),
%     15. q-axis open circuit subtransient time constant
%          T''_{qo}(sec),
%     16. inertia constant H(sec),
%     17. damping coefficient d_o(pu),
%     18. damping coefficient d_l(pu),
%     19. bus number
%
% note: all the following machines use sub-transient model

mac_con = [...
    1 1 900 0.200 0.0025 1.8 0.30 0.25 8.00 0.03 1.7 0.55 0.25 0.4 0.05 6.5 0 0 1;
    2 2 900 0.200 0.0025 1.8 0.30 0.25 8.00 0.03 1.7 0.55 0.25 0.4 0.05 6.5 0 0 2;
    3 11 900 0.200 0.0025 1.8 0.30 0.25 8.00 0.03 1.7 0.55 0.25 0.4 0.05 6.5 0 0 11;
    4 12 900 0.200 0.0025 1.8 0.30 0.25 8.00 0.03 1.7 0.55 0.25 0.4 0.05 6.5 0 0 12];

%
%      Exciter data format
% column data
% 1      exciter type
% 2      machine number
% 3      input filter time constant
% 4      voltage regulator gain K_A
% 5      voltage regulator time constant T_A(sec)
% 6      voltage regulator time constant T_B(sec)
% 7      voltage regulator time constant T_C(sec)
% 8      maximum voltage regulator output VR_max
% 9      minimum voltage regulator output VR_min
% 10     exciter constat K_e
% 11     exciter time constant T_E
% 12     E_1
% 13     saturation function S_E(E_1)
% 14     E_2
% 15     saturation function S_E(E_2)
% 16     stabilizer gain K_f
% 17     stabilizer time constant(T_f)

exc_con = [...
    0 1 0.01 200.0 0 0 0 10.0 -10.0 0 0 0 0 0 0 0 0 0 0;
    0 2 0.01 200.0 0 0 0 10.0 -10.0 0 0 0 0 0 0 0 0 0 0;
    0 3 0.01 200.0 0 0 0 10.0 -10.0 0 0 0 0 0 0 0 0 0 0;
    0 4 0.01 200.0 0 0 0 10.0 -10.0 0 0 0 0 0 0 0 0 0 0];

% governor model
% column      data      unit
% 1      turbine model number (=1)
% 2      machine number
% 3      speed set point    wf      pu
% 4      steady state gain 1/R      pu
% 5      maximum power order Tmax    pu on generator base
% 6      servo time constant Ts      sec
% 7      governor time constant Tc    sec
% 8      transient gain time constant T3 sec
% 9      HP section time constant T4  sec
% 10     reheater time constant T5    sec

```

```

tg_con = [...
    1  1  1  25.0  1.0  0.1  0.5  0.0  1.25  5.0;
    1  2  1  25.0  1.0  0.1  0.5  0.0  1.25  5.0;
    1  3  1  25.0  1.0  0.1  0.5  0.0  1.25  5.0;
    1  4  1  25.0  1.0  0.1  0.5  0.0  1.25  5.0];

% motor model Double Cage
% column      data
% 1      mbase
% 2      zsource
% 3      xtran
% 4      gentap
% 5      T'
% 6      T''
% 7      H
% 8      X
% 9      X'
% 10     X''
% 11     Xl
% 12     E1
% 13     S(E1)
% 14     E2
% 15     S(E2)
% 16     D

motor_dat = [...
105.0 0.00 0.102 0.00+j0.00 1.00 1.959 0.021 5.70 3.897 0.183 0.102 0.1029 1.00 0.122 1.1500 0.4610 2.00]

```

B.2 Fifty machine system

Machine and Exciter data file for the fifty machine system

```

% Machine data format
% 1. machine number,
% 2. bus number,
% 3. base mva,
% 4. leakage reactance x_l(pu),
% 5. resistance r_a(pu),
% 6. d-axis synchronous reactance x_d(pu),
% 7. d-axis transient reactance x'_d(pu),
% 8. d-axis subtransient reactance x''_d(pu),
% 9. d-axis open-circuit time constant T'_do(sec),
% 10. d-axis open-circuit subtransient time constant
%     T''_do(sec),
% 11. q-axis synchronous reactance x_q(pu),
% 12. q-axis transient reactance x'_q(pu),
% 13. q-axis subtransient reactance x''_q(pu),
% 14. q-axis open-circuit time constant T'_qo(sec),
% 15. q-axis open circuit subtransient time constant
%     T''_qo(sec),
% 16. inertia constant H(sec),
% 17. damping coefficient d_o(pu),
% 18. damping coefficient d_l(pu),
% 19. bus number
%
% note: all the following machines use sub-transient model

mac_con = [ ...

```

```

1  93  100  0.012  0  0.098 0.024 0 8.5  0 0.096 0.036 0 1.24 0  115  0 0  93  0.0654  0.5743 0 0;
2  104 100  0.008  0  0.102 0.012 0 10  0 0.098 0.014 0 1.50 0  73.8 0 0  104 0.21  0.55  0 0;
3  105 100  0.011  0  0.114 0.021 0 6.6  0 0.109 0.031 0 1.50 0  84.4 0 0  105 0.13  0.4096 0 0;
4  106 100  0.017  0  0.172 0.031 0 6.6  0 0.164 0.047 0 1.50 0  56.2 0 0  106 0.13  0.4096 0 0;
5  110 100  0.012  0  0.098 0.024 0 8.5  0 0.096 0.036 0 1.24 0  115  0 0  110 0.0654  0.5743 0 0;
6  111 100  0.008  0  0.102 0.012 0 10  0 0.098 0.014 0 1.50 0  73.8 0 0  111 0.21  0.55  0 0;
7  60  100  0.00  0.000  0.  0.4769 0 0  0 0 0 0 0 0  1.41  1.41  0.0  60 0 0 0 0;
8  67  100  0.00  0.000  0.  0.0213 0 0  0 0 0 0 0 0  52.1796 52.18 0.0  67 0 0 0 0;
9  79  100  0.00  0.000  0.  0.1292 0 0  0 0 0 0 0 0  6.65  6.65  0.0  79 0 0 0 0;
10 80  100  0.00  0.000  0.  0.6648 0 0  0 0 0 0 0 0  1.2857 1.29 0.0  80 0 0 0 0;
11 82  100  0.00  0.000  0.  0.5291 0 0  0 0 0 0 0 0  2.115  2.12  0.0  82 0 0 0 0;
12 89  100  0.00  0.000  0.  0.0585 0 0  0 0 0 0 0 0  20.5602 20.56 0.0  89 0 0 0 0;
13 90  100  0.00  0.000  0.  1.6  0 0  0 0 0 0 0 0  0.7628 0.76 0.0  90 0 0 0 0;
14 91  100  0.00  0.000  0.  0.3718 0 0  0 0 0 0 0 0  1.6848 1.68 0.0  91 0 0 0 0;
15 94  100  0.00  0.000  0.  0.0839 0 0  0 0 0 0 0 0  17.3424 34.69 0.0  94 0 0 0 0;
16 95  100  0.00  0.000  0.  0.1619 0 0  0 0 0 0 0 0  5.4662 5.46 0.0  95 0 0 0 0;
17 96  100  0.00  0.000  0.  0.4824 0 0  0 0 0 0 0 0  2.1216 2.12 0.0  96 0 0 0 0;
18 97  100  0.00  0.000  0.  0.2125 0 0  0 0 0 0 0 0  5.4912 5.49 0.0  97 0 0 0 0;
19 98  100  0.00  0.000  0.  0.0795 0 0  0 0 0 0 0 0  13.96  13.16 0.0  98 0 0 0 0;
20 99  100  0.00  0.000  0.  0.1146 0 0  0 0 0 0 0 0  17.108 17.1 0.0  99 0 0 0 0;
21 100 100  0.00  0.000  0.  0.1386 0 0  0 0 0 0 0 0  7.56  7.56  0.0  100 0 0 0 0;
22 101 100  0.00  0.000  0.  0.0924 0 0  0 0 0 0 0 0  12.2844 12.3 0.0  101 0 0 0 0;
23 102 100  0.00  0.000  0  0.0135 0 0  0 0 0 0 0 0  78.43 78.4 0.0  102 0 0 0 0;
24 103 100  0.00  0.000  0.  0.1063 0 0  0 0 0 0 0 0  8.16  8.16  0.0  103 0 0 0 0;
25 108 100  0.00  0.000  0.  0.0248 0 0  0 0 0 0 0 0  30.432 30.4 0.0  108 0 0 0 0;
26 109 100  0.00  0.000  0.  0.2029 0 0  0 0 0 0 0 0  2.6622 2.66 0.0  109 0 0 0 0;
27 112 100  0.00  0.000  0.  0.0924 0 0  0 0 0 0 0 0  12.2844 12.3 0.0  112 0 0 0 0;
28 115 100  0.00  0.000  0.  0.0024 0 0  0 0 0 0 0 0  97.33  97.3 0.0  115 0 0 0 0;
29 116 100  0.00  0.000  0.  0.0022 0 0  0 0 0 0 0 0  105.50 105.5 0.0  116 0 0 0 0;
30 117 100  0.00  0.000  0.  0.0017 0 0  0 0 0 0 0 0  102.16 102.2 0.0  117 0 0 0 0;
31 118 100  0.00  0.000  0.  0.0014 0 0  0 0 0 0 0 0  162.74 162.5 0.0  118 0 0 0 0;
32 119 100  0.00  0.000  0.  0.0002 0 0  0 0 0 0 0 0  348.22 348.2 0.0  119 0 0 0 0;
33 121 100  0.00  0.000  0.  0.0017 0 0  0 0 0 0 0 0  116.54 116.5 0.0  121 0 0 0 0;
34 122 100  0.00  0.000  0.  0.0089 0 0  0 0 0 0 0 0  39.24  39.2 0.0  122 0 0 0 0;
35 124 100  0.00  0.000  0.  0.0017 0 0  0 0 0 0 0 0  116.86 116.9 0.0  124 0 0 0 0;
36 128 100  0.00  0.000  0.  0.0001 0 0  0 0 0 0 0 0  503.87 503.9 0.0  128 0 0 0 0;
37 130 100  0.00  0.000  0.  0.0010 0 0  0 0 0 0 0 0  230.90 230.9 0.0  130 0 0 0 0;
38 131 100  0.00  0.000  0.  0.0001 0 0  0 0 0 0 0 0  1101.72 1101.7 0.0  131 0 0 0 0;
39 132 100  0.00  0.000  0.  0.0016 0 0  0 0 0 0 0 0  120.35 120.4 0.0  132 0 0 0 0;
40 134 100  0.00  0.000  0.  0.3e-4 0 0  0 0 0 0 0 0  802.12 802.1 0.0  134 0 0 0 0;
41 135 100  0.00  0.000  0.  0.0008 0 0  0 0 0 0 0 0  232.63 232.6 0.0  135 0 0 0 0;
42 136 100  0.00  0.000  0.  0.1e-4 0 0  0 0 0 0 0 0  2018.17 5000.2 0.0  136 0 0 0 0;
43 137 100  0.00  0.000  0.  0.0004 0 0  0 0 0 0 0 0  469.32 469.3 0.0  137 0 0 0 0;
44 139 100  0.00  0.000  0.  0.0001 0 0  0 0 0 0 0 0  2210.20 2210.2 0.0  139 0 0 0 0;
45 140 100  0.00  0.000  0.  0.0003 0 0  0 0 0 0 0 0  889.19 889.2 0.0  140 0 0 0 0;
46 141 100  0.00  0.000  0.  0.0001 0 0  0 0 0 0 0 0  1474.22 1474.2 0.0  141 0 0 0 0;
47 142 100  0.00  0.000  0.  0.0003 0 0  0 0 0 0 0 0  950.80 950.8 0.0  142 0 0 0 0;
48 143 100  0.00  0.000  0.  0.0023 0 0  0 0 0 0 0 0  204.30 204.3 0.0  143 0 0 0 0;
49 144 100  0.00  0.000  0.  0.0004 0 0  0 0 0 0 0 0  443.22 443.2 0.0  144 0 0 0 0;
50 145 100  0.00  0.000  0.  0.0018 0 0  0 0 0 0 0 0  518.08 518.1 0.0  145 0 0 0 0]

```

```

%      Exciter data format
% column data
% 1      exciter type
% 2      machine number
% 3      input filter time constant
% 4      voltage regulator gain K_A
% 5      voltage regulator time constant T_A(sec)
% 6      voltage regulator time constant T_B(sec)
% 7      voltage regulator time constant T_C(sec)
% 8      maximum voltage regulator output VR_max
% 9      minimum voltage regulator output VR_min
% 10     exciter constat K_e

```

```

% 11    exciter time constant T_E
% 12    E_1
% 13    saturation function S_E(E_1)
% 14    E_2
% 15    saturation function S_E(E_2)
% 16    stabilizer gain K_f
% 17    stabilizer time constant(T_f)

exc_con = [...
0  1  0.02  185.0  0.0  0.0  0.0  8.89  -2.0  0  0  0  0  0  0  0;
0  2  0.015 253.0  0.0  0.0  0.0  8.86  -7.0  0  0  0  0  0  0  0;
0  3  0.468 54.63  0.0  0.0  0.0  7.38  0.0  0  0  0  0  0  0  0;
0  4  0.468 54.63  0.0  0.0  0.0  7.38  0.0  0  0  0  0  0  0  0;
0  5  0.02  185.0  0.0  0.0  0.0  8.89  -2.0  0  0  0  0  0  0  0;
0  6  0.015 253.0  0.0  0.0  0.0  8.86  -7.0  0  0  0  0  0  0  0];

```

Appendix C

Power Analysis Toolbox models

Figure C.1: Block diagram used for linearization of the two-area system

Figure C.2: Block diagram used for simulation of the two-area system

Figure C.3: Block diagram used for simulation of the fifty machine system

Figure C.4: Block diagram used for linearization of the fifty machine system

Appendix D

C++ code

D.1 MicroGA interface to MATLAB

multiGA.cpp

```

/*
 * This routine defines a class MultiGA, used to interface the original microGA code provided
 * by Carlos Coello with MATLAB. To compile:
 *   mex -f mexopts.bat multiga.cpp randEvolutiva.c DrC.c magm.cpp
 * Where randEvolutiva.c DrC.c magm.cpp are provided with the original microGA code.
 * To call from MATLAB type:
 * mexcpp3(ObjFunc,MinMax,NumObj,Constr);
 * where:
 *   ObjFunc - Name of the MATLAB function that describes the objective functions
 *   MinMax - Matrix defining the minimum and maximum values for parameters in the
 *             form [Min1 Max1; Min2 Max2;...]
 *   NumObj - Number of objectives
 *   Constr - Name of the MATLAB function that describes the constraints
 */
#include <iostream.h>
#include <math.h>
#include "mex.h"
#include "magn.h"
#include "drc.h"
#include "randEvolutiva.h"
extern void _main();
class MatlabGA:public MicroAG{
public:
    char* _nameO;
    char* _nameR;
    MatlabGA(int itot, int gmax,int m,double pc,double pm,int ngenes,int nobjs,
    int tampareto,int tammem, int ndivs,int b,double *linf,double *lsup,int *pres,
    int iguales,int sndelit,double pNRem,char *arch):
    MicroAG(itot,gmax,m,pc,pm,ngenes,nobjs,tampareto,tammem,ndivs,b,linf,lsup,pres,iguales,sndelit,pNRem,arch){};
public:
    void evalua(int *cromosoma,double *aptitud);
    void salida(Individuo *ind);
    int restricciones(int *genotipo);
};
void MatlabGA::evalua(int *cromosoma,double *aptitud){
    double x[nGenes];

```

```

    mxArray *lhs,*T;
    T = mxCreateDoubleMatrix(1, nGenes, mxREAL);
    for (int j=0;j<nGenes;j++)
    {
        x[j]=decodifica(j,cromosoma);
    }
    memcpy((void *)mxGetPr(T), (void *)x, nGenes*sizeof(double));
    mexCallMATLAB(1,&lhs,1, &T, _nameO);
    memcpy((void *)aptitud,(void *)mxGetPr(lhs) ,nObjs*sizeof(double));
    mxDestroyArray(T);
    mxDestroyArray(lhs);
}
int MatlabGA::restricciones(int *genotipo)
{
    if (_nameR)
    {
        double violadas[1];
        double x[nGenes];
        mxArray *l,*P;
        P = mxCreateDoubleMatrix(1, nGenes, mxREAL);
        for (int j=0;j<nGenes;j++)
        {
            x[j]=decodifica(j,genotipo);
        }
        memcpy((void *)mxGetPr(P), (void *)x, nGenes*sizeof(double));
        mexCallMATLAB(1,&l,1,&P,_nameR);
        memcpy((void *)violadas,(void *)mxGetPr(l) ,sizeof(double));
        mxDestroyArray(P);
        mxDestroyArray(l);
        return (int) violadas[0];
    }
    else
    {
        return 0;
    }
}
void MatlabGA::salida(Individuo *ind)
{
    for(int i=0;i<posPARETO;i++)
    {
        almacena(ind[i].aptObj,nObjs);
        archivo<<" ";
        for (int j=0;j<nGenes;j++)
        {
            double k=decodifica(j,ind[i].genotipo);
            archivo<<k;
            archivo<<" ";
        }
        archivo<<"\n";
    }
}
static void multiGA(char* name,double* linf,double* lsup,int numgenes,int* pres,int nO,char* resN)
{
    char archivo[20];
    int tamPARETO=100;
    int tamMem=50;
    int GMax=1000;
    int M=4;
    int nTope=2;
    int nGenes=numgenes;
    int nObjs=nO;
    int base=2;
    int subDivs=30;

```

```

double Pc=0.7,Pm=(double)1.0/200.0;
int sndelit=50;
double pNRem=0.3;
strcpy(archivo,"one.tx");
MatlabGA* mag = new
MatlabGA(GMax,nTope,M,Pc,Pm,nGenes,nObjs,tamPARETO,tamMem,subDivs,base,linf,lsup,pres,0,sndelit,pNRem,archivo);
mag->_nameO=name;
mag->_nameR=resN;
mag->Alg();
delete(mag);
return;
}
void mexFunction(
    int          nlhs,
    mxArray      *plhs[],
    int          nrhs,
    const mxArray *prhs[]
)
{
    char *input_buf1,*input_buf2;
    double *vin2,*nObjs;
    int buflen,status,numgenes,j;
    double *linf,*lsup,*pr;
    int *pres;
    /* Check for proper number of arguments */
    if ((nrhs != 3) && (nrhs != 4))
    {
        mexErrMsgTxt("MEXCPP requires 3 or 4 input arguments.");
    }
    else if (nlhs >= 1)
    {
        mexErrMsgTxt("MEXCPP requires no output argument.");
    }
    if (mxIsChar(prhs[0]) != 1)
        mexErrMsgTxt("Input 1 must be a string.");
    if (!(mxIsDouble(prhs[1])))
        mexErrMsgTxt("Input array must be of type double.");
    if (mxGetN(prhs[1])!=2)
        mexErrMsgTxt("Second Input must have 2 columns");
    if (nrhs==4)
    {
        if (mxIsChar(prhs[3]) != 1)
        {
            mexErrMsgTxt("Input 4 must be a string.");
        }
        buflen = (mxGetM(prhs[3]) * mxGetN(prhs[3])) + 1;
        input_buf2 = new char[buflen];
        status = mxGetString(prhs[3], input_buf2, buflen);
        if(status != 0)
            mexWarnMsgTxt("Not enough space. String is truncated.");
    }
    else
    {
        input_buf2=0;
    }
    numgenes=mxGetM(prhs[1]);
    pr = (double *)mxGetPr(prhs[1]);
    nObjs = (double *)mxGetPr(prhs[2]);
    linf = new double[numgenes];
    lsup = new double[numgenes];
    pres = new int[numgenes];
    for(j = 0; j < numgenes; j++)
    {

```

```
        linf[j]=pr[j];
        lsup[j]=pr[numgenes+j];
        pres[j]=6;
    }
    buflen = (mxGetM(prhs[0]) * mxGetN(prhs[0])) + 1;
    input_buf1 = new char[buflen];
    status = mxGetString(prhs[0], input_buf1, buflen);
    if(status != 0)
        mexWarnMsgTxt("Not enough space. String is truncated.");
    multiGA(input_buf1, linf, lsup, numgenes, pres, (int)nObjs[0], input_buf2);
    delete [] input_buf1;
    delete [] input_buf2;
    return;
}
```

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