On the Analysis and Design of Genetic Fuzzy Controllers

An Application to Automatic Generation Control of Large Interconnected Power Systems Using Genetic Fuzzy Rule Based Systems

Craig D. Boesack

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I declare that this thesis is my own unaided work. It is being submitted to the Degree of Doctor of Philosophy to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.

Signature :

Student : Craig D. Boesack

Date :

Supervisor : Prof. Tshilidzi Marwala

Co-Supervisor: Prof. Fulufhelo V. Nelwamondo

Dedicated to my father Charles and to the memory of my mother Eva for their love.

Abstract

Frequency Control of large interconnected power systems is governed by means of Automatic Generation Control (AGC), which regulates the system frequency and tie line power interchange at its nominal parameter set points. Conventional approaches to AGC controller design is centered around the Proportional, Integral and Derivative (PID) controller structures, which have found widespread application within industry.

However, the dynamic changes experienced throughout the life cycle of power systems have many contributing factors, in part attributed to unknown knowledge of system behavior, neglected process dynamics and a limited knowledge of system interactions, which makes modeling for AGC systems particularly trying for conventional AGC controller design approaches.

Therefore, in this study, Genetic - Fuzzy controllers (GA - Fuzzy) are applied as plausible candidates for Automatic Generation Controller design and application. In GA - Fuzzy controllers, genetic algorithms which are based on the foundation of evolutionary heuristics are used as a global search method for FLC design. This is particularly motivated by the fact that Fuzzy controllers, especially where there are large data sets, unknown process knowledge and insufficient expert data available, FLC controller design proves to be a daunting task.

Therefore, this thesis explores the automatic design of FLC controllers through evolutionary heuristics and applies the designed controller to the AGC problem of large interconnected power systems. The design methodology followed is to understand power system interactions through power plant modeling and the simulation power plant models for the basis for AGC controller design.

It is shown in this study that the performance of the GA - Fuzzy controller have favourable characteristics in terms of robust performance, robustness properties and compares favorably with conventional AGC controller techniques. The analysis of the GA - Fuzzy controller shows that problem formulation and chromosome encoding of the problem search space forms an important prerequisite for controller design by evolutionary methods.

Therefore the study concludes by stating that GA - Fuzzy controllers are plausible for application within the power industry because of its desirable attributes and that future work would include extending this research into areas of renewable energy for study and application.

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List of Abreviations

$\Delta f(t)$	Change in System Frequency
ACE	Area Control Error
ACO	Ant Colony Optimization
AGC	Automatic Generation Control
ANN	Artificial Neural Networks
ECS	Evoluationary Computational Systems
ED	Economic Dispatch
FC	Frequency Control
FLC	Fuzzy Logic Control
GA	Genetic Algorithms
GFRBS	Genetic - Fuzzy Rule Based Systems
HC	Hard Computing
IPS	Interconnected Power Systems
IRL	Iterative Rule Learning

KB	Knowledge Base
LFC	Load Frequency Control
NF	Neural Fuzzy
PI	Proportional and Integral Controller
PID	Proportional, Integral & Derivative
PSO	Particle Swarm Optimization
RB	Rule Base
SA	Simulated Anealing
TEC	Time Error Correction
UoD	Universe of Discourse
VSD	Variable Speed Drives

Acknowledgments

Completing this doctoral work has been a wonderful, rewarding and often an overwhelming experience. It is indeed a humbling experience, not only to appreciate the theory, in writing an academic paper, in presenting a coherent discussion but also to be part of various working parties dedicated to completing the task set before them.

It has been a pleasure to work with my adviser, Prof. Tshilidzi Marwala, who has guided me into the right direction, for his intuitive approach to problem solving and he has greatly contributed to the completion of this work. His contribution to this work is appreciated.

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Chapter 1

Introduction

Automatic Generation Control (AGC) plays an important role in the control of frequency within Interconnected Power Systems (IPS) and has been employed as an energy regulator since the inception of power generation. For this reason, AGC has found widespread application as a secondary frequency control regulator to firstly control the frequency following random load disturbances and secondly to modulate inter area power exchanges.

One of the network conditions which makes the AGC control problem challenging is that the electrical network is constantly changing, loads are connected and disconnected at will, the size and complexity of the national grid is continuously increasing thereby changing the dynamic behavior of the electrical network over time. Therefore, from an AGC perspective these conditions place strict performance demands upon the AGC controller to yield good controller robustness in the presence of unknown and unmodeled dynamics.

In this regard, conventional PI controller strategies as applied to the AGC control problem has been predominately implemented within modern power utilities today and have found widespread industrial success. However, as the network grows in size and complexity, routine controller retuning is often required. This ensures that the control performance is maintained within the stated control objectives and it also guarantees the integrity of the electrical grid.

Therefore the premise of this work is to show that network frequency control performance can be improved by the application of more advanced controller design techniques, with attributes which inherently consider unknown and unmodeled dynamics. Furthermore, advances in hardware technology and soft computing techniques has made it possible for the application of more advanced control design methodologies to be implemented for use within AGC. In particular, the proposed AGC controller is based on the principles of Genetic - Fuzzy Rule Based Systems (GFRBS).

Characteristically GFRBS compensates for imprecision and vagueness where there is limited knowledge of the process under control and it provides for a mechanism by which systems can learn and adapt its inherent control characteristics with the explicit objective of improving on closed loop performance.

1.1 Background

The Automatic Generation Control problem of large Interconnected Power Plants have a long history and date back to the inception of power systems, where the control of frequency have been achieved through mechanical means such as the flywheel governor of the synchronous machine (Kumar and Kothari, 2005).

Although the flywheel governor has been proven to be a very practical means of regulating speed, it suffers from its inability to regulate frequency after a disturbance without supplementary control action. This is also true of modern digital governing systems where supplementary control action is required for good disturbance rejection properties following a frequency incident. This has lead to a field of study known as Automatic Generation Control, which emphatically deals with Frequency Control and power regulation on electrical networks and the control of their respective generating units.

Traditionally, power utilities have been structured around Control Areas, where each control area is responsible for the regulation of frequency within it's own area, and also to maintain Tie-Line power flows within prescribed specifications. Because each Control Area operates as an independent business unit, there exists an economic objective within AGC control and thus strict regulation of generating units are required to obtain this objective. It is also noted that in order to meet this objective, a compromise between strict and tight regulation and long term equipment life cycle management needs to be achieved. This function is typically granted to the judgment of the power utility.

In order to meet this objective within a changing power industry, and as network complexity grows, new control methods and new techniques for frequency regulation are required to maintain the integrity of supply and to ensure supply quality, reliability and security amidst an unknown dynamic system.

It is for this reason that extensive AGC research is needed, to validate control techniques, to analyze system behavior within a changing power system environment, and to study the impact of alternative forms of energy such as renewable energy on AGC performance, which has fast become a topic of note.

In this research, we focus specifically on AGC controller design, to define a control system to meet the objective, of a robust AGC design via GA-Fuzzy and soft computing techniques. It is shown that this will contribute to the plight of AGC controller design rationale, to meet the challenges of a world in an energy crisis and to contribute to the body of knowledge at large.

1.2 Motivation for GA-Fuzzy Controller Design Techniques

The design and optimization of feedback controllers consist of the parametric selection of control variables to enhance the performance of the closed loop control system. By so doing, the inherent characteristics of the closed loop control system are manipulated in favor of the desired performance objectives. Therefore, with this in mind, classical control theory describes a plethora of design tools and methods specifically tailored for the purpose of controller design, Figure 1.1.

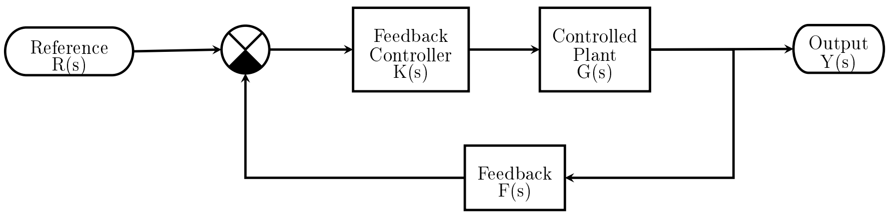

Figure 1.1: A Conventional Feedback Control Loop

This process can be broadly described by two fundamental procedures for controller design. Firstly, controller selection in terms of structure and specification and secondly controller optimization to achieve the stated specification criteria. The former process is concerned with the merits of controller design, its structure and its interactions to best achieve the control objective. The latter process of controller optimization tends to be an acquired skill, requiring careful analysis, assessment of performance and controller redesign.

The next question is, how far should we go in the design analysis to obtain optimal or near optimal control? This is a frequently asked question within control system design circles, and with no all round best application, but the designed solution is specifically dedicated to the problem at hand (Cordón et al., 1996; Tavakoli et al., 2007). Therefore, we would use a performance measure either intuitively in manual design to indicate the success with which the designed controller adheres to the specified control objectives.

This in a Soft Computing context is known as a Performance Index, or Fitness Function within an Evolutionary Computational context (De Jong, 1988). In Genetic Fuzzy control systems, one of the main functions in its application is the selection of an appropriate performance measure and the translation of the control problem into an encoded representation for Genetic application. This in some cases may be a non-trivial function, but it has to sufficiently encapsulate all possible performance regimes.

When all these aspects are put together, a mechanism exists for automatic controller design by Computational Intelligence methods. This is especially advantageous in instances where there are limited information, unknown or unmodeled system dynamics and also the lack of a complete process model. In a similar manner to cognitive design of control systems, Computational Intelligence methods such as GA-Fuzzy design applies heuristic techniques for design, emulating human intelligence.

One added advantage of using GA-Fuzzy approaches to design is that stability of the control systems are inherently considered by the selection of the fitness function, when appropriately chosen. Although, a specific stability criterion can be incorporated into the fitness function, this would inherently penalize weaker solutions and encourage stronger individuals.

It is with this in mind that we explore GA-Fuzzy techniques of AGC controller design, with the expectation that plausible control of the network can be achieved through its application.

1.3 Conventional AGC Control

The methods for designing Automatic Generation Controller for large interconnected power systems have traditionally followed the Proportional Integral (PI) and Proportional, Integral and Derivative (PID) control law strategies.

However, these controllers do not perform adequately in the presence of uncertainty and suffers from poor transient performance in the presence of non - linearity. It is because of this inherent weakness in conventional methods that GA - Fuzzy controller design is explored as an AGC solution.

1.4 Summary of Contributions

This section briefly highlights certain contributions made to the international literary community of papers accepted for publication.

1.4.1 Application of GA-Fuzzy Controller Design to Automatic Generation Control

Portions of Chapters 1, 2, 4, 5, 6 and 7 have appeared in the following paper:

> Application of GA-Fuzzy Controller Design to Automatic Generation Control, Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, Third International Workshop On Advanced Computational Intelligence (IWACI2010).

1.4.2 A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems

Large portions of Chapters 2, 6 and 7 have appeared in the following paper:

> "A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems", Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, Fourth International Workshop On Advanced Computational Intelligence (IWACI2011).

1.4.3 On the application of Bezier Surfaces for GA - Fuzzy controller design for use in Automatic Generation Control

Large portions of Chapters 2, 6 and 7 have appeared in the following paper:

> "On the application of Bezier Surfaces for GA - Fuzzy controller design for use in Automatic Generation Control", Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, 2nd International Conference on Advances in Energy Engineering (ICAEE2011).

1.4.4 Dynamic governor model development for grid code compliance in South Africa

Portions of Chapter 3 is found in the following paper:

> "Dynamic governor model development for grid code compliance in South Africa", Graeme Chown, Craig Lucas, Mike Coker and Rahul Desai - PPA Energy, Jean vd Merwe and Christelle - MTech, Bunty Kiremire, Craig Boesack, Preshen Moodley and Albert Smit - Eskom.

To be submitted to Energize 2012.

1.5 The Taxonomy of the Thesis

This section discusses the taxonomy of the thesis and provides a description of the content of each section, its peculiar attributes and its main points of discussion.

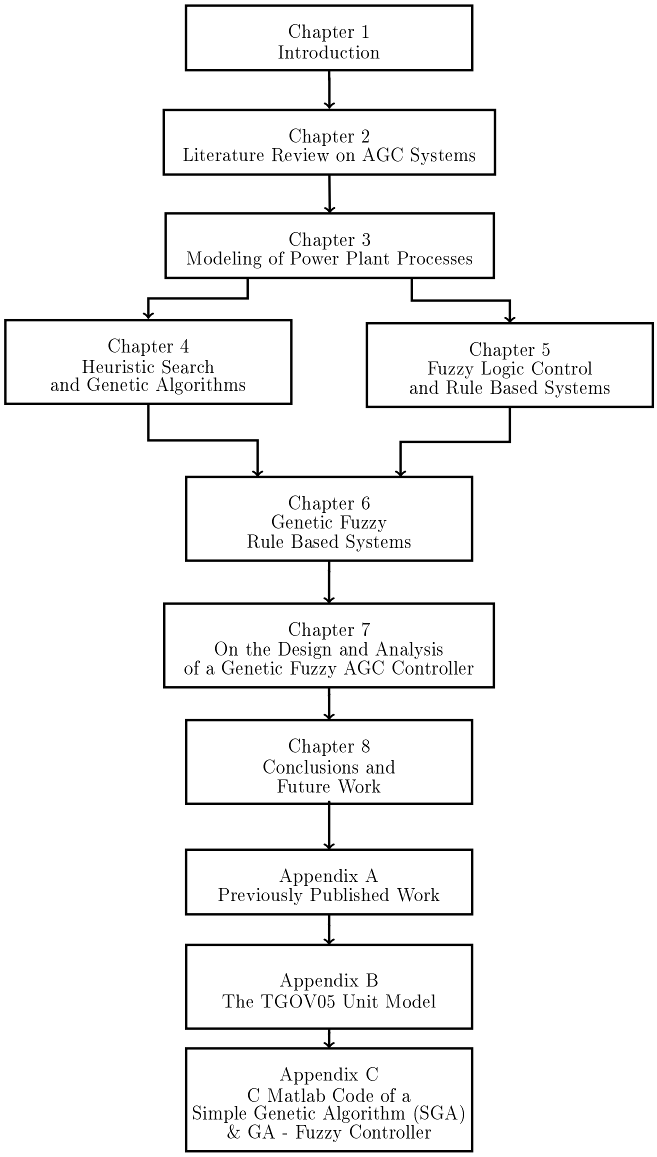

Figure 1.2: Flow chart of the structure of the thesis

Chapter 1, Introduction

The Introduction provides an overview of the thesis by describing the relevant background of this work. It focuses on giving a general introduction to Automatic Generation Control, it expounds on a few limitations within existing structures of control and proposes the application of GA-Fuzzy Rule Based System design as a plausible AGC controller to meet stated multi-objective criteria.

It continues by summarizing literary contributions of this work, and concludes be describing the taxonomy of the thesis.

Chapter 2, Literature Review

In this chapter a review of current literature is performed. It presents a foundation for the rest of the thesis and gives a detailed overview of Automatic Generation Control and associated modeling of interconnected power systems. It starts by giving and exposition of Tie-Line Bias control and how it is applied to the AGC control problem of modern power utilities.

Further, it reviews AGC controller design approaches, culminating in discussion on the modeling of interconnected power plants.

Chapter 3, Power Plant Modeling and Control

Chapter 3 addresses aspects of power plant modeling and control, especially from a model parameter estimation perspective, highlighting techniques for obtaining power plant mechanical characteristics through dedicated power plant tests. This section is aimed at providing a comprehensive understanding of power plant control, its processes and how the behavior of both boiler and turbine control systems play a role in appreciating its influence on network frequency incidents and analysis.

This chapter also illustrates that fairly accurate results for turbine and boiler systems can be obtained from experimental testing of power plants. In particular it illustrates that the boiler plant and its control system play a significant role in frequency response dynamics of interconnected power systems, for effective load disturbance rejection properties and sustained responses.

Chapter 4, Genetic Algorithms and Its Applications

The chapter on Genetic Algorithms and Its Applications present an introduction to Heuristic search and expounds on the rudiments of Genetic Algorithms. It establishes that GA's are good global search methods, which can be accurately applied to many industrial optimization and learning problems.

It further reviews the fact that GA's are rather sensitive to fitness function selection and care should be taken in its appropriate selection for the problem at hand. This chapter forms the foundation of how the amalgamation of GA's and Fuzzy systems can be combined to produce GA-Fuzzy Rule Base Systems.

Chapter 5, Fuzzy Logic Control

This chapter is a fundamental review of Fuzzy Logic Control Systems and Rule Base Systems. Its particular application in GA-Fuzzy design is to establish the tunable parameters, control structure and rule base mechanisms for heuristic learning.

In addition, this chapter shows that FLC design is intuitive, however it could be a challenging task to design an optimal FLC controller when limited knowledge is available.

Chapter 6, Genetic Fuzzy Rule Based Systems

This section combines Chapters 4 and 5 to form a discussion on Genetic Fuzzy Rule Based Systems. In particular it studies various approaches to Genetic Fuzzy Design. In particular, mention is made of the Michigan and Pittsburgh approaches to Genetic Fuzzy Rule Base design (GFRBS).

It establishes that the two GFRBS's methods are fundamentally different in it encoding of the chromosome, and on the application of the GA population. In the Michigan approach, the entire population represents a prospective solution whereas in the Pittsburgh approach, each chromosome represents an entire solution to the problem.

It concludes by stating that the Michigan approach is best suited for online adaptation and learning, and the Pittsburgh for offline approaches, each with their peculiar attributes for control.

Chapter 7, On the Design and Analysis of a Genetic Fuzzy AGC Controller

In chapter 7 AGC controllers are designed and weighed upon how well they meet the stated performance measures. It illustrates GA-Fuzzy genetic tuning of the Knowledge Bases and Rule Bases and contrast AGC performance with conventional design approaches.

Key contributions illustrate that the encoding of the search space parameters plays an important role in final controller performance. It also shows that favourable characteristics are obtained of the final GA-Fuzzy controller.

It further continues by discussing the performance of the GA, and that under certain circumstances dynamic GA parameter updates are required to improve algorithm performance and convergence properties.

Chapter 8, Conclusions and Future Work

In this section a conclusion is presented and a few recommendations are made. It also discusses future work and highlights potential improvements in the GA - Fuzzy design methodology. It is concluded that evolutionary methods for controller design is a plausible method of learning and adapting controller behavior to meet the demands and objectives of the stated design problem, provided that suitable chromosome representation is made.

Chapter A, Previously Published Work

This chapter details published work and the contribution made to the body of engineering knowledge. Large portions of the chapters contained within this thesis have formed the foundations of the published work.

The first paper provides a very general introduction to the concepts of Genetic - Fuzzy Control and its application to the Automatic Generation Control problem.

The second paper is an extension of the first highlighting additional aspects of chromosome encoding and its influence on the evolved AGC controller.

The third paper looks at how Bezier Surfaces can be used an a mechanism by which encoding can be realized and shows that any appropriate encoding method of the problem search space can be used for GA - Fuzzy design.

Lastly, the fourth paper presents topics of power plant modeling and experiences.

1.6 Summary of Chapter 1

The Introduction presented the motivation and overview of the thesis. Its chief aim is to introduce GA-Fuzzy AGC control as a viable approach to control system design, especially where system information is uncertain. It also highlights the literary contributions of the thesis and its value added.

The next chapter (Literature Review) presents a detailed review of current techniques used within AGC controller design.

Chapter 2

Literature Review

This literature review discusses the importance of Frequency Control (FC) and the function of Automatic Generation Control (AGC) within large Interconnected Power Systems (IPS). In addition, it establishes the importance of dynamic frequency control and its role within the control of active power by maintaining a balance between load demand and generated power.

It is paramount that strict control of the network frequency is maintained amidst system disturbances and that the frequency is returned to its nominal value within certain boundary conditions. The manner by which this function is achieved is through Automatic Generation Control (AGC), also commonly known as Load Frequency Control (LFC) .

2.1 Frequency Control of Interconnected Power Systems

Frequency Control of large Interconnected Power Systems form an important function for modern power utilities and thus the quality of frequency forms a basic performance measure. In order to achieve satisfactory FC performance, closed loop control of all power generators forming part of AGC is warranted, but not only to maintain performance, FC ensures that synchronous machines operate efficiently within operational boundaries.

In addition, frequency also indicates the health of the electrical network in terms of over generation and under generation. Any excess of frequency above its nominal value would indicate a surplus of energy and likewise any deficiency of frequency below is nominal value would indicate a deficit of energy. Therefore, to minimize frequency deviations, AGC control is needed.

However, at first during a frequency incident, mandatory turbine governor responses (Primary Frequency Control) take effect and thereafter, the integral component of AGC (or Secondary Frequency Control) ramps each generating unit according to the magnitude of the frequency deviation. This is graphically illustrated in Figure 2.1 below.

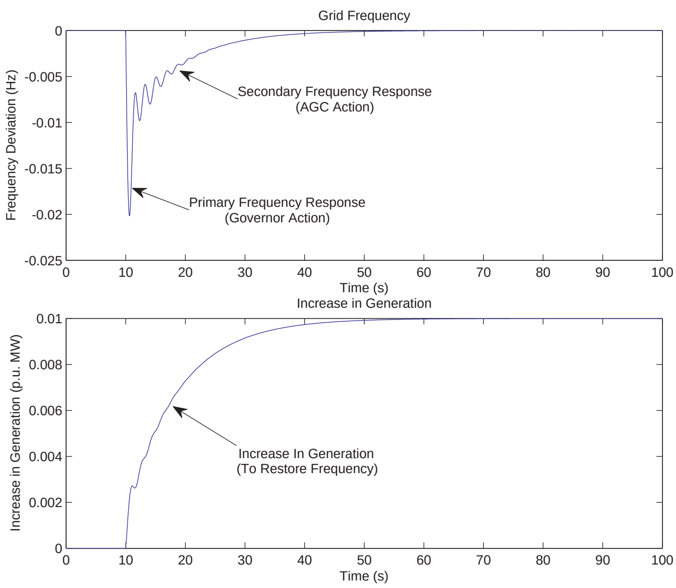

Figure 2.1: Illustration of frequency response due to load disturbance of 0.01 p.u. MW and mandatory governor response and AGC action.

As seen from Figure 2.1 AGC provides an effective mechanism for regulating total power generation in order to minimize the system frequency deviation $\triangle f(t)$. In addition, AGC also regulates the total Tie - Line $\sum_{i=1}^{N} \Delta P_{Tie_i}(t)$ power flows. In practice, AGC sends raise or lower commands to each generating unit for the control of real power.

The dynamic behavior of large interconnected power systems is dependent upon system disturbances, uncertainties due to loading requirements and upon the need to supply electricity of good quality in terms frequency control (Kumar and Kothari, 2005).

Therefore, within an interconnected power system, the network frequency is an important indication of the power mismatch between energy demand and supply. This inherently places strict performance demands upon the AGC controller, not only to maintain good disturbance rejection properties, but also to be robust in terms of controller design and also to exhibit good regulatory performance (Tan and Xu, 2009).

2.1.1 Impact of Frequency on Synchronous Machines and Generators

This section highlights the need for FC and the impact of frequency variations on synchronous machines and generating units. A permanent deviation in frequency has a direct influence on the operation of the power system. It not only affects the quality of control on the frequency but it also influences the performance and efficiency of synchronous machines.

Operating synchronous machines beyond its frequency and voltage boundaries shorten the life of the equipment and can lead to equipment failure. For this reason most equipment manufactures of synchronous machines design equipment, including both motors and generators, to operate within certain boundary conditions. Exceeding these boundary conditions would result in thermal stress to the electrical windings, overheating of windings and consequential failure of the synchronous machine.

According to the International Standard IEC 60034-1, rotating electrical machines should operate at its nominal value (see Figure 2.2, rating point) and should allow for continuous operation in Zone A. Exceeding both frequency and voltage limits (Zone B) is not recommended, however the synchronous machine should be able operate within this area for a limited period of time. This inadvertently places strict frequency and voltage demands upon the electrical grid.

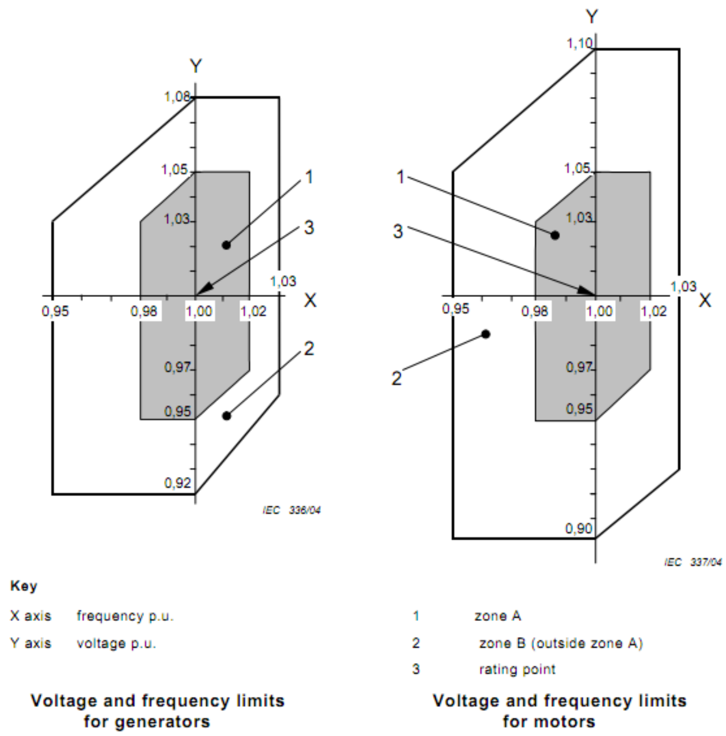

Figure 2.2: Illustration of the Voltage and Frequency Limits of Synchronous Machines (source, IEC 60034-1 Eleventh Edition 2004-04)

In addition to affecting synchronous machines and generators, frequency variation on the electrical grid could also have a substantial impact on steam turbine blades. Operating the frequency outside its boundary conditions could lead to turbine blade failures, increased blade resonance, and causing fatigue of the blades.

In addition, blades could also be susceptible to resonance near the operational speed of the turbine such as when system run-up and shut-down procedures are initiated. This is also true in situations of low and high grid frequency. Thus it is critical to operate the grid frequency fairly tightly to minimize such effects. In summary the operational characteristics of the grid should enable the turbo-generator to function effectively within its performance profile.

2.1.2 Impact of Frequency Variations on System Load

Electrical load can either be resistive, capacitive or inductive. Pure resistive loads are insensitive to frequency variations, while capacitive and inductive loads are frequency dependent. Within industry a large amount of inductive loads are synchronous machines fed directly from the electrical grid. In certain instances use is made of Variable Speed Drives (VSD) which can tolerate a certain amount of frequency variation, however, if the frequency deviation is extreme, deteriorating performance and efficiency of the synchronous machine would result. Table 2.1 highlights the implications of frequency variations on system load.

2.1.3 Impact on Time Correction

Time Error Correction (TEC) forms one of the functions of the Automatic Generation Controller. During the operation of AGC, there are periods of time when there is either over or under generation. This tends to cause the average frequency

Table 2.1: The Effects of Frequency Variations on Different Types of Loads

Load Type	Examples	Effects of Frequency Variations	Discussion
Resistive Loads	Heaters, Lamps	Frequency insensitive.	Although resistive loads are insensitive to frequency variations, a large load disturbance results in a proportionally equivalent frequency deviations.
Inductive Loads	Generating Sets, Motors, Transformers	Loss of performance and overheating	In generating sets, over fluxing is a condition which is aggravated by system frequency variations, which could have detrimental effects on the synchronous machine. In all cases overheating due to frequency affects operates the machines close to their respective physical limits.
Capacitive Loads	Capacitor Banks	Loss of performance	Capacitor banks play a vital role in the control of reactive power on the electrical grid and as such frequency variations would negatively impact on reactive power control.

to either be high or low and consequently leading to a time error.

The time error on average needs to be corrected over time. If the time error is positive it indicates that in the past there has been over generation and similarly, when the time error is negative it indicates that there has been a period of time in the past when the system was under generating.

In order to correct this, TEC compensates by adjusting the Area Control Error (ACE) over time in such a manner as to bring the time error to zero. This TEC controller is a slow acting controller.

The network frequency of interconnected power systems is a primary indication of the health of the electrical grid. It's not only a measure of network stability, but also provides a mechanism by which the generating supply and demand energy balance is assessed. An increase in frequency indicates an energy surplus while a decrease in frequency is indicative of under generation. Therefore, control of network frequency by means of increasing or decreasing generation is known as Automatic Generation Control (AGC).

2.2 Automatic Generation Control

Conventional Proportional and Integral (PI) Controllers as applied to Automatic Generation Control (AGC) have been studied extensively as contained within the literature and have been successfully applied to many large scale interconnected power systems (Kumar and Kothari, 2005; Bevrani and Hiyama, 2007).

In this section, the design of Automatic Generation Controllers are studied and evaluated, in particular the control methodology employed is that of Genetic - Fuzzy Control as contained within this research. The reliability and availability of large interconnected power systems are crucial to national infrastructure, both in terms of meeting quality of supply demands and on ensuring that the load demand balance is maintained at all times.

Especially when considering that quality of electrical supply, which is viewed primarily by the stability of system frequency and by maintaining electrical power, it is paramount, that power utilities achieve good control of their generating units. Although network stability is also viewed from a voltage perspective, the relationship between network frequency and voltage is closely related. This multi-objective control function is achieved by AGC, which forms a supervisory controller on all generating units contained within the power utility, and voltage control is achieved by the Automatic Voltage Regulator (AVR) (Kumar and Kothari, 2005).

In this research, we take a deeper look into AGC and the application of Genetic - Fuzzy Control system technology as a viable control strategy for large interconnected power systems. The attraction of Genetic - Fuzzy Control technology for this application stems from the fact that Genetic based adaptation and robustness properties, which is an inherent characteristic of this method, may prove beneficial for generation control purposes.

2.3 AGC Objectives

Modern power systems are typically controlled by a proportional and integral type control law, which aims at minimizing the Area Control Error (ACE) of the power system, thereby maintaining system frequency and tie - line power exchanges. Recent research effort have focused on the application of fuzzy logic control (Talaq and Al-Basri, 1999; Du and Li, 2006; Anower et al., 2006; Shayeghi et al., 2009; Anand and Jeyakumar, 2009a), hybrid artificial neural network (Liu and Zhang, 2009; Panda et al., 2009a,b) control strategies for the application of AGC, in which, improvements in control strategy and control system performance is reported.

Therefore, the present study focuses on applying GA-Fuzzy controller design techniques as applied to modern AGC of large interconnected power systems. The main contribution of this work is to review current literature and to analyze the performance of the designed controller by means of simulation.

In this section, a review of the current literature is performed. It focuses primarily on AGC and the application of Genetic - Fuzzy Controller design techniques as contained within the literature. The primary research methodology employed is that of answering the following questions which forms part of the key design objectives for the design rationale.

- What is AGC and why is it an important function for large interconnected power systems?
- What are the key associated problems with AGC as found within industry?
- What are the design objectives for AGC?
- In terms of controller design, it is proposed to apply Genetic - Fuzzy controller design methodologies as a proposed solution to the AGC problem.
- Fundamental questions are as follows.
  - How are Genetic - Fuzzy controllers designed and what are the key design considerations?
  - Since Genetic Algorithms are based on random selection and probabilistic search methods, how is the stability of the system guaranteed especially when Genetic - Fuzzy controllers are applied?
  - How does Genetic Fuzzy controllers compare with conventional controller techniques in terms of performance and robustness, what is its advantages and limitations when applied to AGC?

These questions forms the basis of the literature review section and is aimed at establishing the required theoretical and practical knowledge for applying Genetic - Fuzzy controllers to AGC. Therefore, the discussion begins by describing AGC, followed by an account of fuzzy logic controllers and the operation of Genetic

Algorithms.

2.3.1 AGC and Tie-Line Bias Control

Conventional approaches to the AGC control problem have been based on Tie-Line Bias control, where a proportional and integral type control strategy is employed (Skaar and Nilssen, 2004; Alrifai and Zribi, 2005; Shayeghi et al., 2009). Since during normal electrical load variations, AGC provides a convenient means by which frequency deviations are returned to nominal parameters. This maintains frequency deviations and tie line power exchanges at zero steady state error values.

However, Tie-Line Bias control does not lead to optimal closed loop control performance, which tend to be more oscillatory in nature, especially when considering modeling uncertainties, unknown non-linear plant characteristics and the complex behavioral interactions of large interconnected power systems (Ha, 2000; Venkat et al., 2008) and inter area oscillating modes.

For this reason, much research effect have been focused on the development of AGC controller design methodologies for good robustness performance objectives as well as maintaining good load disturbance rejection properties (Bevrani et al., 2004; Shayeghi and Shayanfar, 2005; Bevrani and Hiyama, 2007; Shayeghi et al., 2007; Taher et al., 2008; Venkata Prasanth and Jayaram Kumar, 2008; Khodabakhshian and Edrisi, 2008; Taher and Hematti, 2008; Tan and Xu, 2009), to produce robust AGC controllers.

Contained within the literature, various AGC controller design methodologies have been proposed in response to unknown process dynamics, with improvements in performance being cited when compared to established AGC techniques. These can be summarized as follows. Conventional PID approaches are considered in (Malik and Kumar, 1988; Khodabakhshian and Edrisi, 2008; Sinha et al., 2008; Tan, 2009), where a new design approach to PID tuning is detailed based on maximum peak resonance specification (MPRS), citing improvements in control system performance and improved robustness properties (Tan, 2009). MPRS is a frequency domain loop shaping controller design method.

In addition to conventional I, PI and PID controller design strategies (Nanda et al., 2006), the application of optimal control (Yuksel et al., 2008), variable structure control, model predictive control (Venkat et al., 2008) and the application of linear matrix inequalities (Rerkpreedapong and Hasanovic, 2003; Bevrani et al., 2004; Raj and Raja, 2009) to the AGC control problem of interconnected power systems have found widespread research interest and application (Shayeghi and Ali, 2004; Shayeghi and Shayanfar, 2005; Shayeghi et al., 2007, 2009).

This is particularly motivated by the fact that the aforementioned controller design strategies are inherently robust to model uncertainty, and when applied to AGC yield desirable closed loop characteristics. This would include robustness against network growth and complexity, unknown non-linear dynamics and complicated network interactions.

However, the former controller design techniques are model dependent and may prove to be a challenge to obtain especially when dynamics are not well known nor accurately modeled or when system identification is not readily available, limiting the performance of the controller.

This inadvertently led to the application of more intelligent design methods, including fuzzy logic control (Anand and Jeyakumar, 2008; Cam, 2007), fuzzy gain scheduling (Talaq and Al-Basri, 1999; Jianhong et al., 2002; Juang and Lu, 2005; Anower et al., 2006), artificial neural networks (Shayeghi and Ali, 2004) and fuzzy neural networks (Liu and Zhang, 2009) to name but a few. These techniques are founded upon expert knowledge and human reasoning, taking into account system unknowns from a linguistic perspective.

In view of this, one of the main aspects which makes intelligent control methods such as fuzzy logic control (FLC) and artificial neural networks (ANN) a non-trivial task is that of rationalization and neural network training. Fuzzy systems depend upon expert knowledge, however, an expert may not always be available (Castro and Camargo, 2004), making the fuzzy logic controller design and rule base generation non trivial.

In addition, when considering multiple input and multiple output systems and their respective interactions, large numbers of fuzzy rules are involved and the parametrization of the membership functions including its scaling gains, FLC design can become overwhelming. In the case of ANN, especially large networks, training and optimization can become an issue. For this reason, it is proposed to use genetic algorithms for the optimization of fuzzy controllers.

With application to control systems and power systems, genetic algorithms have found universal application (Chang et al., 1996; Cordón et al., 1996; Wang and Spronck, 2003; Dalci et al., 2004; Ghoshal, 2005; Du and Li, 2006). Their heuristic search characteristics makes genetic algorithms suitable for finding appropriate solutions to complex control problems via optimization methods. In this research, we apply genetic algorithms to the optimization of a fuzzy logic controller, applying them to the Automatic Generation Control problem of interconnected power systems.

Automatic Generation Control (AGC) can be considered as a supervisory control strategy for large interconnected power systems, with the express aim to regulate system frequency and tie-line interchange power (Kumar and Kothari, 2005). This forms an important function within modern power utilities and forms a primary business objective, especially when viewed from a power regulatory perspective.

Interconnected power systems can be divided in sections known as control areas which represents a coherent group of electrical Generating Units operating under synchronized frequency conditions.

In each control area, the AGC controller strives to meet its scheduled demand by regulating each Generating Unit up or down (controlled by raise or lower pulses) according to its scheduled load demand. The load demand depends upon the system frequency $\Delta f(t)$ and its relative power exchange deviations $\Delta P_{Tie}(t)$ with its neighboring control areas (Rerkpreedapong and Hasanovic, 2003).

This is graphically illustrated in Figure 2.3.

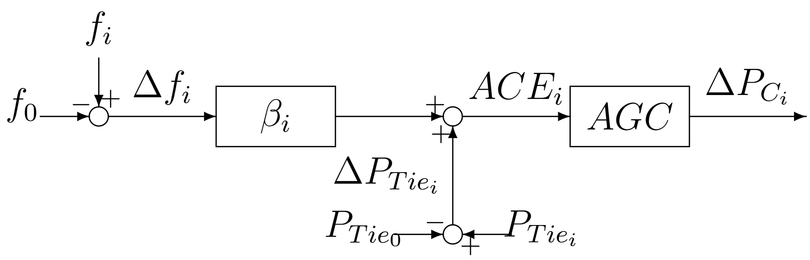

Figure 2.3: Conventional Tie - Line Bias Control for Automatic Generation Control

The dynamic behavior of large interconnected power systems is dependent upon system disturbances, uncertainties due to loading requirements and upon the need to supply electricity of good quality in terms frequency control (Kumar and Kothari, 2005).

Therefore, within an interconnected power system, the network frequency is an important indication of the power mismatch between energy demand and supply.

This inherently places strict performance demands upon the AGC controller, not only to maintain good disturbance rejection properties, but also to be robust in terms of controller design and also to exhibit good regulatory performance (Tan and Xu, 2009).

2.3.2 Generating Unit Governing and Control

By considering typical Generating Units which are controlled by turbine governing systems upon load disturbances does not yield a zero steady state error for system frequency. In fact, as the loading on the electrical network increases, the frequency tends to decrease, due to the increased energy demand and vice versa (as the loading decreases the frequency tends to increase)(Shayeghi et al., 2009). This implies that there needs to be a continuous energy balance in terms electrical demand and supply.

Therefore, due to governor action there is an immediate governing response to frequency deviations, however, this does not return the system frequency to its nominal value. This is known as primary frequency control. However, in order to return the frequency to its nominal value, secondary frequency control is required or AGC.

2.3.2.1 Conventional AGC Control

Conventional control approaches to solving the AGC problem has been based on tie-line bias control (Kumar and Kothari, 2005) and by making use of the classical PI controller strategy. In this approach, corrections due to frequency deviations Δf are made via the area frequency response characteristic β. This is in turn used to form the the Area Control Error (ACE) as described by the equation 2.1

below, where ΔP_{Tie} represents the tie-line interchange power. The subscript i denotes the i^{th} control area within the interconnected power system.

The equation (2.1),

$$ACE_i = \Delta P_{Tie_i} + \beta_i * \Delta f_i \tag{2.1}$$

is the Area Control Error (ACE), where i is the i^{th} control area with $i \in (1 \cdots N)$ and N representative of the total number of control areas, $\Delta P_{Tie_i} = P_{Tie_i} - P_{Tie_0}$ is the inadvertent Tie-Line power exchange deviation and $\Delta f_i = f_i - f_0$ is the frequency deviation from its nominal value.

Effectively the ACE manages the power frequency balance in order to maintain system frequency by manipulating system power. The Frequency Bias factor $-10B$ depends upon the system capacity and size of the generating electrical network, and is synonymous to the area frequency response characteristic β.

In conventional Tie-Line Bias Control it is recommended that $-10B = \beta$ (Bakken and Grande, 1998; Egido et al., 2004; Kumar and Kothari, 2005), in that it would tend to reject internal area disturbances more effectively. This is an important criteria for system stability as well.

The term ΔP_{C_i} represents the power demand required by all Generating Units participating within AGC control. This signal is proportioned accordingly by means of the capabilities of the Units in terms of power generation limits and are proportioned by means of participation factors.

2.3.2.2 AGC Controller Design Approaches

Contained within the literature there are many controller design methodologies which have been applied to the Automatic Generation Control problem (Kumar and Kothari, 2005). The studies presented have focused on classical approaches such as the PI controller design methods to the application of more robust controller design theories, such as H_∞ Optimal Control. The present study will therefore highlight a few of these design methods and will expound on their application to AGC.

The conventional AGC controller is based on the classical Proportional and Integral (PI) controller structure. This can be written as follows, where K_P and K_I represent the Proportional and Integral controller gains respectively (Kumar and Kothari, 2005; Khodabakhshian and Edrisi, 2008; Tan, 2009).

$$\Delta P_{C_i} = K_P * ACE_i + K_I * \int ACE_i dt \tag{2.2}$$

Typically, the controller parameters (K_P and K_I) are designed conservatively to meet the stated performance objectives in terms of robustness and system stability. This is of importance to the interconnected power system since it ensures good quality of frequency and power supply to the grid.

More recently, fuzzy logic controller design techniques have been applied (Du and Li, 2006; Cam, 2007; Anand and Jeyakumar, 2008, 2009a,b) and various hybrid approaches (Ferrari-Trecate et al., 2004; Khan and Iravani, 2007; Panda et al., 2009b,a). These techniques provides superior performance as stated within the literature in terms of robust performance, particularly because the nature of these techniques considers design uncertainty.

Moreover, robust controller design techniques have also been applied to the AGC control problem. These include Variable Structure Control (Ha, 2000; Al-Hamouz et al., 2005, 2007; Huddar and Kulkarni, 2008), Genetic Fuzzy Gain Scheduling (Talaq and Al-Basri, 1999; Jianhong et al., 2002; Juang and Lu, 2005; Anower et al., 2006) , techniques based on evolutionary optimization and hybrid approaches (Grantner and Fodor, 2002; Ting and Rao, 2006; Xianbo and Jingqi, 2007; Kim et al., 2008a; Panda et al., 2009b,a).

Apart from the conventional controller design criteria (such as robust performance and stability), the AGC controller design aims at maintaining adequate load rejection regulation, as well as minimizing the Generating Units movement to the control demand. This minimizes production costs, by optimally controlling the unit for regulating performance . In addition, the importance of this to power utilities is that it guarantees substantial production cost savings, reducing routine maintenance due to wear and tear (caused by Unit cycling) but more importantly it aims at meeting the business objectives of the power utility.

In general, frequency control of power systems are governed by what is known as primary speed (or frequency) governing, secondary frequency control (or Automatic Generation Control) and should the frequency continue to deviate beyond operational limits, tertiary control (or load shedding) becomes effective. Each of these control mechanisms has a stabilizing effect on the frequency.

2.3.3 Primary Governing Of Turbo-Generators

Turbine Governing control systems forms a critical component for modern rotating machinery, such as turbo-generating systems. This is necessary to perform fast turbine speed regulation and once the turbo-generator is synchronized to the national electrical grid, it provides a means by which the loading on the generator is varied. Opening or closing of the main steam admission control valves to the turbine (water gate valves in the case of a hydro turbine), leads to an increase in generated energy. However, it should be noted that primary governing on its own does not lead to zero steady state error.

2.3.4 Automatic Generation Control

Electrical power systems fulfills a vital role within society today, amid national growth in electrical demand and the need for reliable electrical networks have placed strict demands upon Power Utilities to provide sustainable energy as well as to adhere to the performance standards of the National Grid.

In order to achieve this, Power Utilities have implemented various controlling strategies aimed at providing network stability, assurance in terms of meeting energy demand versus energy supply and on enabling that systems are in place for the recovery of system frequency upon any external network disturbances. This regulatory process is known as Automatic Generation Control.

Therefore, to drive the network frequency to zero steady state error, AGC is employed. It forms a load reference input to the turbine governor control system of generating units. Its primary objectives are to (Bakken and Grande, 1998; Egido et al., 2004; Shayeghi et al., 2009),

- Maintain frequency deviations $\Delta f(t)$ at zero in the presence of electrical load disturbances.

- Maintain Tie-Line power $\Delta P_{Tie}(t)$ exchange deviations at zero with all neighboring control areas contracted for AGC.

- Maintain the Area Control Error (ACE) $ACE(t)$ at zero. Both the frequency and the ACE can be considered as a health measure for the interconnected power system.

2.4 Modeling Of Interconnected Power Systems

Modeling of systems and subsystems are fundamental to control system design and analysis (Changliang et al., 2001; Cordero-Cruz et al., 2002; Egido et al., 2004; Ferrari-Trecate et al., 2004; Barbieri and Lastra, 2007). This is particularly true in power plant design for controller development, where a good knowledge of the process is required for effective control operations.

This section therefore introduces modeling of interconnected power systems, especially from a dynamic frequency response perspective, and describes the importance of understanding the dynamic behavior of power systems, its dynamic interactions and paves the way for effective control system design.

The presence of a good validated model enables system analysts, electrical network operators and utility engineers to perform effective network planning, fault analysis and system diagnostic exercises (Egido et al., 2004). This forms an important function for Systems Operations and National Control Dispatch, where the planning for efficient energy regulation is performed on a day by day basis. In addition, effective model development ensures that sufficient conditions are met to ensure the robustness of the controller design.

However, unit modeling can be a daunting task, since modern power plants are large complex interacting systems (Peet and Leung, 1995; Flynn and O'Malley, 1999; Hain et al., 2000). The only way to compensate for this is to divide the modeling task into manageable sections representing the major system dynamics of the power plant.

This is well achieved within the TGOV series of power plant models, for single and multi-area interconnected networks (see Appendix B), which is a simplified turbine governor model and can also model the effects of boiler dynamics and associated control systems for use within dynamic power plant frequency studies (Hain et al., 2000; Barbieri and Lastra, 2007; Ažubalis et al., 2009).

Developed as part of an international working group, the TGOV model is a representative unit model used to model various unit control modes of operation when enabled by appropriate parameter selection (Hannett and Khan, 1993; Flynn and O'Malley, 1999; Hain et al., 2000). However, finding appropriate parameters may prove to be a demanding task, since a large portion of these parameters represents the dynamic physical behavior of the turbine and boiler respectively.

2.4.1 Model Validation Tests

Model validation tests are aimed at establishing good input output correlations of model response to test data characteristics. In this process, tests are based on the normal mode of operation of the Generating Unit and coincide with daily unit operational practices. Table 2.2 describes a selection of model validation tests which can be performed on a generating unit.

As an example, where the unit is controlled in Coordinated Boiler follow Mode, the model will be parametrized for this case, and tests will be aligned for this particular outcome. Therefore, based on appropriate model parameter selection, certain key operational features can be modeled within the TGOV model.

Interconnected Power Systems (IPS) consist of a number of generating units operating in synchronization, supplying electrical energy to various resistive, inductive or capacitive loads connected to the electrical grid via transmission lines. Invariably, any variation in loading has a direct impact on the frequency of the electrical system. This places strict demands upon the properties of the AGC controller to maintain frequency stability throughout a wide operating region, given increasing electrical network size and complexity.

Table 2.2: Model Validation Test Procedures

#	Test Description	Comments
1	Gathering of Steady State Data	Gather steady state data from at least four (4) load conditions over the normal operating range. This will guide in model steady state behavior.
2	Ramp Tests	Ramp the Unit (up and down) from minimum loading to maximum loading according to certified ramp rates, allowing for steady state conditions and sufficient settling times. Intermediate load hold conditions may be applicable. Repeat at different ramp rates.
3	Boiler Control Parameters	Initial testing conditions include stable steady state conditions, at a loading of about 90% of MCR. Place the boiler control to manual and step the controller set-point, observe the pressure deviation.
4	Frequency Response Characteristics	Perform simulated frequency ($\Delta f(t)$) injection test. Observe response within governor dead-band and outside the dead-band.
5	Governor Valve Testing	Allow for small step changes in governor valve (gate) position. This will guide in terms of governor response time constants.
6	Turbine Model Tests	Can be calculated by means of heat balance data, and can also be calculated based on dynamic turbine response data.
7	Load Rejection Test	Full or partial load rejection, depending upon the capability of the unit. This test guides in terms of the electrical behavior of the unit, and also assists in providing more information in terms of governor response.

2.4.2 Governor Dead Band

In practice, governor Deadband (DB) forms part of the Turbine Governor and by definition, DB is defined as the continuous magnitude change in turbine speed for which there is no governor valve movement. In effect Deadband eliminates governor movement over the dead-band range but could also contribute to low frequency oscillation of the system (Anand and Jeyakumar, 2009a).

$$y(x, \dot{x}) = y_0 + N_1 * x + \frac{N_2}{\omega_0} * \dot{x} + \cdots \qquad (2.3)$$

In effect as well, DB operates about the operational frequency ω_0. Equation 2.3 represents the Fourier Series approximation, with terms N_1 and N_2 representing its respective coefficients, higher order terms are typically neglected, $y(x, \dot{x})$ is a describing function used to approximate nonlinearities (such as friction and backlash).

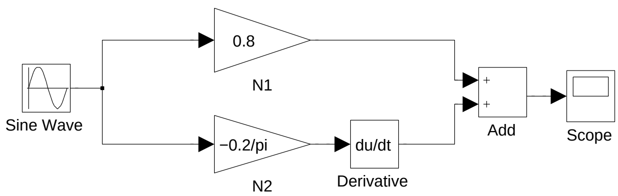

Figure 2.4: Governor Deadband Model

From an AGC perspective, governor deadband influences the performance of the system to a large extent. Inherently governor valve friction and backlash, which are non-linear elements influencing control further contributes to deteriorating closed loop performance.

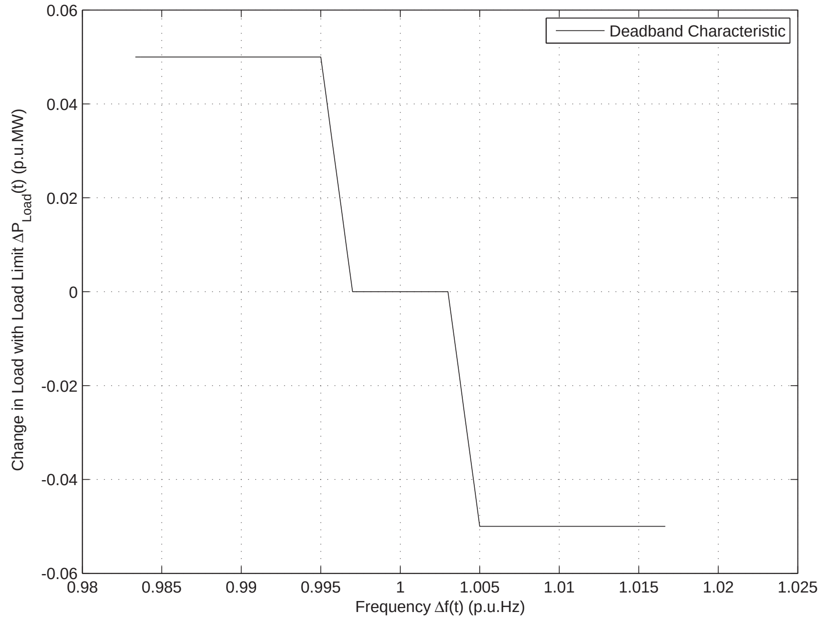

Figure 2.5: Graphical Illustration of Governor Deadband with Response Limits

2.4.3 Governor Droop

The active agent in parallel control of Generating Units of interconnected power systems is the Droop characteristic. Typically this parameter is set to 4% within the South African Power Pool and is defined as the percentage frequency change $\Delta f(t)$ which will result in a 100% change in governor valve opening, and hence Power (see illustration in Figure 2.6).

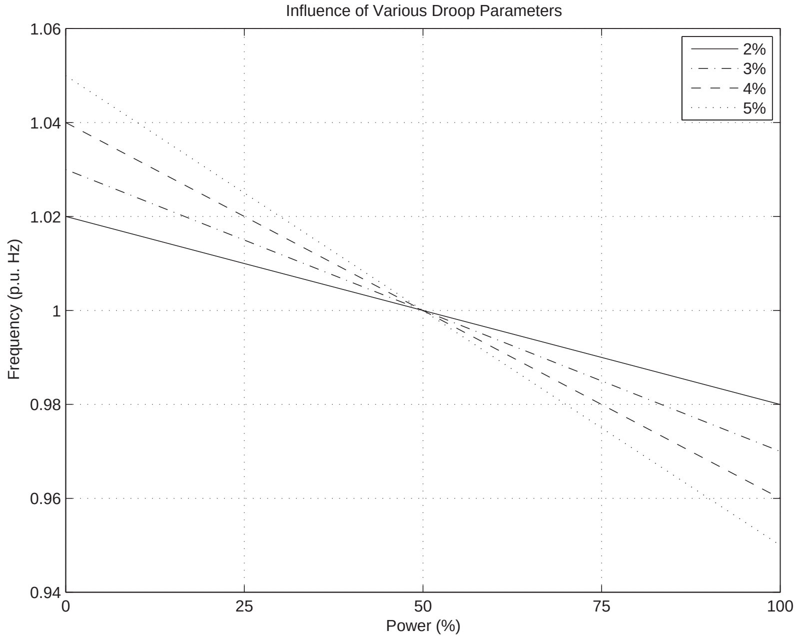

Figure 2.6: Droop Characteristic of Interconnected Power Systems

In addition, Droop also enables Generating Units to share electrical load proportional to their respective load sharing capabilities, for parallel operation on an electrical grid. It is also noted that the application of Droop encourages the use of Secondary Frequency Control, since governing systems are incapable of restoring Frequency deviations after a load disturbance to zero steady state error, without the application of a sustained and modulating Load Reference signal (Figure 2.7 illustrates the influence of Droop on the Governor).

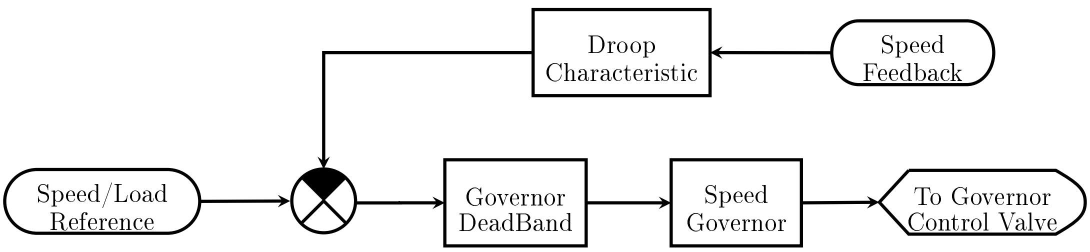

Figure 2.7: Illustration of Governor Droop Characteristic

2.4.4 Generation Rate Constraints

Generation Rate Constraints (GRC) are imposed on real power systems, limiting the rate of change of generation ($\Delta\dot{P}_g$). GRC is dependent upon the mechanical ramp limits (lower and upper limits) of generation and upon the physical properties of the unit, but also ensures that the unit responds within the confines of unit operational margins. In this study, GRC of 0.1 p.u. per minute is considered, as shown in equation (2.4), which is a typical GRC constraint for interconnected power systems.

$$\Delta\dot{P}_g \leqslant \delta = 0.0017 \; p.u. \; MW/s \tag{2.4}$$

Figure 2.8 illustrates the implementation and operation of GRC on a generating unit, where rate limits in the form of upper and lower bounds $\pm\delta$ are implemented within the Turbine Controller.

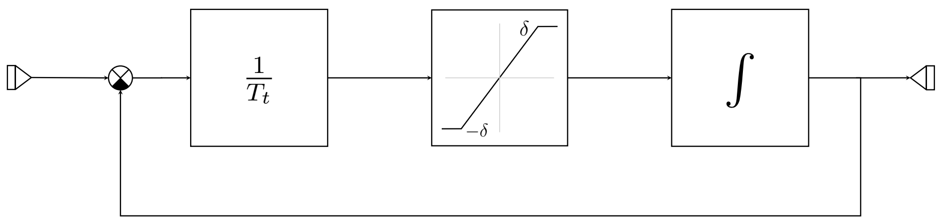

Figure 2.8: Illustration of Generation Rate Constraint

2.4.5 The Turbine Model

Parts of the turbine components can be represented as a vessel under pressure (Figure 2.9). By means of a mass balance analysis and the laws of the conservation of mass flow, the rate of change of weight of steam contained within the vessel can be represent by equation 2.5.

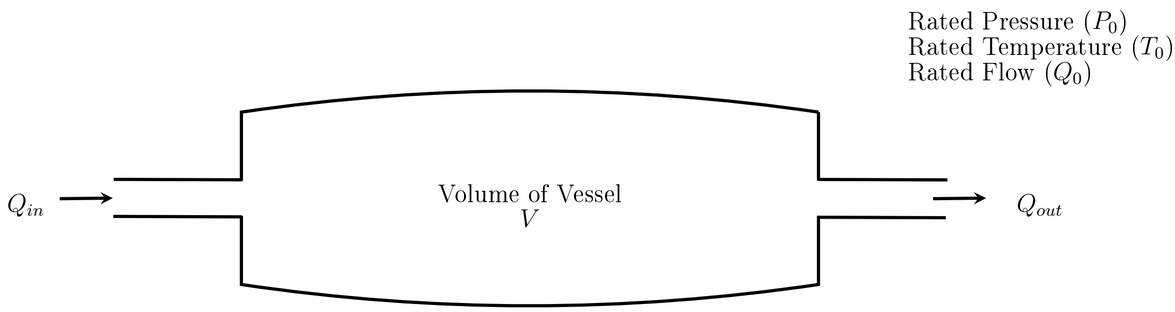

Figure 2.9: A Vessel Under Pressure

$$\begin{aligned} \tfrac{dW}{dt} &= V * \tfrac{d\rho}{dt} \\ &= Q_{in} - Q_{out} \end{aligned} \tag{2.5}$$

In equation 2.5, W is the weight of steam within the vessel (where mass is in $kg = V * \rho$), V is the volume of the vessel in m^3 and ρ is the steam density in kg/m^3.

With the assumption that flow out of the vessel is proportional to the pressure contained within the vessel, equation 2.6 is a function of the rated vessel pressures and flow.

$$\begin{aligned} Q_{out} &= \tfrac{Q_0}{P_0} * P \\ \Longrightarrow P &= \tfrac{Q_{out} * P}{Q_0} \end{aligned} \tag{2.6}$$

Temperature within the vessel is assumed to be constant (Equation 2.7), where the rate of density change within the vessel is given as Equation 2.7 for a given temperature as obtained from thermodynamic steam tables.

$$\frac{d\rho}{dt} = \frac{dP}{dt} * \frac{\partial\rho}{\partial P} \tag{2.7}$$

Therefore, using equations 2.5, 2.6 and 2.7 the following composite relation is obtained (2.8).

$$\begin{aligned} Q_{in} - Q_{out} &= V * \tfrac{dP}{dt} * \tfrac{\partial\rho}{\partial P} \\ &= V * \tfrac{\partial\rho}{\partial P} * \tfrac{P_0}{Q_0} * \tfrac{dQ_{out}}{dt} \end{aligned} \tag{2.8}$$

Let $V * \frac{P_0}{Q_0} * \frac{\partial\rho}{\partial P} = T_{vessel}$, which is the time constant of the vessel dependent upon the physical properties of vessel and its rated pressure and rate of change of density as a function of pressure change within the vessel. Equation 2.8 them becomes,

$$Q_{in} - Q_{out} = T_{vessel} * \frac{dQ_{out}}{dt} \tag{2.9}$$

Taking the Laplace transform of equation 2.9 yields equation 2.10, with s being the Laplace s operator. It illustrates that for a vessel under pressure, it can simply be represented by a first order Laplace model where the time constant is dependent upon the physical properties of the vessel.

$$\begin{aligned} Q_{in} - Q_{out} &= T_{vessel} * s * Q_{out} \\ \Longrightarrow \tfrac{Q_{out}}{Q_{in}} &= \tfrac{1}{T_{vessel}s+1} \end{aligned} \tag{2.10}$$

This can therefore be applied to turbine mechanical components such as the steam chest and crossover pipework for the calculation of their respective time constants (see Figure 2.10).

2.4.5.1 Calculation of the Power Fractions

The steam turbine plays an important role in the process of power generation and for dynamic frequency studies of generating units. It is therefore paramount that accurate turbine models be developed for transient analysis and controller design. Figure 2.10 illustrates a simple turbine model for a small tandem compound turbine.

Admission steam enters the High Pressure (HP) turbine at rated temperature and pressure in the steam chest, which is a vessel under pressure. Since the steam chest is a steam vessel and contains steam volume, it has an associated steam time constant which forms part of the turbine model. Its respective time constant is denoted by T_{SC} (or T_4) and is a function of the physical dimensions of the steam chest, it rated pressure and temperature parameters, which contributes to a small delay from the time steam enters the steam chest to when mechanical power is generated by the HP turbine, with power factor K_1.

Similarly, as steam enters the crossover pipework an associated time constant exists namely, T_{CO} (or T_5) and enters the LP turbine where mechanical $Work$ is performed with an associated power factor K_3.

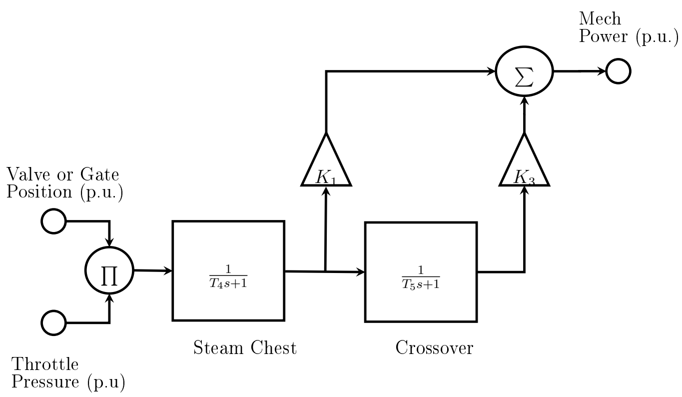

Figure 2.10: A Typical Small Tandem Compound Turbine Model

Contained within the literature, there are many methods of developing turbine models, either through experimental testing or by means of Heat Balance analysis and considering the physical structure of the machine. (Hannett and Khan, 1993; Hain et al., 2000; Stefopoulos et al., 2005; Ažubalis et al., 2009). Table 2.3 shows the unit conversion factors used to illustrate a calculated example of how turbine model parameters can be approximated from heat balance data (Vahidi et al., 2007).

Table 2.3: Table of Conversion Factors

	Original Units	Conversion Factors	Metric Unit
Pressure (P)	ata	101.325	kPa
Enthalpy (H)	$kcal/Kg$	4.186	kJ/kg
Temperature (T)	$°C$	1	$°C$
Mass Flow (Q)	kg/h	$2.78E-04$	kg/sec

Typical heat balance data for both the HP and LP turbines are listed in tables 2.4 (2.5) and 2.6 (2.7) for a typical 200MW tandem compound turbine. Using these tables, an illustration is given of how equations 2.5 through to 2.10 are applied to real turbine data for the calculation of the respective power fractions and vessel time constants for turbine model parameter determination.

Table 2.4: Typical Heat Balance Data for 200MW HP Turbine (Original Units)

HP Turbine Data	Pressure (ata)	Enthalpy ($kcal/kg$)	Mass Flow (kg/h)	Temperature ($°C$)
Inlet Conditions	106.50	828.00	731020.00	538.00
Extraction 1	26.20	743.10	37802.00	344.40
Extraction 2	16.00	716.20	44193.00	283.40
Extraction 3	8.00	682.80	42865.00	207.20
Extraction 4	3.00	641.70	55219.00	129.00

Table 2.5: Converted Data To Metric Units of HP Turbine Heat Balance Data (Metric Units)

HP Turbine Data	Pressure (kPa)	Enthalpy (kJ/kg)	Mass Flow (kg/sec)	Temperature ($°C$)
Inlet Conditions	10791.11	3466.01	203.06	538.00
Extraction 1	2654.72	3110.62	10.50	344.40
Extraction 2	1621.20	2998.01	12.28	283.40
Extraction 3	810.60	2858.20	11.91	207.20
Extraction 4	303.98	2686.16	15.34	129.00

Figure 2.6 tabulates typical heat balance data for the LP turbine, based on OEM design data.

Table 2.6: Typical Heat Balance Data for 200MW LP Turbine (Original Units)

LP Turbine Data	Pressure (ata)	Enthalpy ($kcal/kg$)	Mass Flow (kg/h)	Temperature ($°C$)
Inlet Conditions	3.00	641.70	550941.00	130.00
Extraction 1	1.17	609.00	34261.00	93.45
Extraction 2	0.37	576.00	29522.00	63.08
Extraction 3	0.20	543.00	486758.00	35.00

Table 2.7: Converted Data To Metric Units of LP Turbine Heat Balance Data (Metric Units)

LP Turbine Data	Pressure (kPa)	Enthalpy (kJ/kg)	Mass Flow (kg/sec)	Temperature ($°C$)
Inlet Conditions	303.98	2686.16	153.04	130.00
Extraction 1	118.55	2549.27	9.52	93.45
Extraction 2	37.49	2411.14	8.20	63.08
Extraction 3	20.27	2273.00	135.21	35.00

From Table 2.5, the HP Turbine inlet mass flow is Q = 203.06 kg/sec and the change in Enthalpy $\Delta H_{K=1} = 3466.01 - 3110.62 = 355.39\ kJ/Kg$. Therefore tabulated in Table 2.8 is the calculation of Work Done by each of the turbine stages, from Inlet to Extraction 1 ($K = 1$), Extraction 1 to Extraction 2 ($K = 2$), Extraction 2 to Extraction 3 ($K = 3$) and Extraction 3 to Extraction 4 ($K = 4$), the change in Enthalpy across turbine stages and hence work done by each stage can be calculated, by using equation $W = (H_{In} - H_{Out}) * Q_{sectioned}$, $W = \Delta H_{K=1} * Q_{sectioned}$, as illustrated by Table 2.8.

Table 2.8: Calculation of HP Turbine Power Fractions

K	Sectioned Vessel Mass Flow	Change in Enthalpy	Work Done
1	203.06	355.39	72166.17
2	192.56	112.60	21682.97
3	180.28	139.81	25206.04
4	168.38	172.04	28968.49
		Total Work Done ($Work_{HP}$)	148023.67 (kJ/sec)

Similarly, calculation of the LP turbine power fractions is given as tabulated in Table 2.9 and follows a similar calculation process of energy mass balances and where the conservation of mass is applicable for $Work$ performed according to the aforementioned calculation method.

Table 2.9: Calculation of LP Turbine Power Fractions

K	Sectioned Vessel Mass Flow	Change in Enthalpy	Work Done
1	153.04	136.88	20948.34
2	143.52	138.14	19825.87
3	135.32	138.14	18693.06
		Total Work Done ($Work_{LP}$)	59467.27 (kJ/sec)

By definition the ratio (A_1) of HP power to LP power is given by equation 2.11.

$$A_1 = \frac{Work_{HP}}{Work_{LP}} \tag{2.11}$$

Therefore the power fractions

$$K_1 = \frac{1}{1 + A_1} = 0.71 \tag{2.12}$$

and

$$K_3 = A_1 * K_1 = 0.29 \tag{2.13}$$

. This illustrates that approximately 70% of the mechanical power of the turbine is contributed by the HP turbine and approximately 30% of the total mechanical power is created by the LP turbine respectively. Now in boiler systems with a reheater and turbine systems with an intermediate pressure turbine (IP), similar discussions would be applicable.

2.4.5.2 Calculation of the Time Constants

From equation 2.8, $V * \frac{P_0}{Q_0} * \frac{\partial \rho}{\partial P} = T_{vessel}$ which relates the physical properties of the vessel to the time constant of the vessel. Let $K = \frac{\partial \rho}{\partial P} = \frac{\frac{1}{v_2} - \frac{1}{v_1}}{P_2 - P_1}$, where v is the specific volumes of the steam in the vessel at rated maximum pressure P_2 and rate minimum operating pressure P_1 at average operating temperatures, P is in Pa. P_0 and Q_0 are initial input conditions to the vessel, namely pressure and mass flow according to the heat balance data for the vessel under consideration. Table 2.10 illustrates the calculation of the vessel time constants for both the steam chest and the crossover pipework.

Table 2.10: Calculation of the Turbine Time Constants T_{SC}or and T_{CO}

Steam Chest		Crossover	
Operating Pressure Range		Operating Pressure Range	
P_1 (kPa)	8000	P_1 (kPa)	7.09275
P_2 (kPa)	12000	P_2 (kPa)	303.975
$T_{average}$ $(°C)$	538	$T_{average}$ $(°C)$	150
Specific Volume (from Steam Tables)		Specific Volume (from Steam Tables)	
v_1 (m^3/kg)	0.044367286	v_1 (m^3/kg)	27.51852372
v_2 (m^3/kg)	0.0287243	v_2 (m^3/kg)	0.625504453
K_{SC} Constant		K_{CO} Constant	
K_{sc} (s^2/m^2)	$3.06865E-06$	K_{co} (s^2/m^2)	$5.26259E-06$
Volume of the Steam Chest ($V_{SC} = \pi * r^2$)		Volume of the Steam Chest ($V_{CO} = \pi * r^2$)	
Height_average (m)	1.5	Height_average (m)	10.045
Radius_average (m)	0.125	Radius_average (m)	0.5
V_{SC} (m^3)	0.073631078	V_{CO} (m^3)	7.889324551
Time Constant (T_{sc})		Time Constant (T_{co})	
T_{sc} (s)	0.012007372	T_{co} (s)	0.082465993

2.5 Summary of Chapter 2

Chapter 2 presented a Literature review on the importance of frequency control and the role which Automatic Generation Control plays in power generation. It also highlighted the objectives of AGC and certain aspects of modeling for large interconnected power systems. This chapter also establishes the foundation for the rest of the thesis.

Chapter 3

Power Plant Modeling and Control

The previous sections, namely sections 2.1 through to 2.4 have discussed the importance of Automatic Generation Control and have formed the foundation for understanding the importance of frequency control of large Interconnected Power Systems.

The discussion which follows, highlights in detail the control system approaches to AGC and forms a comprehensive analysis of AGC modeling, control laws and strategies, especially from a power plant modeling, analysis and testing perspective.

It is therefore intended by this discussion to understand the dynamic behavior of power systems, the response of both boiler and turbine controllers on the load following ability of generating units and also its frequency response characteristics.

3.1 Power Plant Modeling and Control

Power plant modeling forms an important part of power system control and analysis. It not only gives an indication of power plant performance, but also provides a mechanism through which system faults and electrical network disturbances are analyzed. This is especially applicable for dynamic frequency response studies of electrical power systems and their related interconnections.

Understanding network interactions and the relationship which frequency have on the performance of the generating unit and to the power grid is a continual field of study and forms an important monitoring criterion for power utilities. To this end, power utilities and independent power producers function and operate within the boundaries of the South African Grid Code (SAGC).

Therefore, in accordance with these ideals and in compliance to the Grid Code, modeling of all generating units connected to the electrical power grid is required. It is the intent of this section to provide a methodology of how modeling of power plants can be performed as seen from a Grid Code perspective, detailing minimal system modeling requirements and also a to describe the process of testing and model parameter estimation.

3.2 The Need for System Modeling

Classical control theory provides the framework for the design and analysis of closed loop power plant control systems for good regulatory behavior and for good disturbance rejection properties. However, one of the more fundamental requirements to these approaches is the development of a validated power plant model for effective controller design and analysis.

Therefore with reference to power utilities, the national power grid is dependent upon dynamic control systems for the operation and control of power plants. It is a requirement that these control systems be adequately optimized for good regulatory and good disturbance rejection properties. In order to achieve predefined controller properties, modeling of the process plant is required. Thus to model and simulate the behavior of large interconnected power systems and to provide for an effective framework for system frequency response studies, power plant modeling forms an important component of power utility operation.

It is crucial that the models and parameters of these dynamic control systems be as accurate as possible to ensure that simulation results are representative of the real world power system behavior. Therefore, as a prerequisite to model development, a series of tests needs to be performed on the generating unit in order to validate the control system parameters and to adequately model the plant within a given boundary of operation.

3.3 Boiler Dynamics and Control

The influence of boiler control and boiler dynamics on frequency control of power systems have typically been neglected in AGC studies, however boiler dynamics play a substantial role in the performance of closed loop AGC control systems.

The performance of frequency regulation on the national electrical grid depends upon many variables. Random load variations influence the controllers ability to adequately control the network frequency, while the performance of generating units also share a large contingent of network performance responsibility.

This is clearly seen by the generating units' ability to follow the required MW load demand and to satisfactorily minimize frequency deviation. In addition, it is required that performance be maintained for rejecting both internal and external load disturbances. This is clearly seen by the performance of AGC and on its ability to regulate frequency and to maintain Tie - Line power exchanges. In particular, the time taken to respond to frequency deviations forms an important performance criteria.

However, the speed of response of the generating unit depends upon many variables, especially on the performance of the steam generator (Boiler). In turn the boiler performance is strongly dependent upon the performance of the milling plant. As pressure of the system decreases; the performance of AGC is consequently affected. Therefore, this section briefly highlights a few important points in the analysis of AGC systems and the influence which boiler dynamics have on frequency control.

This document describes certain fundamental modeling requirements for application within Eskom power plants, and every generator connected to the power grid. It is specifically tailored for application on coal fired generating units. The model used for development and analysis is the TGOV05 power plant model, with associated boiler control systems. The TGOV05 model is a simplified unit model, which makes use of the TGOV01 governing control system and also models boiler dynamics and control. Therefore the following sections of the model form the scope of this document.

1. Turbine modeling, preference is given to compound tandem turbines.

2. Turbine controller modeling, the speed / governing controller and the governing valve controls.

3. Fuel dynamics and boiler storage modeling.

4. Main steam pressure drop modeling.

5. Boiler controller.

6. Model parameter estimation and validation.

3.4 Modeling Methodology

There is an acquired skill in the optimization and tuning of boiler controls systems, which fundamentally stems from a thorough understanding of the process and its interacting systems, but the knowledge and experience of the optimization specialist have a strong bearing on the success of the optimization process. Figure 3.1 illustrates the optimization process for model parameter estimation which play an important role in identifying the open loop dynamic behavior of the process.

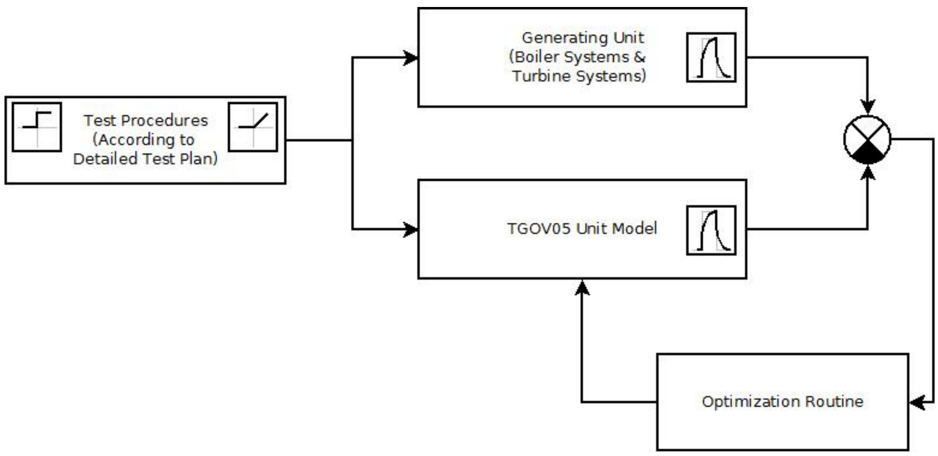

Figure 3.1: Typical Optimization Flow for Model Parameter Estimation of a typical Generating Unit

In order to separate the process interactions, a number of dedicated open loop tests are necessary to identify the inherent mechanical characteristics of the plant, its characteristic time constants and the open loop process gains (see Table 2.2). As shown in Figure 3.1, the parameter estimation process is an iterative process in which the model response to a set of input test procedures are compared with actual plant response for the same set of input test procedures. Thus the estimation of parameters can be classified as a minimization problem.

By placing process controllers in open loop or manual control, the process dynamical responses can be obtained through testing in the form of either ramp or step tests. Each of these tests extracts certain dynamical behavior of the process which enables the development of Laplace transfer function models based upon first principles.

3.4.1 Turbine Model Parameter Estimation

In Chapter 2, section 2.4.5 a description of the turbine model is given. It focuses primarily on understanding the operation of the turbine by means of heat balance data and analysis. This section models the turbine purely based on experimental data via turbine model parameter estimation, using the Non Linear Least Squares (NLLS) technique as part of the Matlab / Simulink optimization toolbox.

Figure 3.2 illustrates the parameter estimation methodology for modeling of the turbine. As can be seen, inputs to the turbine model is the governor valve position (%) and the turbine inlet pressure (MPa). These two quantities are multiplied to form the steam flow entering the turbine. As the steam flows, it passes through the steam chest also known as the valve chest (with time constant T_4), the steam then passes through the HP turbine, assuming adiabatic steam expansion, where $Work$ is performed and this is illustrated by gain K_1, which is known as the HP turbine power factor.

Similarly, for reheater based boilers, where the reheater is a vessel under pressure (as described by section 2.4.5), steam flows through with time constant T_5, where it emerges and passes through the IP turbine and performs $Work$, via power factor K_3. Therefore, likewise for gains K_i where $i = 1$ to 8 a description of each parameter can be given. The crossover pipework is also a vessel under pressure and contributes to steam volumes.

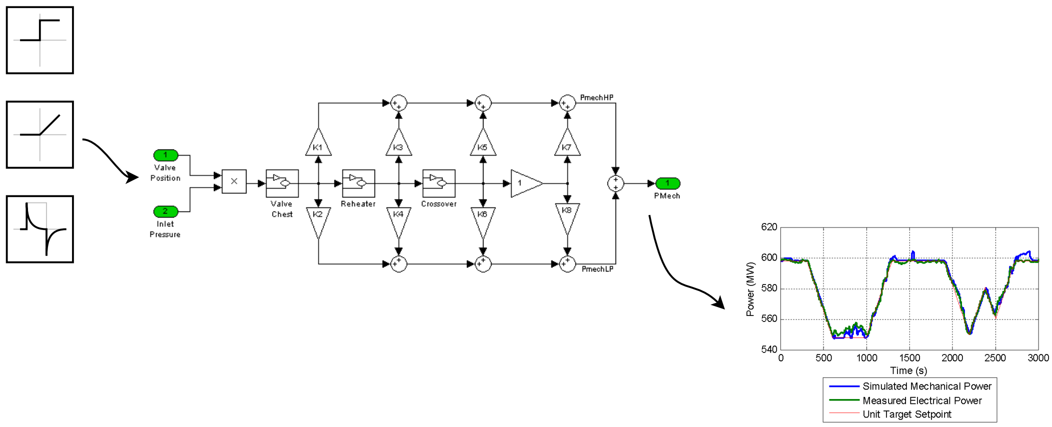

Figure 3.2: Methodology for Turbine Model Parameter Estimation, illustrating the concept of step and ramp test procedures

Figure 3.3 illustrates the turbine response to a step change in governor valve position. As the governor valve is throttled, steam flow increases and performs $Work$ on both the HP and LP turbines to produce mechanical power. This increase in steam flow decreases the turbine inlet pressure accordingly, however, the boiler controller returns the boiler pressure back to it nominal set-point. With the increase in steam flow, the mechanical power increases and allows for the estimation of the turbine parameters via experimental data as shown in Figure 3.3 which show a good correlation between experimental data and simulated responses.

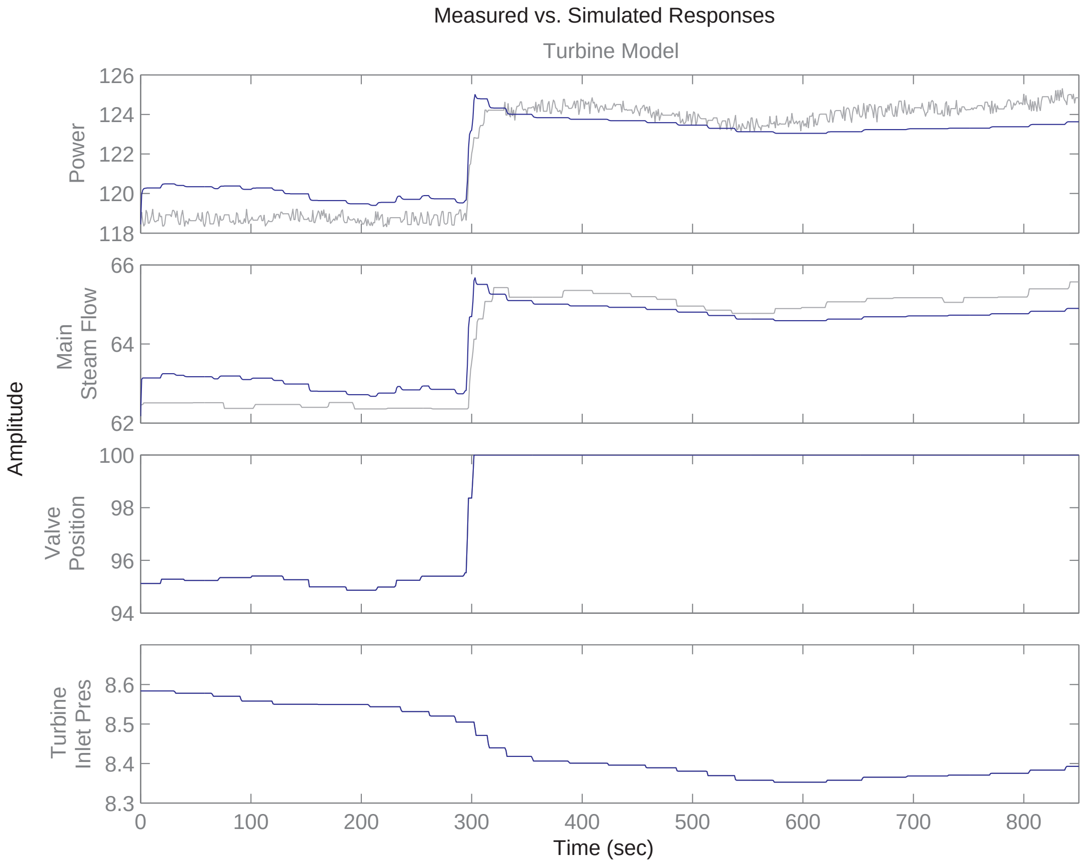

Figure 3.3: Turbine Power Response for 5% Governor Valve Step Test with Boiler on Automatic Control

Shown in Figure 3.4 is the trajectory of the turbine parameters as the estimation of the turbine model converges towards a solution. It is interesting to contrast the performance of the turbine model parameter estimation method via heat balance data and that via experimental testing. Section 2.4.5.1 illustrated the turbine model parameter estimation method via heat balance data and showed for the unit under test, that $K_1 = 0.71$ (equation 2.12) and $K_3 = 0.29$ (equation 2.13). This compares favorably with the data shown in Table 3.1.

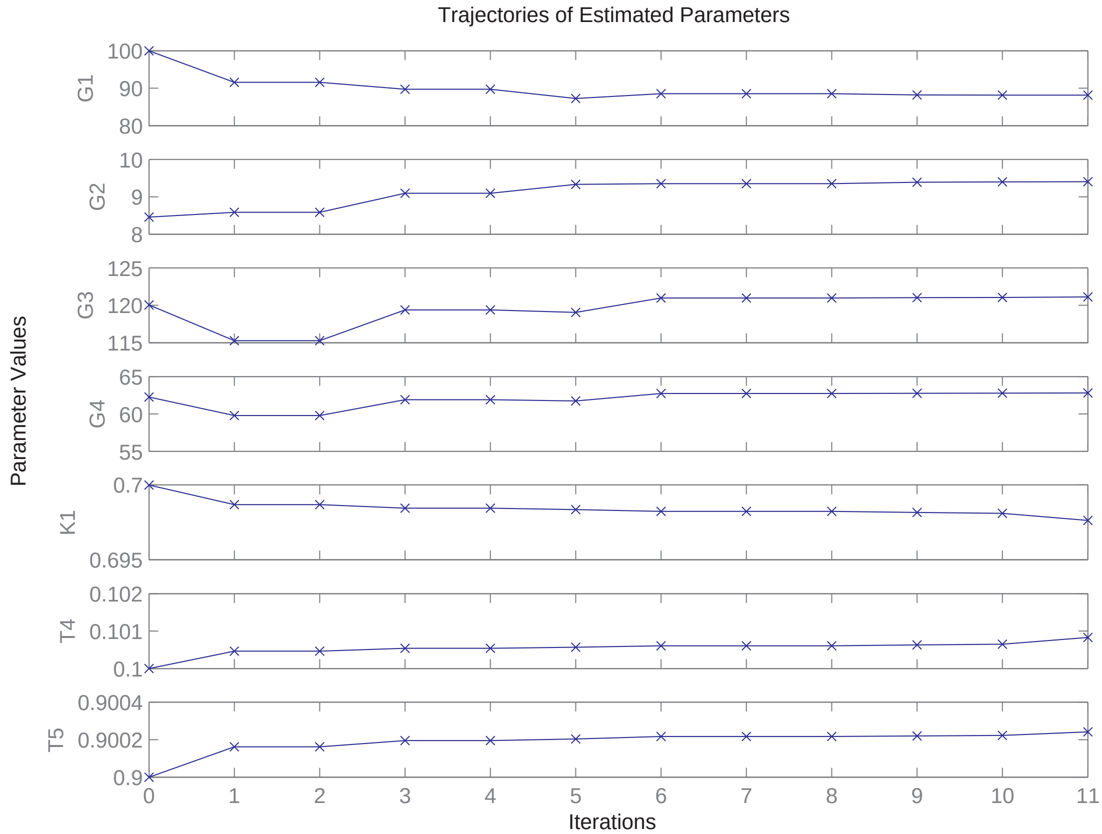

Figure 3.4: Trajectory of Turbine Parameters towards convergence of solution

However, observation of parameters T_4 and T_5 differs from the theoretically calculated values, T_{SC} (or T_4) and T_{CO} (or T_5) as shown in Table 2.10, which are attributed mainly to inaccuracies in mathematical assumptions made in performing the calculation, and also in model uncertainties. Nonetheless, good correlation between observable and simulated results in both cases are realized.

Table 3.1: Optimal Turbine Parameters, showing the normalization parameters

Trial	Normalization Parameters				Turbine Model Parameters			
	Valve Position (%)	Pressure (MPa)	Power (MW)	Steam Flow (Kg/s)	K1	K3	T4	T5
Trial # 1	96.726	8.465	119.635	62.042	0.700	0.300	0.300	1.000
Trial # 2	97.329	8.405	119.523	61.984	0.700	0.300	0.300	1.000
Trial # 3	114.831	7.759	130.181	67.511	0.696	0.304	0.201	0.861
Trial # 4	107.570	8.403	132.074	68.492	0.698	0.302	0.200	0.860
Trial # 5	104.215	8.438	128.480	66.629	0.699	0.301	0.200	0.860
Trial # 6	102.445	8.592	128.602	66.692	0.699	0.301	0.200	0.860
Trial # 7	94.237	8.615	118.624	61.518	0.698	0.302	0.101	0.900
Trial # 8	93.263	9.371	127.687	66.218	0.698	0.302	0.101	0.900
Trial # 9	87.668	8.420	107.846	55.928	0.698	0.302	0.101	0.900
Trial # 10	88.150	9.404	121.123	62.813	0.698	0.302	0.101	0.900
Minimum	87.668	7.759	107.846	55.928	0.696	0.304	0.101	0.860
Average	98.643	8.587	123.377	63.983	0.699	0.301	0.180	0.904
Maximum	114.831	9.404	132.074	68.492	0.700	0.300	0.300	1.000
Std Deviation	8.072	0.477	7.707	3.997	0.001	0.999	0.072	0.048

3.4.2 Main Steam Pressure Drop Modeling

There exists a pressure drop from the boiler outlet pressure through to the turbine inlet pressure, which is a natural pressure decay because of losses within the main steam pipework. This has a bearing on the boiler control system, especially on how the boiler pressure is controlled and needs to be accommodated within the boiler model for effective pressure control. This function is incorporated within the model by means of the pressure drop model (Flynn and O'Malley (1999); Hain et al. (2000)), and is represented by equation 3.1, where $P_T(t)$ represents the turbine inlet throttle pressure, $P_D(t)$ is the drum pressure, $\dot{m}(t)$ is the the main steam flow, K_9 is related to pressure variation, or sliding pressure and C_1 represents the pressure loss, the variable t is time.

$$P_T(t) = P_D(t) - \dot{m}(t)^2 * (K_9 * P_D(t) - C_1) \tag{3.1}$$

Since steam is the medium by which heat is transferred from the boiler to the turbine, $Work$ is performed on the turbine blades as the enthalpy of the steam changes through the turbine. The quality of the steam is dependent upon pressure, since as pressure changes, the steam temperature profile also changes. Therefore steam temperature can also be changed by controlling the pressure. This from a steam generating perspective is well controlled, however, as the length of main steam pipework increases, an adverse effect on steam temperature and pressure occurs. These effects and the drop in pressure needs to adequately controlled, by the pressure and temperature controllers of the boiler.

Figure 3.5 illustrates a typical load ramping profile for a generating unit of 200MW. As can be seen, the boiler outlet pressure $P_D(t)$ and the turbine inlet pressure $P_T(t)$ are related according to a constant error, which represents the main steam pressure drop. This is typically the profile for fixed pressure units where the boiler pressure does not change according to the load demand, hence the parameter K_9 is set to zero. However, K_9 would be applicable to variable sliding pressure units.

Also shown in Figure 3.5(c) is the correlation between the simulated pressure drop and that of the actual pressure drop, where it is clearly seen that there exists a good match between experimental and simulated data. Table 3.2 tabulates the parameter estimation of K_9 and C_1 for a number of different load ramping scenarios and shows good correlation between parameters, with an average value of $C_1 = 0.035$ for a typical 200MW drum unit.

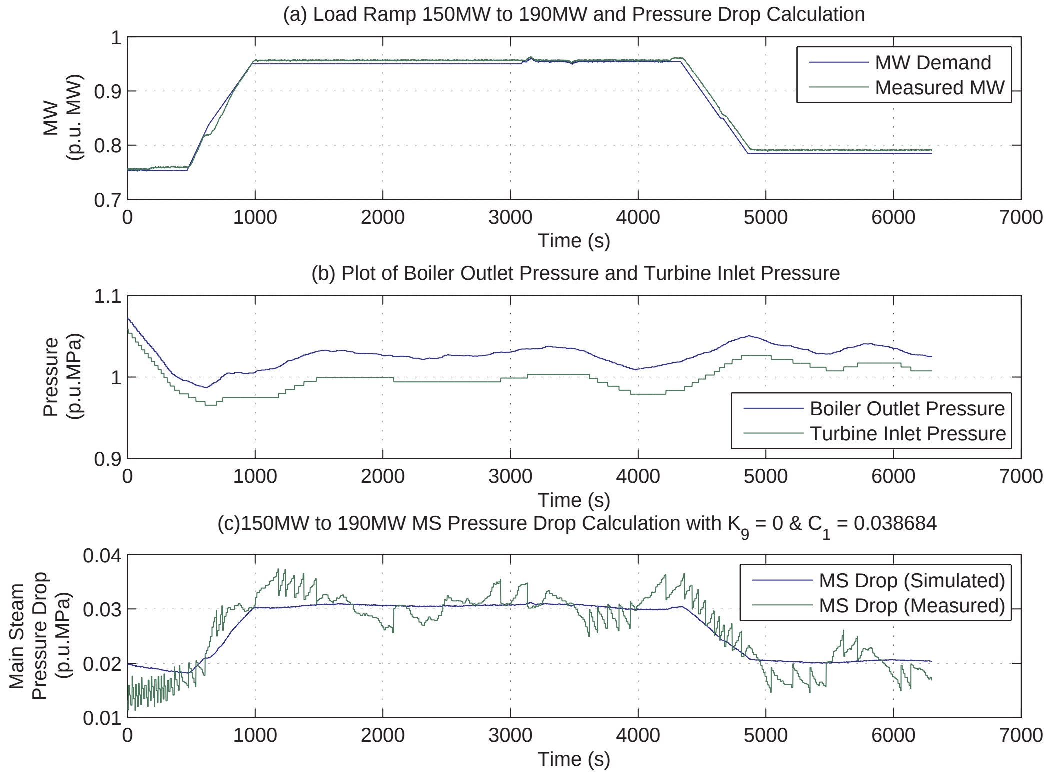

Figure 3.5: Main Steam Pressure Drop Modeling, (a) Typical load ramp, (b) Typical boiler outlet pressure $P_D(t)$ and turbine inlet pressure $P_T(t)$ and (c) Parameter Estimation of Pressure Drop Model.

Table 3.2: Table showing calculation of K_9 and C_1 parameters for the main steam pressure drop

#	Test	K_9	C_1
1	Ramp 150MW to 190MW	0	0.039
2	Ramp 180MW to 150MW	0	0.031
3	Ramp 190MW to 200MW	0	0.031
4	Ramp 200MW to 160MW to 180MW	0	0.037
5	Ramp 160MW to 180MW	0	0.037
6	Min	0	0.031
7	Mean	0	0.035
8	Max	0	0.039
9	Std Deviation	0	0.003

3.4.3 The Influence of Boiler Controls on AGC Systems

Steam generating boilers are complex interacting mechanical systems requiring advanced control strategies for optimal control and for safe operation during a wide range of normal operating conditions. However, poorly tuned boiler control systems can have a significant effect on the performance of AGC control systems, especially during rapid load variations and during low and high frequency incidents.

There are typically two types of boilers used within the power industry, namely Drum type and Bension type boilers. Drum type boilers typically are sub critical boilers, whereas Bension boilers can operate on a wider operating pressure such as critical to super critical pressures and temperatures. The differences in mechanical construction of these boilers contributes significantly to the mode of operation and performance of the unit.

Within AGC studies, the performance of the unit is dependent upon different modes of boiler operation. In Drum type boilers, which typically have large energy storage time constants, inherently leads to large energy reserve margins and thus leads to good sustained AGC performance following a frequency incident.

Bension boilers in contrast typically does not have large energy storage capacity as does equivalent Drum type boilers, thus it cannot maintain a good sustained AGC response. This is important during frequency incidents where a large boiler energy storage capacity and large system inertia is needed to minimize frequency excursions.

However, these limitations can be overcome by appropriate advanced coordinated control of the boiler and turbine to yield an effective generating unit performance response to AGC loading demands. By operating within the super critical pressure ranges, improves the performance of the system substantially and is applied to modern super critical power plants.

It is for this reason that modern boiler implementation is in favor of Bension type boilers and coordinated control system strategies to yield superior AGC response characteristics. In AGC, the speed of response resulting from a frequency incident it is vital to the control the power on the electrical network to maintain a stable supply. If boiler control of especially turbine throttle pressure is slow to recover to within nominal parameters, there is typically an equivalent slow response in electrical energy in response to frequency incidents.

Figure 3.6 illustrates the boiler pressure response and power response to a governor valve step demand with boiler control on manual. It illustrates firstly the turbine response characteristic but is also highlights the boiler response following a load demand, showing a decay in pressure for valve position increases.

The rate at which this decay drops and the final steady state value is indicative of boiler storage (C_b). The more boiler storage there is, the slower the pressure decay and better the AGC performance against network frequency variation. This also means that there is reserve energy available in the system.It is for this reason that boiler storage (C_b) plays an important role in the initial frequency response.

With a large boiler storage value, the generating unit is much more capable of resisting and responding to frequency incidents in a more effective manner. The immediate opening of the governing valves, especially due to low frequency incidents, would drain the energy storage and cause a drop in boiler pressure.

This drop in pressure would be controlled by the boiler pressure controller to increase the rate of firing to the boiler by increasing fuel and air respectively.

However, the boiler control response is slow and its takes time for the pressure to build and to normalize to set-point pressure. Although this is largely a process limitation and a relating safety requirement, the delay in pressure increase has a negative effect on the frequency response.

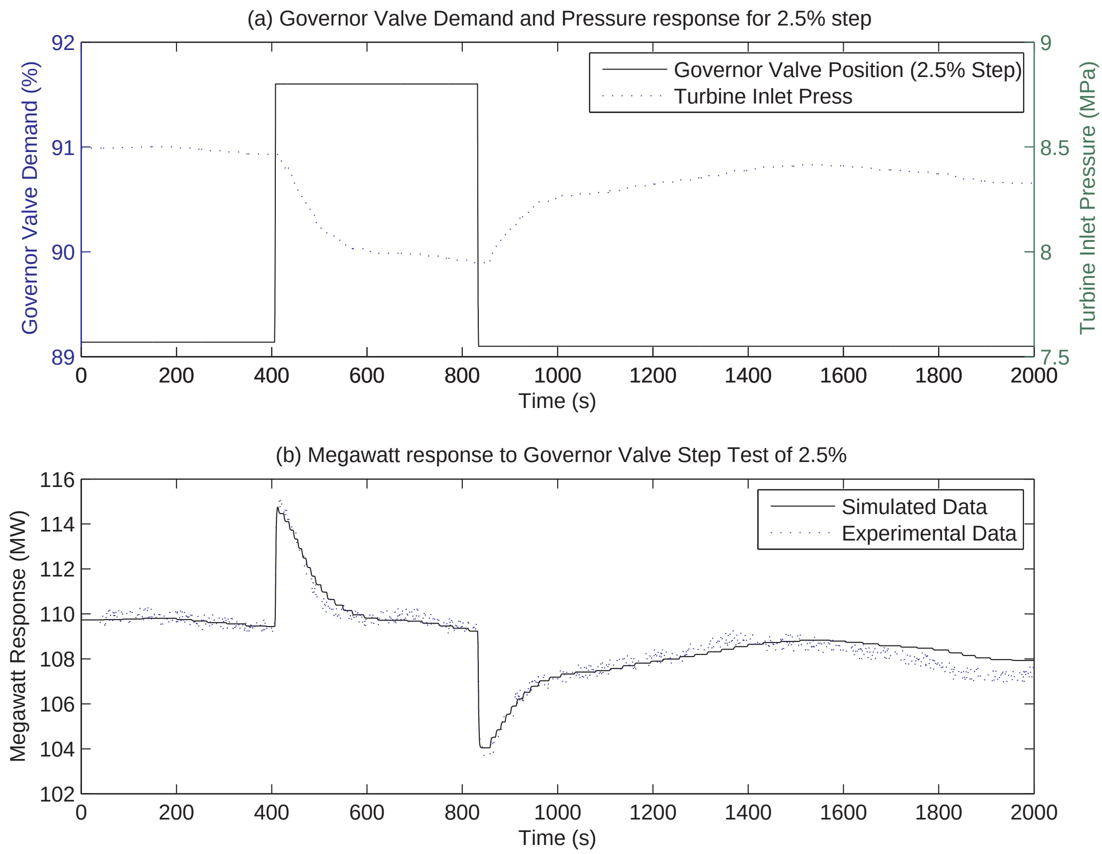

Figure 3.6: Governor valve step response of 2.5% showing megawatt response with Boiler Control on manual, (a) 2.5% Step in Valve position with trend of turbine inlet pressure, (b) Experimental megawatt response and simulated megawatt response

Figure 3.7 shows the boiler controller response for a setpoint change. It illustrates the effectiveness of the boiler controller for regulatory behavior. Predominately, the control strategy is that of the conventional Proportional, Integral and Derivative (PID) type control law, with a strong derivative component. This test models the boiler controller for application in frequency response studies. As can be seen, simulated data compares well with experimental data.

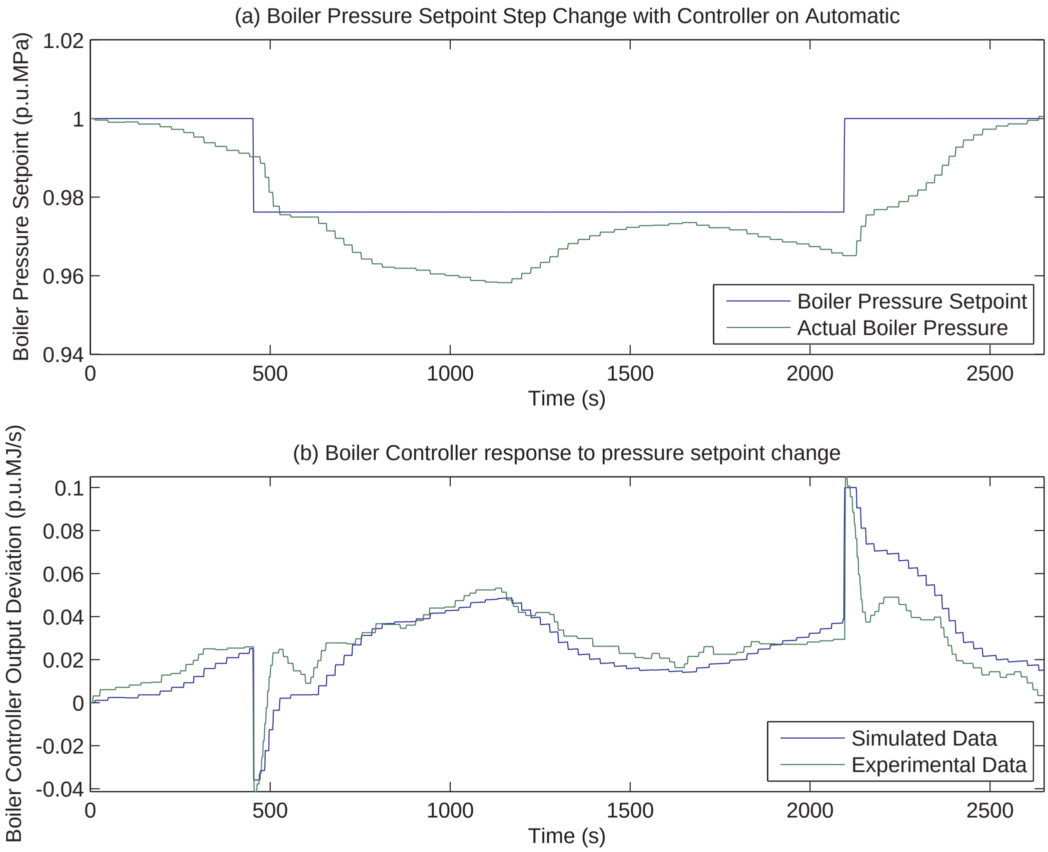

Figure 3.7: Boiler Controller Response to Setpoint Step Change, (a) Boiler pressure setpoint step change with the boiler controller on automatic, (b) Boiler controller response to pressure setpoint change.

3.5 Modeling of Fuel Dynamics and Boiler Storage

Boiler dynamics form an important part of the operation and control of boiler control systems. From a frequency response perspective, boiler dynamics have a significant impact on the performance of generating units, in its loading ability and on its response to electrical load disturbances.

Figure 3.8 shows a Matlab/Simulink model of the fuel dynamics, it illustrates the fuel dynamics model as used within the TGOV05. The model consists of inputs and outputs, approximately scaled (or normalized), and tunable parameters. In the forward path, fuel dynamics is represented by second order transfer functions in T_f and T_w with delay time (T_D), where T_f is representative of the fuel dynamics and T_w is representative of the water dynamics.

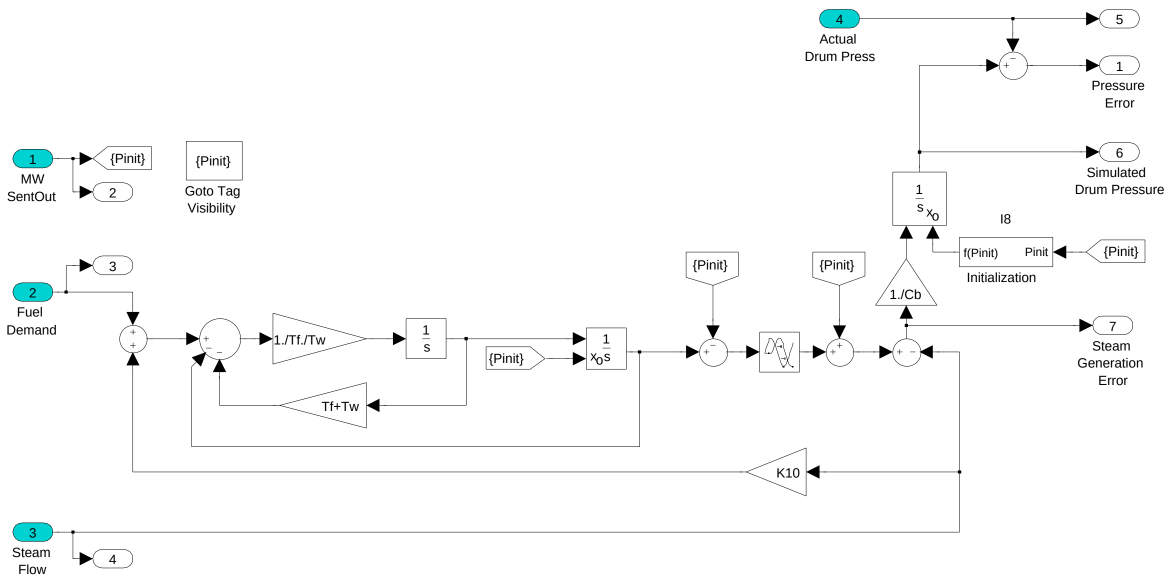

Figure 3.8: Fuel Dynamics Model

Table 3.3 tabulates the optimization results, showing ten (10) individual trials of optimizations. The Matlab optimization toolbox, function fminimax was used. For each trial, different initialization values have been used to ensure that each resultant solution is unique. It is also expected that at convergence, the average of all solutions should lie within close proximity of each other.

Table 3.3: Optimization of the Fuel Dynamics Model, using Matlab / Simulink (using the fminimax optimization routine)

Trial	Recommended Scaling Gains (Normalization)				Optimal Parameters				
	MegaWatt (MW)	Fuel Setpoint (MJ/s)	Steam Flow (Kg/s)	Drum Pressure (MPa)	Tf	Tw	TD	Cb	Error
1	121.47	394.36	60.65	9.94	1.48	1.48	22.08	101.09	0.0023
2	129.25	427.18	65.67	10.56	4.10	4.01	26.12	97.82	0.0031
3	139.40	453.88	69.80	11.39	1.38	1.35	24.51	78.47	0.0055
4	143.04	467.65	71.91	11.69	1.63	1.61	24.43	93.59	0.0023
5	130.93	412.15	63.34	10.81	2.12	2.06	27.53	274.13	0.0078
6	123.11	399.20	61.33	10.14	4.59	4.59	28.05	270.31	0.0091
7	131.36	409.08	62.88	10.85	3.67	3.67	23.59	270.07	0.0077
8	117.07	405.91	62.34	9.57	4.10	4.10	17.85	270.28	0.0096
9	119.76	414.67	63.40	9.78	19.91	19.91	39.81	272.14	0.0168
10	127.59	437.63	66.54	10.44	47.52	47.52	60.11	270.86	0.0224

Parameter observations

1. T_f and T_w are closely related, especially when seen from a block diagram perspective. T_f is representative of the fuel time constant and T_w is representative of the water time constant and their respective correlation to steam generation. Since the model structure does not allow for their separation, identifying each parameter uniquely is not presently possible. However, weve assumed that the response to fuel and water are relative fast, namely of the order of 1 5 seconds. In the optimization routine, $T_f = 1.48$ (1.5) and $T_w = 1.48$ (1.5) seconds respectively.

2. $T_D$is known as dead time and represents the delay in response due to a fuel demand. Manual review of the data indicates that T_D is of the order of 23 seconds, considering the fastest response time. This is also confirmed via optimization where the best average value ranges from about 22s to 29s. This is graphically indicated in Figure 3.9. It is clearly seen from the transient response that T_D ranges from [23s 29s 76s] for each of the respective fuel demand step tests (up step, down step and then the up step

again).

3. The parameter C_b represents the boiler storage time constant and is synonymous with inertia of the systems, in a pressure sense and is the stored energy contained within the boiler. A large value of C_b is indicative of large energy reserves in the boiler and depends upon the volume of steam within the boiler tubes. The larger the volume under pressure, the larger the storage time constant. In its relation to T_f and T_w, C_b is the dominant time constant, and thus it is expected that C_b will contribute very strongly to the transient response characteristic.

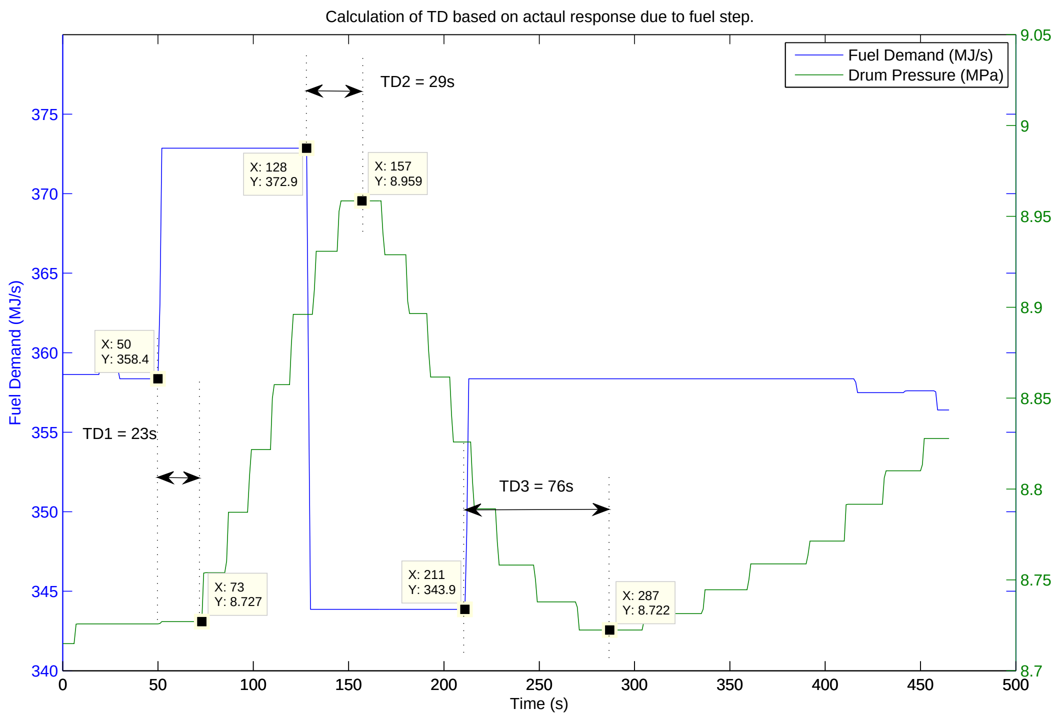

Figure 3.9: Calculation of fuel delay T_D by manual observation of transient response data

A comparison of simulated data and experimental data is shown in Figure 3.10. It is clearly seen that the fuel dynamics and the boiler storage dynamics is an integral process. This type of process is an interesting process, since conventional PI has difficulty in controlling such a process. This is in part due to the double integrator within the open transfer function making the system unstable in closed loop configuration. Therefore, most boiler controller have a strong derivative action, with either no, or very small integral action to stabilize the closed loop process. Thus most boiler control system are typically of PD type. This is confirmed via controller structure and the closed loop process response as shown in Figure 3.10.

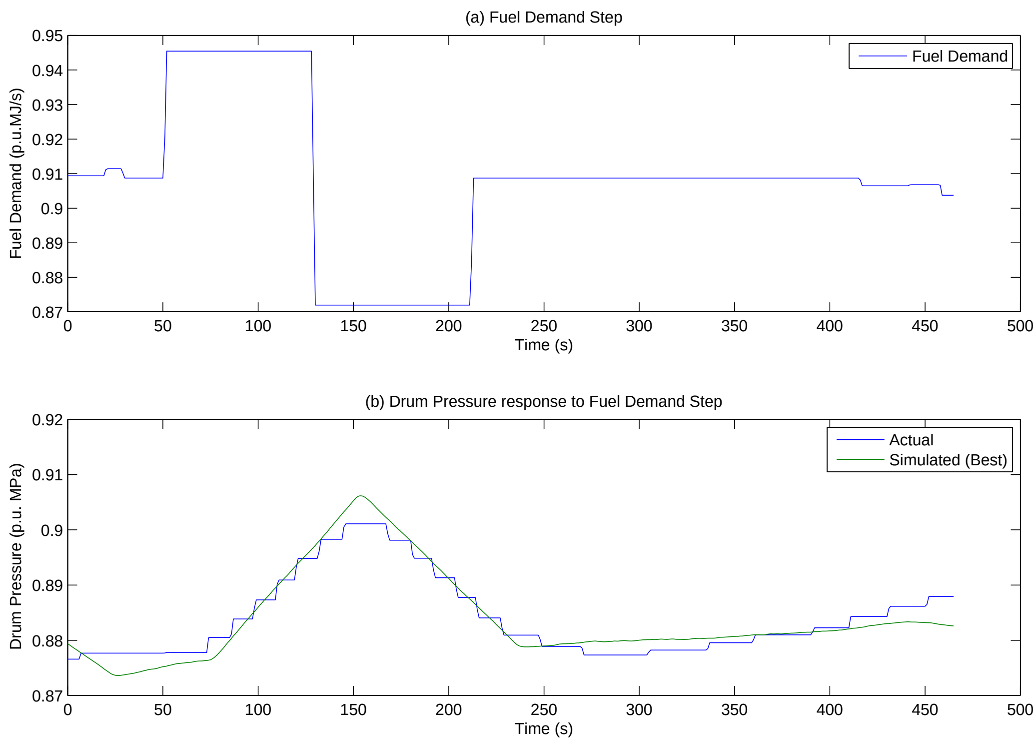

Figure 3.10: Boiler pressure response due to fuel demand step change.

3.6 Summary of Chapter 3

Chapter 3 present an overview of power plant modeling and analysis, focusing of understanding the major dynamics of generating units in relation to boiler control and turbine control. It highlighted the importance of diligent preparation for power plant testing and listed the main phases to unit model testing.

Chapter 4

Genetic Algorithms and Its Applications

Genetic Algorithms are heuristic search techniques based on the principles of natural selection and on natures survival of the fittest rule. In the late 1800's, Darwin observed the micro evolutionary principles of finches and their ability to adapt to their peculiar environments, in order to perpetuate life and to have the best chance of survival (De Jong, 1988; Bodenhofer, 2004), amidst constrained resources.

Typically within nature, it is the battle for obtaining resources, competing for a mate, or the hunt for prey which singles out the weakest member of the population and ensures that the fittest individual survives and who then is able to procreate for the next generation. This is known as reproduction, and plays a significant role within the population not only by adding population diversity but also strengthening the genetic bond. The premise here is that by mating of the fittest individuals, it would lead to a fit population.

With this in mind, Genetic Algorithms emulate the genetic process which forms part of the evolutionary process of finding solutions to problems heuristically rather than relying on strict mathematical modeling techniques. This in many instances is advantageous, since the genetic process embraces two main properties as found within nature, namely Exploration and Exploitation. These concepts will be discussed further within this thesis (see section 7.4.3.4).

The past few decades have seen a gradual deviation from strict mathematical modeling techniques in favor of more computer based soft computing paradigms and naturally inspired optimization techniques, such as;

1. Artificial Neural Networks (ANN) (Nguyen and Widrow (1990); Curley (2002); Bishop (2008); Marwala (2012)).

2. Fuzzy Logic Control (FLC) (Jantzen (1999); Grantner and Fodor (2002); Cordon et al. (2004)).

3. Simulated Annealing (SA) (Castro and Camargo (2004); Xianbo and Jingqi (2007); Marwala (2009)).

4. Genetic Algorithms (GA) and other heuristically based optimization routines (De Jong (1988); Goldberg (1989); Bodenhofer (2004); Eksin (2008)).

5. Hybridized approaches, such as Neural Fuzzy (NF) Liu (2002) for modeling and control and Genetic Fuzzy (GF) and Cordón et al. (1996); Wang et al. (1998); Cordon et al. (2004); Mucientes et al. (2007); Sharkawy and Others (2010) controller design approaches).

The former soft computing techniques (items 1 to 4) models natural behavior to problem solving while the latter (item 5) combines the advantages of the aforementioned techniques to yield prospectively better optimization results.

4.1 An Overview of Genetic Algorithms

Genetic Algorithms are based on Darwin's theory of natural selection and survival of the fittest. Primarily a heuristic optimization technique, it has found application within a wide area of industry, namely;

1. Flight control (Chang et al. (1996)).
2. Process control (Cordón et al. (1996)).
3. Learning (De Jong (1988); Brownlee (2000); del Jesus et al. (2004); Bacardit (2008); Bennett et al. (2008)).
4. Self tuning systems (Dalci et al. (2004); Adriansyah and Amin (2005); Bouserhane et al. (2008); Casillas et al. (2005); Griffin (2003)).
5. Power Systems (Bodenhofer (2004); Ghoshal (2005); Hermawan (2006); Eksin (2008)).
6. Finite element analysis (Marwala (2010)).
7. Genetic Fuzzy Systems (Herrera (2005); Ishibuchi (2007)).

This is in part due to the fact that genetic algorithms search for the most optimal solution (fittest individual) from a global perspective but more importantly, it provides a mechanism by which solutions can be found to complex optimization problems robustly, fairly quickly and reliably. It is for this reason that GA's have found widespread industrial application.

Shown in Figure 4.1 is a flow chart of a typical Genetic Algorithm. As can be seen, the Genetic Algorithm is an iterative process whereby the fittest individuals are selected from the population, sacrificing the weaker individuals. This process attempts to emulate the natural environment where only the strongest individuals survive and is propagated through to the next population via reproduction.

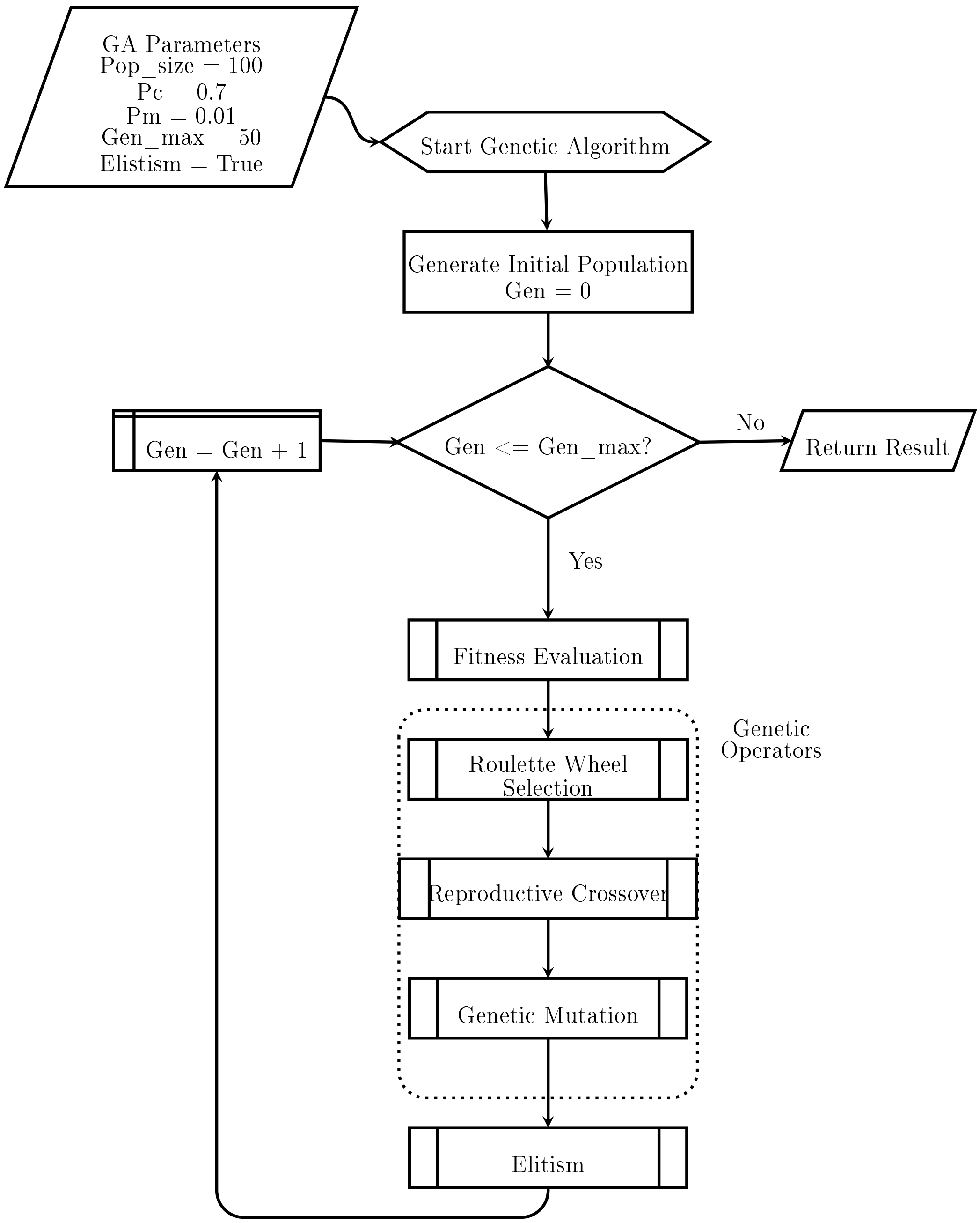

Figure 4.1: Flow chart of the Simple Genetic Algorithm (SGA), showing Genetic Operators for reproduction and the Elitist strategy for the survival of the fittest individuals.

The genetic algorithm starts by initializing a population of candidate solutions to the optimization problem, these are typically initialized randomly. It then follows by evaluating the fitness of the population, which is equivalent to the objective function within standard optimization routines. This is then followed by individual selection, reproduction by means of genetic crossover and mutation.

Within the natural reproduction process, genetic information is transferred from the parent individuals to the offspring via a process known as crossover. Under certain conditions, the offspring undergoes a genetic mutation which influences the phenotype characteristic of the individual. It is this adaptation behavior which ensures the versatility of the Genetic Algorithm. Each of these processes are described below (Louis and Rawlins (1992); Miller and Goldberg (1995); Wang and Spronck (2003); Valdes (2003); Teng et al. (2003); Skaar and Nilssen (2004); Tavakoli et al. (2007); Marwala and Lagazio (2011)).

4.1.1 Individual Selection

The reproduction process as found within nature occurs between two individuals composed of the same genetic make-up (i.e. the same species). Thus the process of reproduction leads to a strong competitive drive to finding a suitable mate, and often nature competes with itself and only the strongest individual would survive. This genetic process of finding a mate and reproducing is initiated by means of individual selection.

Within the context of Genetic Algorithms, individual selection is performed by means the Roulette Wheel method, which most often is the commonly applied method of selection. There are other means of selection as well, such as Stochastic Sampling, Stochastic Universal Sampling and Remainder Stochastic Sampling with Replacement. However, the Roulette wheel method is the most commonly method applied due to its simplicity and has found widespread application (Goldberg (1989)).

Figure 4.2 illustrates the Roulette wheel selection method. It is a probabilistic approach, where each individual is selected based on its fitness strength. The fitter the individual the greater the chance of being selected.

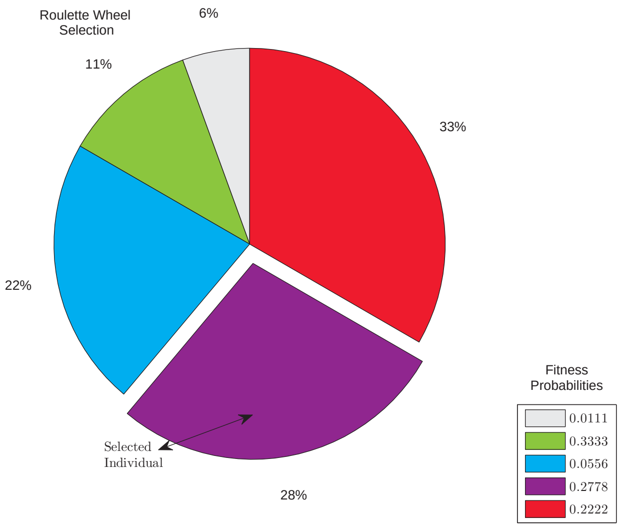

Figure 4.2: Illustration of Roulette Wheel Selection

4.1.2 Chromosome Reproduction and Crossover

In nature, during reproduction the genetic material of the parents are transferred to the offspring, with inherited characteristics. Each genotype of the chromosome relates to an associated characteristic in the phenotype.

Therefore, the genetic algorithm emulates this process by crossover. During crossover, a random position within the chromosome is selected. The bits of the parents between the crossover position are exchanged to form two new offspring.

Figure 4.3 illustrates the crossover principle. Two fit parents are selected by means of Roulette wheel selection, and their respective genetic material are exchanged through reproduction. Although shown in Figure 4.3, a bit wise crossover is performed, assuming that the individual chromosome is represented by a bit string, there are other methods of crossover available and particularly depends upon the encoding mechanism of the search variables.

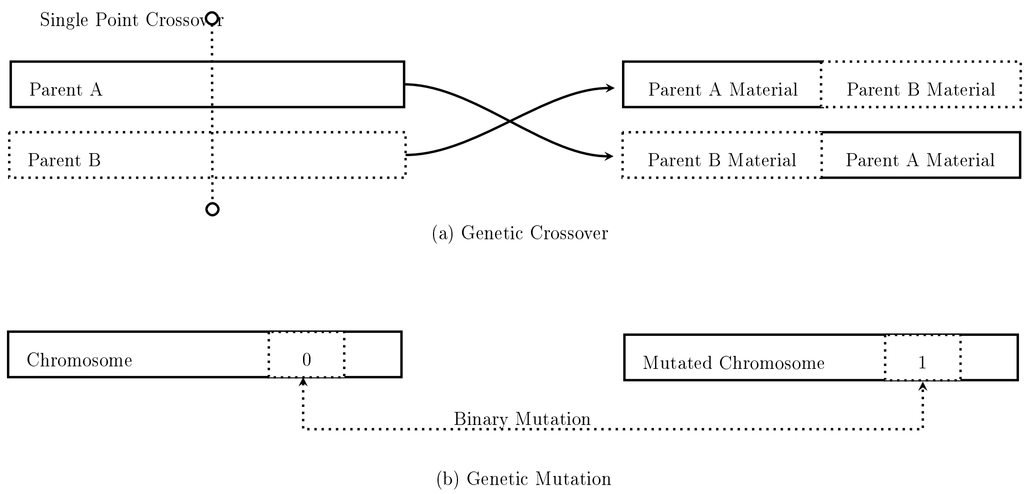

Figure 4.3: The Functioning Of Genetic Operators, (a) Genetic Crossover and (b) Genetic Mutation

The pairs of individuals selected for crossover are selected with a probability P_c. A random number R_c is generated between 0 and 1, where the parent individual undergo crossover only if the random number $R_c \leq P_c$. Natural processes for crossover includes multiple points for crossover, which can also be emulated by the algorithm.

Figure 4.4 illustrates the influence of P_C variation on the crossover process. Given enough generation, each P_C converges to a common solution over a number of genetic generations. Since the performance of the system depends upon random selection, the convergence of the population occurs at different generation points and is stochastic in nature. Typically a value of 0.7 is used for P_C.

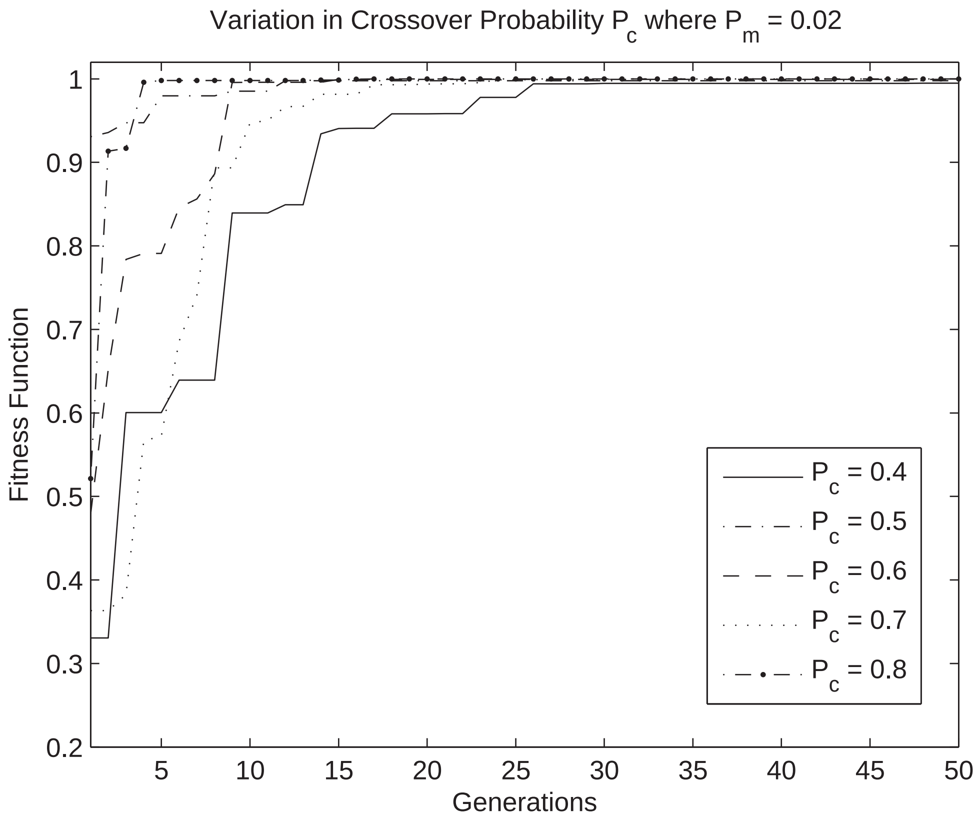

Figure 4.4: Influence of Crossover Probability (P_c) during Genetic Operations

In addition, Figure 4.5 shows the influence of three types of crossover mechanisms, namely, Single Point, Two Point and Scattered crossover on the performance of the optimal solutions. The transient response curves illustrates the performance of the system on the Tie - Line power exchange signals, where it can be clearly seen that the type of crossover mechanism employed during a genetic run results in very similar results, given enough generations to converge to a final solution.

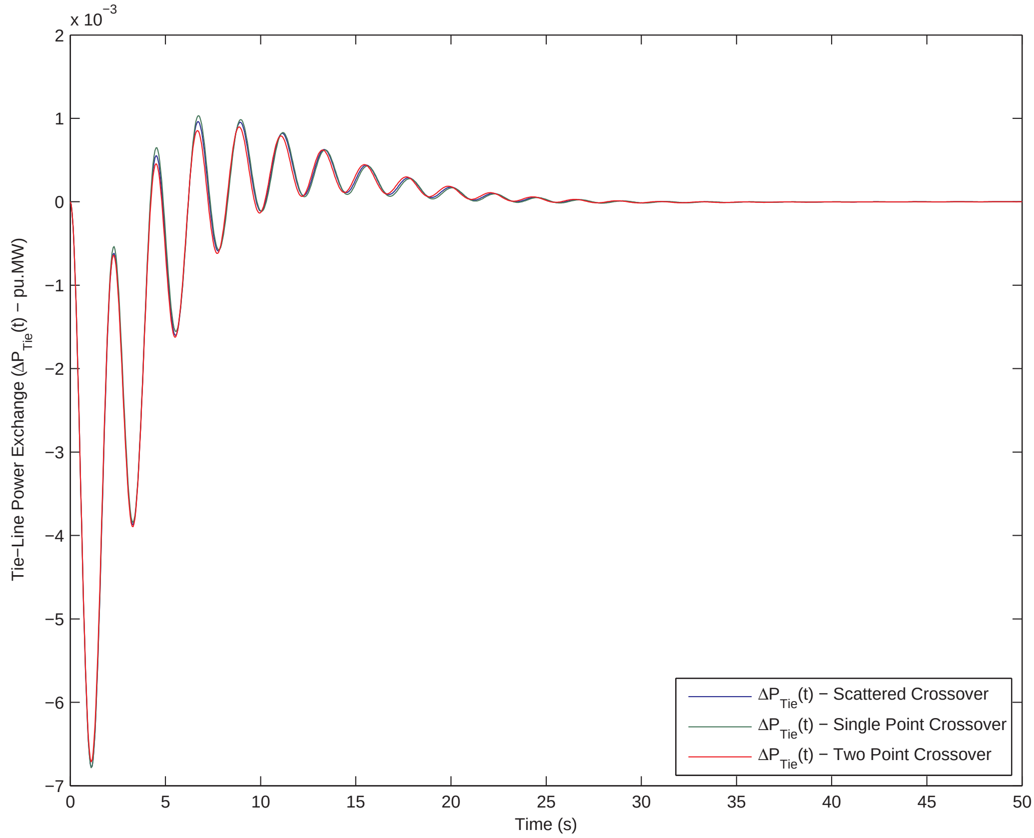

Figure 4.5: Transient Comparison of Different Types of Crossover Techniques, illustrating performance on Tie - Line Power

4.1.3 Chromosome Mutation and Adaptation

The natural world has processes in place for the adaptation of systems to meet the demands of present survival situations over time. As more constraints are experienced by the organism, a method for ensuring survival is to adapt to changes quickly and robustly. Within the genotype of the individuals genetic breakdown, variations within the genetic code are activated, with characteristic attributes for ensuring organism survival. This process is classified as Mutation and forms the active means of introducing new genetic material within the population.

In Figure 4.6 the operation of mutation is illustrated, by changing the mutation probability P_m. It is noted that variations in P_M influences the rate of convergence and also prevents premature convergence of the population.

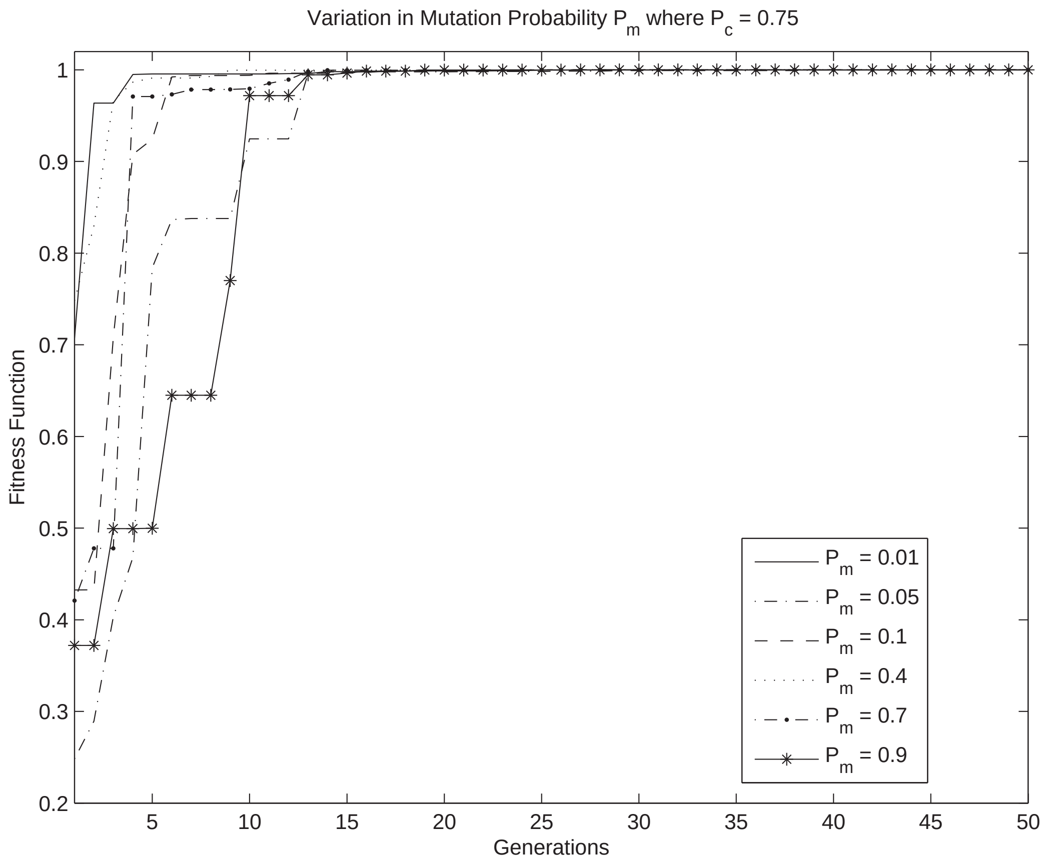

Figure 4.6: Influence of Mutation Probability (P_m) during Genetic Operations

It should be noted as well, that not all mutation have a positive impact on the organism, typically, mutation is destructive in its effects on the phenotype and occurs seldom within nature. However, since the genetic code contained within the chromosome allows for a wide spectrum of attributes, Mutation is vital to the survival of the individual.

Therefore, with the genetic algorithms ability to mutate its individuals, that it is possible to find solutions heuristically. The mutation function is performed by means of the appropriate selection of the mutation probability P_m. In this process, a random bit within the chromosome length is chosen and bit wise inverted.

Typically, this probability value is chosen very small, typically of the order 0.001 or thereabouts.

It is important to note that Mutation increases the population diversity of each generation as time progresses, and its effectiveness to solving the problem at hand depends upon the following factors.

1. The Problem Type - Problem complexity plays an important role in the selection and performance of the mutation operator. The more complex the problem, the more robust the mutation method needs to be, this guarantees that adequate levels of algorithm convergence takes place.

2. Size of the Population - There is a distinct relation between Population size and the convergence properties of Genetic Algorithms. The larger the Population, individual diversity increases and hence convergence properties and time to convergence improves. However, in order to achieve satisfactory performance, the rate at which mutation takes place and the associated Mutation mechanism, is more conducive to larger Population sizes.

3. The Method of Mutation - Without Mutation, the Population would be limited to individuals contained within the initial population. Therefore, Mutation introduces more possibilities for new genetic material to enter the Population Genotype and increases its diversity. Therefore, the method of how this diversity is created, depends upon the selected method of Mutation. One of the more widely used methods is Binary Mutation (Figure 4.3b), however, advantages can be obtained by using alternative methods of problem encoding (such as Real Valued Encoding). This affords the opportunity to define more mutation possibilities, such as as Uniform Mutation (Goldberg (1989)) and Gaussian Mutation (Bodenhofer (2004); Skaar and Nilssen (2004)).

4.1.4 Elitism

Within each generation of the population, superior genetic material and the fittest individual may be lost due the functions of selections (where fit individuals are not chosen) crossover and mutation may lead to the deterioration of fittest individuals. Therefore, to preserve the good character traits of the population, good genetic material needs to be preserved within the algorithm. This function is known as Elitism.

4.2 Summary of Chapter 4

This chapter briefly laid the foundation for heuristic search by Genetic Algorithm's. Genetic algorithms are global search methods and forms a good means of finding near optimal solutions. It is an established fact as noted within this chapter that the performance of the Genetic Algorithm depends upon many factors, including the Population size, mechanisms for Crossover and Mutation and more specifically upon the encoding of the search space. In this research, focus is specifically given to single point Crossover and Binary Mutation, based upon its ease of implementation and that satisfactory results are obtained based on these methods.

Chapter 5

Fuzzy Logic Control

First introduced by Lotfi A. Zadeh in 1965 (Zadeh (1965)), Fuzzy Logic is based on human cognitive ability and reasoning. The operational principle of Fuzzy Logic as based on fuzzy set theory is to describe precise information of system dynamical responses by a set of rules described colloquially.

Instead of presenting information in a crisp or strongly mathematical manner, information is presented imprecisely by linguistic terms of notation, such as Hot or Cold (Reznik (1997)), where the distinction between what is Hot or Cold is a relative concept with no concrete mathematical separation boundary.

Figure 5.1 illustrates the relation between Crisp relationships and Fuzzy relationships. As show be equation 5.1, the variable A represents a clear boundary between what is Cold and Hot, namely the value of A in degrees centigrade.

Alternatively, in a fuzzy relation the distinction between Cold and Hot is relative and depends upon its respective Degree of Membership $\mu(x)$, where x is the independent variable within the Universe of Discourse (UoD). This is also mathematically expressed by equation 5.2, where the measure of temperature can be expressed as a relative Cold value and a relative Hot value.

Fuzzy systems have been applied successfully to areas such as conflict modeling (Tettey and Marwala (2006)), finance (Patel and Marwala (2006)) and biomedical engineering (Perez et al. (2010)) and have found a general acceptance as a robust method of controller design as well.

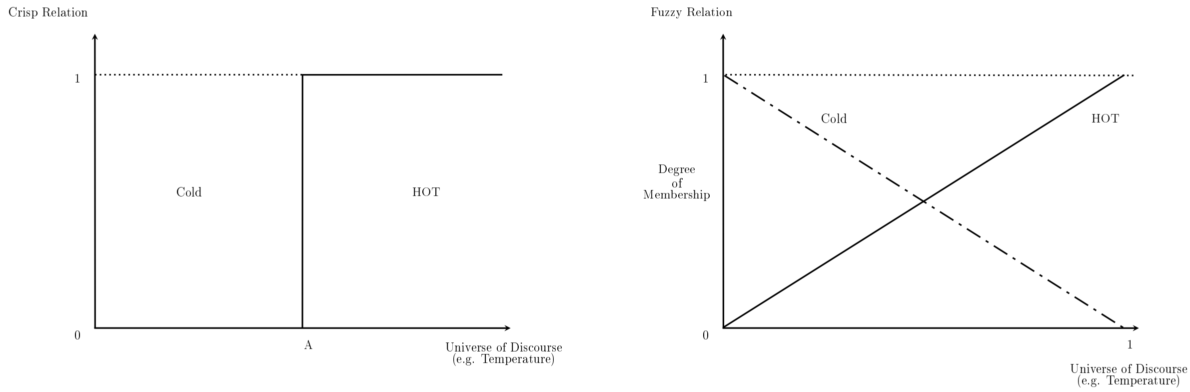

Figure 5.1: A Comparison between a Crisp relation and a Fuzzy Relation

$$\mu(x) = \begin{cases} 0, & x < A,\ Cold \\ 1, & x \geq A,\ Hot \end{cases} \tag{5.1}$$

$$\mu(x) = \begin{cases} -x+1, & x \in \{0,1\}\ Cold \\ x, & x \in \{0,1\}\ Hot \end{cases} \tag{5.2}$$

Now, the principles of presenting information cognitively has many advantages.

1. Firstly, information is processed easier and places the operational platform within a human paradigm of understanding, making process control intu-

itive to the plant operator.

2. Secondly, expert knowledge of process control operations can be constructed linguistically and incorporated within the structure of control systems for primary and supervisory control functions.

Therefore, this chapter reviews Fuzzy Logic Control with the intention of forming a foundation for subsequent chapters for Genetic Fuzzy Rule Based Systems (GFRBS). As noted previously, determining a set of linguistic rules for Fuzzy Rule Base Systems (FRBS) may be difficult under certain circumstances such as a lack of expert knowledge, large input output systems and unknown or unmodeled system dynamics.

It is therefore the subject of this chapter to focus on manual FLC design based on expert knowledge and tuning, it further highlights manual optimization mechanisms within FLC which can later be used for automatic optimization and learning of rule bases.

5.1 Basic Fuzzy Set Theory

Fuzzy Logic utilizes simple "If and Then" rules as an approach to solving problems of complexity rather than mathematical models in modeling and control applications. These fuzzy models are based on Fuzzy Set Theory (Nagai and de Arruda (2002); Golden (2003)), representing the internal operations of the controller in solving problems.

This section therefore briefly examines the fundamental concepts of fuzzy set theory and its application to the design of Fuzzy Logic Controllers.

5.1.1 A Fuzzy Set

A fuzzy set forms the foundation of Fuzzy Set Theory by extending conventional sets of information into degrees of membership. If x is an independent variable, forming part of the Universe of Discourse, in range $x \in \{0, 1\}$, then a fuzzy set A is defined as a set of ordered pairs $(x, \mu_A(x))$ as shown below in equation 5.3. $\mu_A(x)$ represents the Membership Function (MF) of A.

$$A = \{x,\ \mu_A(x),\ where\ 0 \leq \mu_A(x) \leq 1\} \tag{5.3}$$

In contrast to logical theory, where a membership variable can only represent one of two variables, either true ($\mu_A(x) = 1$) or false ($\mu_A(x) = 0$), fuzzy theory introduces the concept of membership degree ($0 \leq \mu_A(x) \leq 1$). Thus it forms an effective mechanism by which information can be classified, based on human judgment it provides a way of making decisions in a "soft" manner rather than "hard", precise and crisp presentations of information. Figure 5.2 illustrates the concept of a Fuzzy Set.

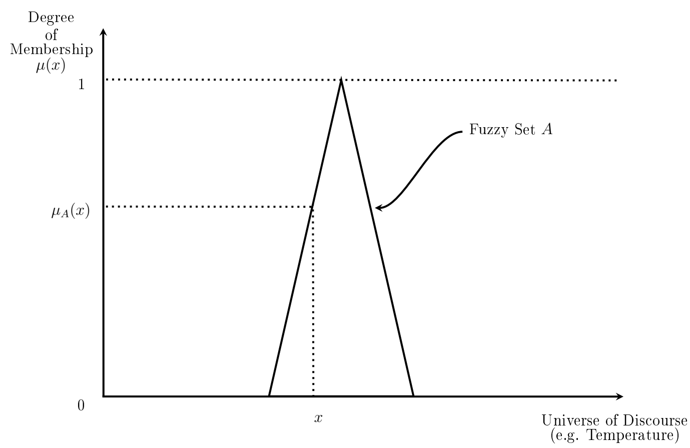

Figure 5.2: Illustration of a Fuzzy Set

Traditionally, triangular membership functions are chosen, this is due in part to their simplicity and ease of implementation (Wang et al. (1998); Kaya and Alhajj (2006)). However, more complicated functions can be used during the design stages of FLC such as quadratic and exponential membership functions. More higher order fuzzy sets does not necessarily reflect significant changes in control effort.

5.1.2 A Few Fuzzy Set Operations

Membership functions form the primary mechanism by which fuzzy set theory is applied. In order for this to be effective a few basic fuzzy set operations are defined. For a deeper analysis of fuzzy set operations and its performance influence on FLC controllers, a detailed review is given in (Reznik (1997); Herrera and Peregrin (1997); Jantzen (1999)) .

5.1.2.1 The Complement of a Fuzzy Set

In a similar manner to the logical NOT operation, the complement of a fuzzy set is defined as a membership function as shown in equation 5.4.

$$\overline{\mu_A(x)} = 1 - \mu_A(x) \tag{5.4}$$

5.1.2.2 Union of Two Fuzzy Sets (Disjunction)

The Disjunction of two fuzzy sets is also known as the S-Norm, and represents the union of two fuzzy sets on a mutual universe of discourse. By definition, it is the algebraic sum of the two fuzzy sets less its algebraic product of $\mu_A(x)$ and $\mu_B(x)$ as shown in equation 5.5.

$$\mu_{A\cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) * \mu_B(x) \tag{5.5}$$

5.1.2.3 Intersection of Two Fuzzy Sets (Conjunction)

The Conjunction of two fuzzy sets is also known as the T-Norm, and represents the intersection of the two fuzzy sets on a mutual universe of discourse. By definition, it is the algebraic product of $\mu_A(x)$ and $\mu_B(x)$ as shown in equation 5.6.

$$\mu_{A\cap B}(x) = \mu_A(x) * \mu_B(x) \tag{5.6}$$

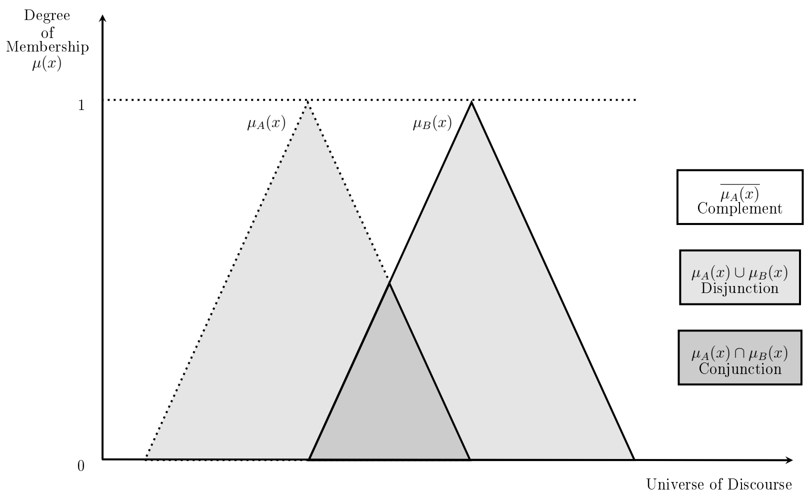

Figure 5.3: Basic Fuzzy Set Operations

5.2 The Fuzzy Logic Controller

Since its inception, Fuzzy Logic Control has developed progressively and has seen many industrial successes. It has been shown that FLC controller design and application have yielded superior closed loop performance, especially amidst parametric model uncertainty or unknown system dynamics (Battle et al. (1999); Foran (2002); Giron-Sierra and Ortega (2002); Anand and Jeyakumar (2008); Hagras (2008)).

In contrast to linear control theory, which conventionally accepts a linear process model for closed loop controller design, FLC is inherently nonlinear by nature and also functions well when nonlinear process dynamics are present.

Figure 5.4 illustrates the basic architecture of the Fuzzy Logic Controller. As can be seen, the FLC controller consists of the following sections, namely;

1. Fuzzification.

2. Defuzzification.

3. A portion including their respective scaling gains, this is known as the Knowledge Base.

4. A section dedicated to the implementation of $If\ and\ Then$ rules which is known as the Rule Base.

Conventionally controller derivation is established via process modeling of the controlled process, however, in FLC design the controller is directly obtained from process experts or plant operators, who have a detailed knowledge (Knowledge Base) of manual plant operation, its process interactions and dynamic process response. These rules are collated to form a comprehensive Rule Base.

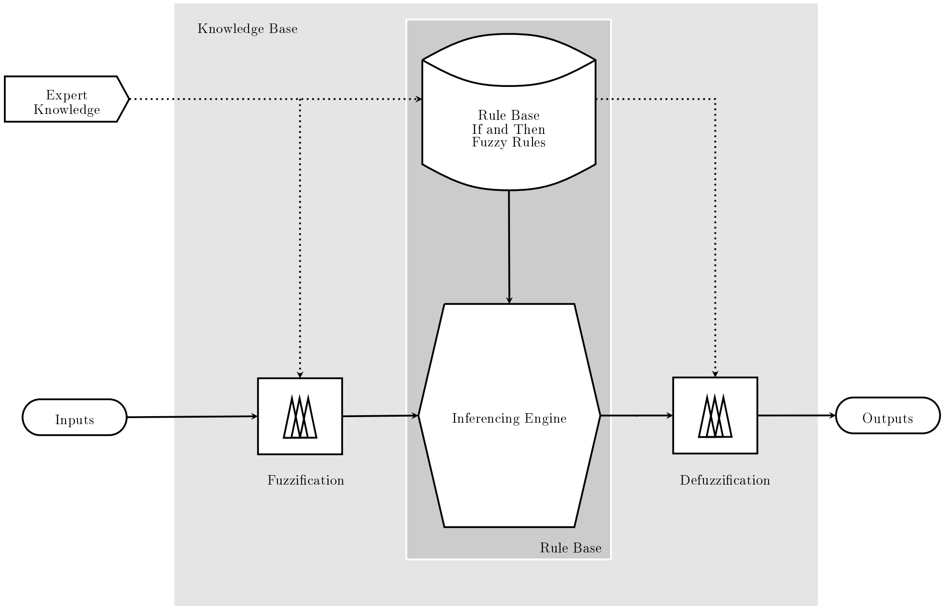

Figure 5.4: Basic Architecture of a Fuzzy Logic Controller

5.2.1 Fuzzification

One of the more critical functions in FLC design is the conversion of real process information into linguistic language. Imprecise language constructs of human cognitive processing is expressed as linguistic terms. This process occurs through fuzzification, see Figure 5.5 where the linguistic terms for fuzzification are Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZZ), Positive Small (PS), Positive Medium (PM) and Positive Big (PB). The following important characteristics of the membership functions contained within fuzzification are as follows.

1. Since membership functions divide the Universe of Discourse (UoD) into sections, it is important that the membership functions cover the entire Universe of Discourse. This ensures that every possible crisp input has an associated linguistic term which can be used for processing within the Inference Engine.

2. Linguistic terms should be clear, descriptive of its function and distinct. This typically reflects the plant operators analysis of the input output space and describes for a range of values the Universe of Discourse.

3. Typically a normalized Universe of Discourse is used, with scaling gains used for adjustments according to the required performance criteria. The UoD can also be expressed in engineering units.

4. The Degree of Membership $\mu(x)$ is representative of the grade of a variable within the Universe of Discourse where $0 \leq \mu_A(x) \leq 1$.

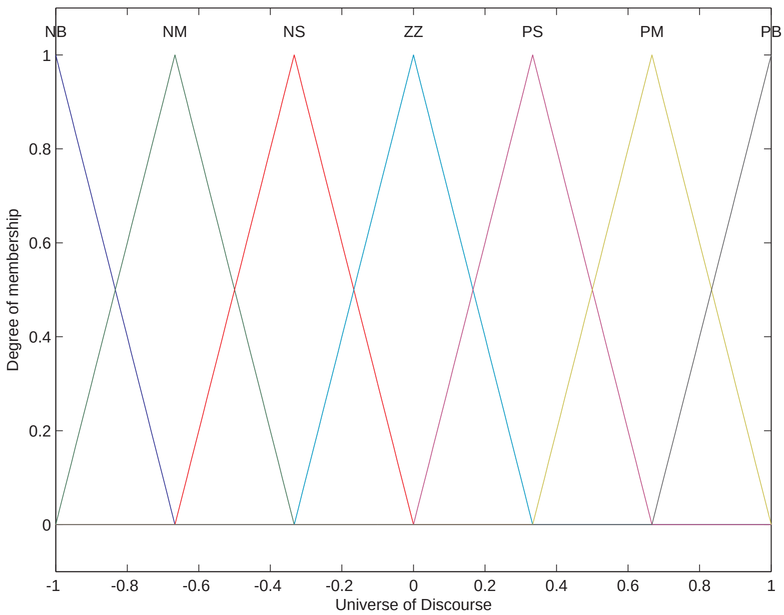

Figure 5.5: Typical Triangular Membership Functions

5.2.2 The Fuzzy Rule Base

The foundation of fuzzy rule based systems are the IF and Then rules. These rules encapsulate the dynamic performance data of the fuzzy model or controller being designed, and bear with it the imprint of system dynamical responses. The size and number of the rules used within the fuzzy controller are typically problem specific, but depends to a large extent on the number of inputs and outputs of the system. As the problem input output space increases, the relating rule base size increases exponentially thereby increasing the complexity of the fuzzy system.

$$If\ e(t)\ is\ E_i\ and\ \dot{e(t)}\ is\ CE_j\ Then\ u(t)\ is\ U_{Rij} \tag{5.7}$$

In equation 5.7 $e(t)$ is the input error and $\dot{e(t)}$ is the change in error $(\frac{d}{dt}e(t))$ as a function of time (t), $u(t)$ is the output signal and U_{Rij} is the fuzzy rules matrix, with the indices i and j representing the number of membership functions of E and CE.

Increasing fuzzy system complexity can be a challenging problem when conventional FLC design is considered. To the human operator, analyzing and processing large volumes of data can be a daunting task, especially when appropriate expert knowledge is unavailable. To this end methods of optimizing FLC rules bases are contained within the literature. One technique for optimizing rule bases is by applying Genetic Algorithm.

5.2.3 Defuzzification

The process of converting fuzzy information into crisp information is known as Defuzzification. Defuzzification therefore forms the primary actuating mechanism by which fuzzy models and fuzzy controllers interact with the process, environment or plant under control. It is by this means that linguistic information is transformed into action, interpreted as the controlled variable within control theory and applied to solved the specific problem at hand.

By means of the fuzzy inference engine, a set of control rules U_{Rij} are "fired" and their respective control actions are combined through Defuzzification for an aggregate control action according to the prescribed information as contained within the Rule Base and Knowledge Base respectively.

There are a number of Defuzzification techniques (Saade and Diab (2004)), namely, Center of Area or Gravity (COG), Bisector of Area (BOA), Mean of Maximum (MOM), Smallest of Maximum (SOM), Largest of Maximum (LOM) and Weighted Average Formula (WAF) to name but a few. Of these the more commonly used Defuzzification methods applied within industry is COG and MOM, these are briefly described below.

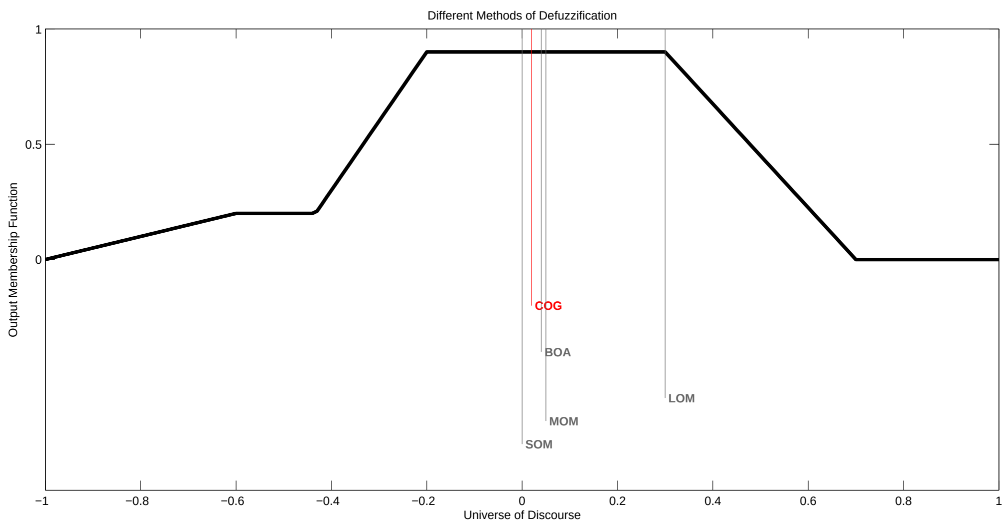

Figure 5.6: Illustration of Different Methods of Defuzzification

5.2.3.1 Center of Gravity (COG)

The Center of Gravity (COG) method for Defuzzification is described by equation 5.8. As can be seen, the COG method finds the centroid of the output membership function $\mu_B(z)$, where z is the output Universe of Discourse.

$$u_{crisp}(z) = \frac{\int \mu_B(z) * z dz}{\int \mu_B(z) dz} \tag{5.8}$$

In its discrete form, the COG method can be approximated by equation 5.9, where the Universe of Discourse is sampled by a number of samples N, and the output result is obtained by taking the union of all the "fired" consequent parts of each rule.

$$u_{crisp}(z_i) = \frac{\sum_{i=1}^{N} \mu_B(z_i) * z_i}{\sum_{i=1}^{N} \mu_B(z_i)} \tag{5.9}$$

5.2.3.2 Mean of Maximum (MOM)

The Mean of Maximum (MOM) method of Defuzzification is given by equation 5.10, effectively the average of the maximum values over the Universe of Discourse is taken, and in the discrete case, a few samples over the maximum is averaged.

$$u_{crisp}(z) = \frac{\int_a^b z dz}{\int_a^b dz} = \frac{(a+b)}{2} \tag{5.10}$$

5.3 Summary of Chapter 5

Chapter 5 introduced Fuzzy Logic Control (FLC), its design and certain key aspects of implementation which forms the foundation of GA Fuzzy Control. It highlights the design rationale for FLC control and the parameters required for tuning and optimization of the controller.

It is concluded that because there are many parameters and functions required for optimization, manual design in its own poses a significant challenge when detailed knowledge of the process is lacking and also especially when the design space is large, with multiple inputs and outputs to the system, which exponentially increase the problem search space considerably.

Therefore, Chapter 6 discusses the role of Genetic Fuzzy Rule Based System and how it can be applied to solve this problem as applied through the means of Evolutionary Strategies.

Chapter 6

Genetic Fuzzy Rule Based Systems

In Chapter (2) a review of current literature was performed. It focused specifically on frequency control and on the techniques used in the design of Automatic Generation Controllers for interconnected power systems. It highlighted the importance of frequency control and identified the need for robust AGC controllers.

In addition, it further described deficiencies with conventional AGC control techniques, especially when considering increasing plant complexity and uncertainty. Therefore, this chapter expounds on Genetic Fuzzy Rule Based Systems and its applications, focusing specifically on it design rationale, and its application as a viable AGC controller design tool.

6.1 Soft Computing

Soft Computing (SC) methodologies, which is the integration of Artificial Neural Networks (ANN), Fuzzy Logic Control (FLC) and Genetic Algorithms (GA) have found wide-spread application within the process industry today. This is particularly motivated by the increased computational power of modern Distributed Control Systems (DCS) but also by the effectiveness with which SC techniques have been used to solve real world problems.

Becoming increasing more favourable are solutions which can be found more easily, effectively and robustly amidst various unknowns, and Soft Computing techniques affords this opportunity. The mechanism of modeling and controlling based on classical methods can be expensive and time consuming, but SC provides very promising results for such situations. See Figure 6.1 for an illustration of Soft Computing.

In essence, Soft Computing includes techniques for solving real world problems by means of computer algorithms modeling natural processes such as;

1. Expert Systems and Fuzzy Models (Nagai and de Arruda (2002); Pedrycz (2008); Marwala and Lagazio (2011)).

2. Artificial Neural Networks (Nguyen and Widrow (1990); Patel and Marwala (2006)).

3. Probabilistic Models (Prandini (2005)).

4. Search Heuristics (Abraham (2005)).

Each of the aforementioned methods models the physical world and imitates the characteristic behavior of these systems to find solutions to stated problems. Hence their field of application is vast. This is the strength of soft computing, in that it is versatile and robust, adaptable to any particular problem.

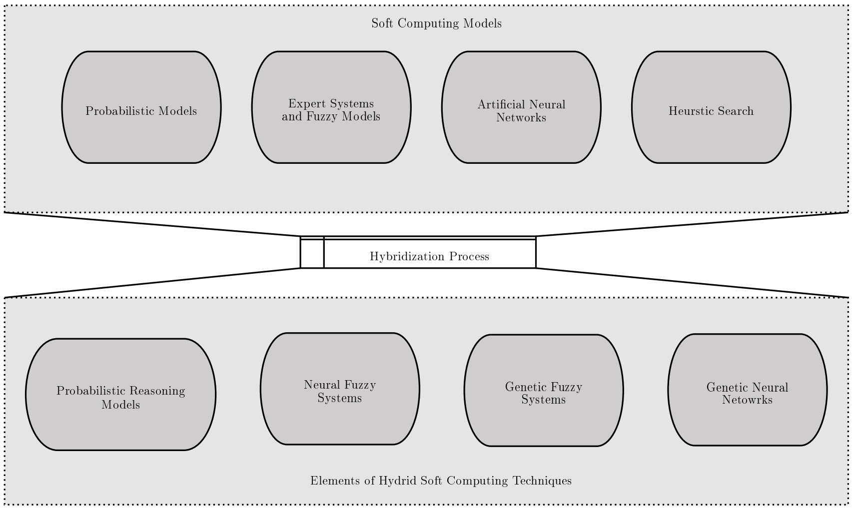

Figure 6.1: Soft Computing Models and Hybridization

In contrast to more empirical mathematical models, which require strict mathematical formalization, SC's have typically been applied to problems that embrace model uncertainty, to systems in which there is a lack of a priori knowledge of the process under control and to problems which lends themselves to high complexity.

Therefore, in finding solutions to these problems, SC's sacrifice exact precision in favour of abstraction to remove complexity, with the expectation that sound solutions will be found to complicated problems. The solutions obtained adequately solve stated problems, although it may not be absolute, it provides a mechanism by which problems are solved quickly, reliably and robustly.

In contrast, Hard Computing (HC) techniques such as Proportional, Integral and Derivative (PID) controllers, Optimal Controllers (H_2 *or* H_∞) and other parametric type controllers are largely dependent on detailed process models, which if ill tuned, could lead to poor performance, overshoot and oscillation.

Table 6.1 illustrates a few examples of Hard and Soft Computing techniques used within industry today. Although the listing is not exhaustive, it highlights the major trends between the two methods. One is highly model-based and the other is based primarily on computational intelligence. The former has been extensively used within the realms of classical control over the past few decades and the latter is a relatively new branch of control, which is gaining extensively more acceptance within industry (Marwala (2004)).

Table 6.1: Various Examples of Hard and Soft Computing

Hard Computing	**Soft Computing**
PID Controllers (PID)	Fuzzy Logic Control (FLC)
Optimal Control (H_2 *or* H_∞)	Expert Systems (ES)
Model Predictive Control (MPC)	Artificial Neural Networks (ANN)
Quantitative Feedback Theory (QFT)	Evolutionary Computing (EC)
Other Parametric Controllers	Genetic - Fuzzy Systems (GFS)

It is thus the aim of Soft Computing techniques to improve on system performance where conventional controller methodologies fail, and especially by hybridization of these methods, the benefits of each method could be transferred to the final controller.

The next section briefly discusses Heuristic Search methods followed by a review of Genetic Fuzzy System design and the factors which should be considered in the design of the GA-Fuzzy Controller. The latter, highlights the approaches to Genetic Fuzzy design, the mechanisms by which the Fuzzy Controller and its contained Rule Base are optimized as well and how learning of fuzzy rules take place within the optimization process.

6.2 Heuristic Search Methods

Heuristic search algorithms falls into the category of Soft Computing as optimization routines emulating natural behavior. This would include,

1. Genetic Algorithms (GA) (Wang and Spronck (2003); Bodenhofer (2004); Herrera (2005); Eksin (2008)).
2. Particle Swarm Optimization (PSO) (Marwala (2005); Ko and Wu (2008); del Valle et al. (2008); AlRashidi and El-Hawary (2009); Blondin (2009)).
3. Ant Colony Optimization (ACO) (Abadeh et al. (2008); Xing et al. (2010)).
4. And other meta heuristic approaches such as Tabu Search (Al-Hamouz et al. (2005, 2007)) and Simulated Annealing (SA) (Falk et al. (2007)).

In these techniques, a control problem is solved iteratively by applying candidate solutions to the problem and analyzing its performance until the appropriate performance measure is obtained. Each method typically follows a flow path and a mechanism by which existing solutions are modified to yield better solutions. This has definite advantages above conventional derivative based search methods and lends itself to near optimal solutions.

In equation 6.1, $f(x)$ is the objective function, x is a vector representing the search parameters and χ is the search space. It represents the typical optimization problem of finding solutions (x) over a certain search space.

$$\underset{x \in \chi}{max} f(x) \tag{6.1}$$

Generally, heuristic search approaches to optimization cover a wide spectrum of application, since they are based on natural observation, and have been proven to be near global optimization routines.

Although heuristic search methods in some cases are not deterministic, they do not always guarantee plausible solutions and need to be iteratively evaluated for best performance. Nonetheless, they provide solutions to problems, where the knowledge of the problem is minimal or unknown, the search space is large with many global modals and provide advantages over classical gradient methods.

6.3 Genetic Fuzzy Systems

The relationship between classification problems and those employed within the realms of control theory is closely related. Classification problems consists of the identification of patterns, structures and the assessment of system behaviour based on the principles of Genetic - Fuzzy classification techniques (Ishibuchi (2007)).

These techniques endeavour to find solutions to problems where human knowledge of system dynamics fall short and where the problem search space is of a high dimension. This to the human expert or plant operator, especially when control tasks are numerous, the decision making process for effective classification and control is large and poses a real demand upon the skills and abilities of the expert to solve the problem.

Similarly, in control systems and control related problems the key objectives are for efficient, accurate and robust control over the entire operating region of function. This inevitably requires robust controller tuning and demands strict closed loop performance amidst uncertainty and disturbances. In response to this there has been a great deal of interest in the development of autonomous control systems, with the ability for learning and continual closed loop control performance, based on past behavioral experiences.

In the light of this, there has been a general trend of combining the human cognitive ability for decision making with the effectiveness of heuristic search techniques to problem solving. This is graphically illustrated by Figure 6.2, which shows an expert system optimized by a Genetic Algorithm. In this application, Fuzzy Logic encapsulates the cognitive processing of human thinking, while the heuristics of Genetic Algorithms effectively explores the search space for plausible solutions for the problem at hand. This forms Genetic - Fuzzy Rule Base Systems (GFRBS) .

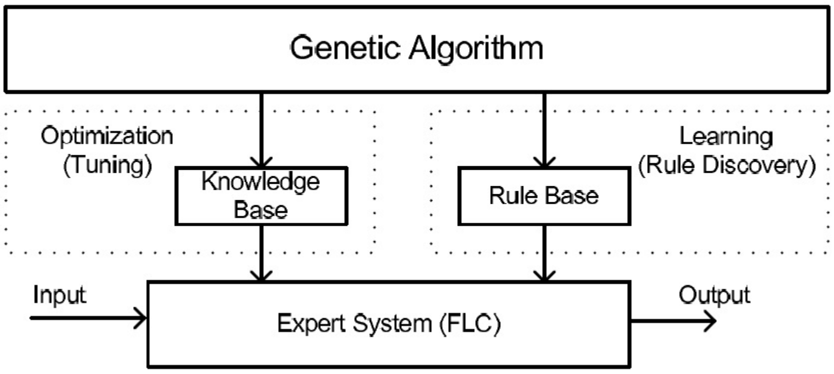

Figure 6.2: Illustration of a Genetic - Fuzzy Rule Base System (GFRBS).

Thus in response to GFRBS, contained within the literature there are three main areas of active research, namely (?Herrera (2005); Czekalski (2006));

1. The Michigan Approach (Pipe and Carse (2001); Casillas et al. (2007)),

2. The Pittsburgh Approach (Abraham (2005); Preen and Bull (2009)),

3. The Iterative Learning Approach (del Jesus et al. (2004)).

6.3.1 The Michigan Approach

One approach to problem classification, which can be extended to control systems, is that of the Michigan Classifier. The Michigan Classifier is a robust GFRBS system which uses a Genetic Algorithm as the mechanism of rule learning and discovery (De Jong (1988)). In this work we particularly review the XCS type Michigan Classifier which was introduced by Wilson (Wilson (1994); Butz and Wilson (2001)).

In its most fundamental form, it is based on the principle of Reinforcement Learning (RL) and system payoff for effective rule discovery (Grefenstette (1988); Lin and Jou (2000); Bacardit (2008)). In addition, the Michigan classifier encodes individual chromosomes as a fuzzy rule and thus the entire population of the GA as a whole represents the entire Fuzzy Rule Base.

In Figure 6.3 a graphical representation of the Michigan Classifier is shown (Casillas et al. (2005, 2007)). As can be seen, the Michigan type GFRBS is based on message passing, whereby messages are sent to and from the environment, describing the state of the environment at any given point in time (Casillas et al. (2007); Bishop (2008)).

6.3.1.1 Detectors

In GFRBS, especially as applied to Fuzzy XCS systems, the terms for Fuzzification (5.2.1) and Defuzzification (5.2.3) are Detectors and Effectors respectively (see Figure 6.3) and forms the interface boundaries of the XCS system and the Environment (Casillas et al. (2007)).

In conventional Fuzzy Rule Base systems, the Fuzzification and Defuzzification process converts crisp process information into a unitary value of membership degree $\mu_A(x)$, this is categorically based upon the definition of the membership functions. In contrast Detectors and Effectors makes use of a binary encoding scheme based upon the linguistic terms of the membership functions as defined

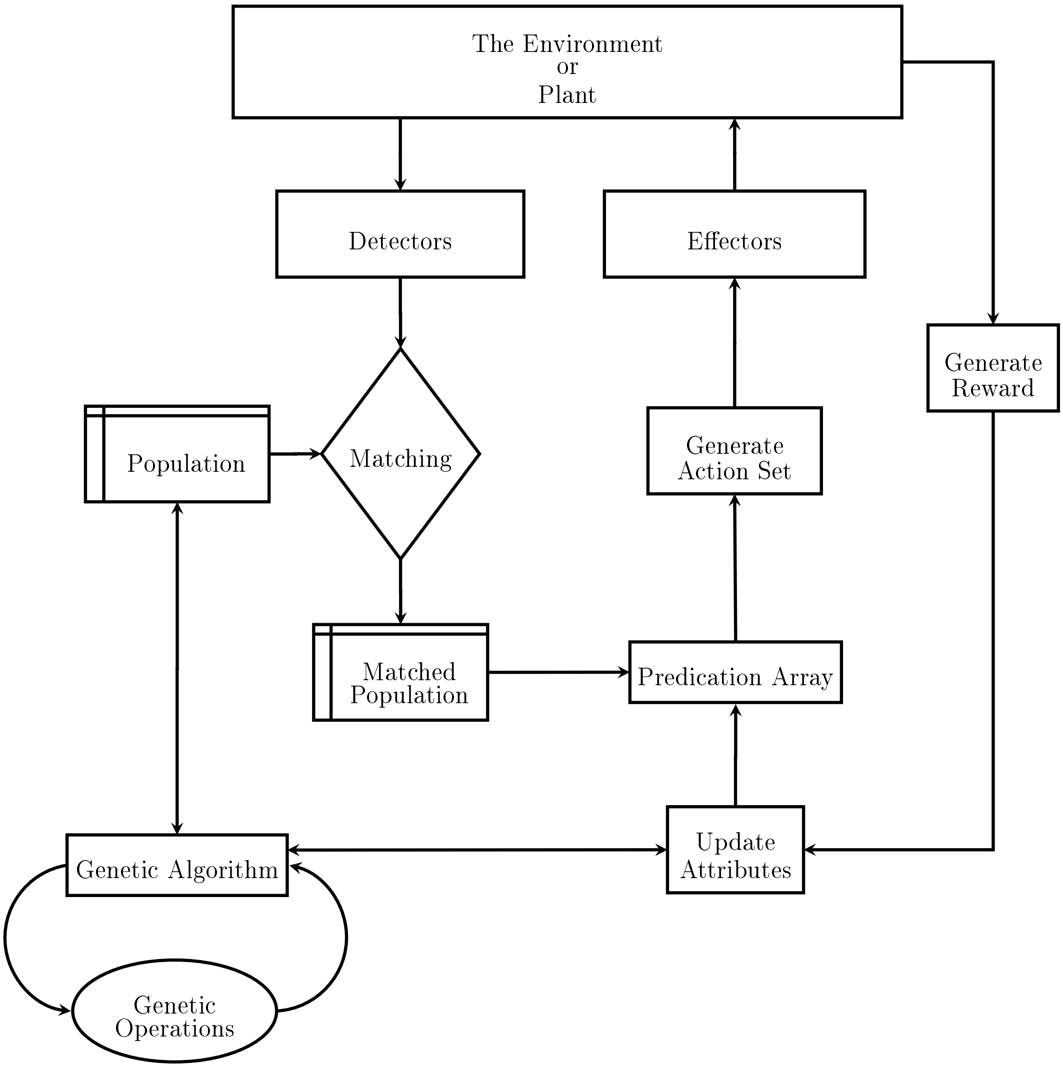

Figure 6.3: Illustration of the Michigan Type Classifier (Source, Casillas et al. (2007))

by the Fuzzy Rule (5.7).

By means of illustration, in equation 6.2, the binary encoding for the Effector is given as shown in Table 6.2.

$$If\ e(t)\ is\ (NS\ or\ ZZ)\ and\ \dot{e(t)}\ is\ (ZZ\ or\ PS)\ Then\ u(t)\ is\ PS \tag{6.2}$$

For each of the inputs forming part of the Universe of Discourse (UoD), a number of Fuzzy Rules are "fired". These "fired" rules are evaluated by the Detector

Table 6.2: Typical Encoding of the Detectors for use in Fuzzy XCS Systems

Description	$e(t)$			$\dot{e}(t)$			$u(t)$
MF's	NS	ZZ	PS	NS	ZZ	PS	$(NS = 1, ZZ = 2, PS = 3)$
Binary Encoding	1	1	0	0	1	1	3

and a message in the form of a binary encoded signal is placed on the Message List (Brownlee (2000)). The encoded signal is the binary concatenation of input variables, according to whether the respective variable forms part of the "fired" membership function.

In addition to binary encoding methods of inputs to Detectors, recent research have focused on real encoding mechanisms (Stone and Bull (2003)). These methods provides for a more general approach to real world problems, and forms a more intuitive representation of real data.

6.3.1.2 Matching

The learning ability of conventional population based search heuristics such as Genetic Algorithms, makes it a valuable tool for finding new solutions, by taking advantage of population dynamics. In the Michigan approach to Rule Base systems and GA learning, an additional step in the processing of the encoded signal as contained within the Message List is required, namely the Matching of the Detected binary encoded signal with that of the Population individuals (Bull (2004); Casillas et al. (2007)).

Initially, the XCS system is initialized with randomly determined individuals to form a Population set P. Defined randomly, certain individuals are initialized with "Don't Cares - #". In the matching process, the Population and the Detected signals are compared for similarity and in instances where the "Don't Cares" match with the detection, a match is also recorded as part of the Matched Set M

which are then used for further processing by the XCS (see Figure 6.3) (Casillas et al. (2005, 2007)).

The Population set P is initialized with a set of attributes, keeping track of the performance of each classifier or fuzzy rule, and is also utilized within the XCS algorithm for its effective functioning. In Matching, an attribute by attribute comparison is performed, new individuals are introduced by GA operation and are initialized to nominal attributes.

Throughout the operation of the XCS system, attributes are updated according to its own classifier performance and the system reward payoff (Bacardit (2008)). This is comparable to the Fitness Function in Genetic Algorithms.

6.3.1.3 The Prediction Array

Based upon the contents of the Matched Set and the respective properties of each classifier attribute, a Prediction Array PA is generated. By considering past experiences of classifier performance and based upon the principles of Reinforcement Learning (RL), a prediction is made on which classifier will yield the greatest reward.

The Prediction Array also guides in terms of defining an Action Set AS, for use within the Effectors.

6.3.1.4 Effectors

As in Defuzzification, Effectors in XCS systems interacts with the Environment to perform a given Action A. The values as contained within the Prediction Array PA, forms the basis by which actions are made. Typically there are two approaches to selecting an action, either by pure Exploitation or by Exploration.

In Exploitation, the best classifier with the maximum Prediction is selected and sent via the Message List to the Effectors for actuation of the environment. Exploration on the other hand, randomly selects an action as contained within the PA. By means of the Effectors regulation of the environments is obtained. The success of this actuation is rewarded by the environment in the form of Payoff or Reward.

6.3.2 The Pittsburgh Approach

The Michigan approach for GFRBS is based upon an online approach to learning of the appropriate classifiers for problem solving. In contrast, the Pittsburgh approach is more suitable for offline adaptation and learning of classifiers and utilizes more directly the standard implementation of Genetic Algorithms (Pipe and Carse (2001); Cervantes et al. (2007); Bacardit (2008)). This invites a more natural appeal for the application of the Pittsburgh approach to many industrial processes for problem solving.

Similar to the the Michigan approach, the Pittsburgh classification system maintains a population of individuals which represents plausible solutions to the problem at hand. However, the encoding structure of the genetic chromosomes differs in its application and function. In the Michigan type classification system the entire population of individuals represents a solution and hence the evolution of solutions occurs in a more iterative manner, while the Pittsburgh classifier represents the entire solution as an individual chromosome and is more conducive to parallelism of implementation.

Figure 6.4 illustrates the Pittsburgh Fuzzy Rule Base System. As can be seen, the Genetic Algorithm is used as a rule discovery and learning mechanism by which new solutions are evolved.

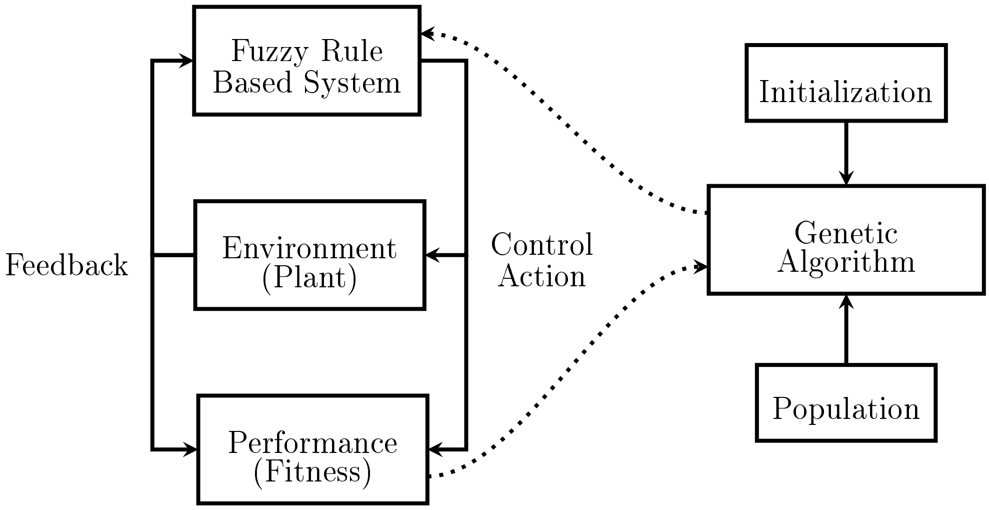

Figure 6.4: Illustration of the Pittsburgh Approach to Fuzzy Rule Based Systems

6.3.3 The Iterative Rule Learning Approach

Another method of GFRBS is the Iterative Rule Learning (IRL) approach. In this method, a multifaceted approach to rule learning is employed and consists of the following constituent sections, namely, a Genetic Generation Stage, a Post Processing Stage and a Genetic Tuning Stage (Bodenhofer and Herrera (1997)). Each of these stages are briefly described below.

IRL combines the advantages of both the Michigan and the Pittsburgh classification methods and thus also inherits the peculiar attributes of both GFRBS's. In particular, IRL borrows its iterative nature from the Michigan approach, as well as its encoding mechanism where the entire population of individuals contributes to the full solution. The commonality which the IRL method have with the Pittsburgh approach is that it inherits the fitness evaluation mechanism of where the entire chromosome of solutions needs to work together to reach a common goal.

6.3.3.1 The Genetic Generation Stage

The Genetic Generation Stage closely mimics the Michigan approach for rules generation. Individual chromosomes forming part of the Population is representative of the fuzzy rule or classifier. With each successive genetic iteration, rules are updated and fitness evaluations are performed to identify the best set of classification rules for solving the problem.

6.3.3.2 The Post Processing Stage

After the Genetic Generation Stage, a Post Processing Stage is required. Since the rules generated does not consider their respective peer chromosomes, a process of redefining and improving the quality of the generated Population is needed. This tend to improve the performance of the classifier system.

6.3.3.3 The Genetic Tuning Stage

The final stage in the Iterative Learning Approach is the Genetic Tuning Stage. In the stage, membership functions are optimized and the Knowledge Base adjusted to yield better overall system performance.

6.4 Summary of Chapter 6

Chapter 6 focused on providing an introduction to Soft Computing and its application to Genetic Fuzzy Rule Base Systems. It showed how evolutionary search heuristics such as Genetic Algorithms can be used for Rule Discovery and Learning. The chapter then concluded by describing three of the more widely applied Genetic Fuzzy systems, namely, the Michigan Approach, the Pittsburgh Approach and the Iterative Rule Learning Approach.

The next chapter (7), focuses particularly on the Pittsburgh type GFRBS and discusses certain key aspects of how it can be applied to AGC controller design for large interconnected power systems.

Chapter 7

On the Design and Analysis of a Genetic Fuzzy AGC Controller

The Automatic Generation Control (AGC) problem as highlighted in the previous chapters (1, 2) is one of the main functions of modern power utilities, especially for power system design and operation. The complexity of power systems and its dynamic nature makes it difficult to realize an AGC controller capable of minimizing a global performance criteria over all operating regimes. This would include exhibiting good disturbance rejection properties, minimizing inter area dynamic frequency oscillations and adequately responding to varying electrical load characteristics. These character traits and AGC controller properties are necessary for good power system frequency control performance.

In the light of these considerations, this chapter focuses on the design of a GA - Fuzzy AGC controller, based on the Pittsburgh GFRBS approach. Typically in practice, the well known PI control strategy is used for AGC control. However, because the PI controller parameters are selected based on trial and error methods, this method of control suffers from poor dynamic performance especially as power system complexity and network size varies according to network growth. This would inevitably require additional PI control law tuning and optimization routines throughout the operational life of the controller.

Therefore, there has been substantial research effort in the design of AGC controllers for improved dynamical performance (Kumar and Kothari (2005); Patel (2007); Tan and Xu (2009); Monga et al. (2010)). It is therefore envisaged that as network complexity increases, the relating control strategies needs to be adapted for optimum control. The GA - Fuzzy AGC controller is therefore designed as an offline heuristic controller with the benefit of yielding improved dynamical performance for online closed loop control of interconnected power systems. This in part guarantees that the controller performance can be assessed offline and validated for best performance before it is implemented as part of any real time control strategy (Hagras et al. (2001); Sijak et al. (2002); Bevrani and Hiyama (2007); Alrifai and Zribi (2005)).

7.1 Elements of GA - Fuzzy Control

The modeling of biological systems has played a dominant role in creating control strategies with near cognitive ability (Bouchon-Meunier et al. (2008)). This is clearly seen within Fuzzy Logic Controller design, where the controller is comprised of a set of expert rules dictating a desired control action given a specific set of inputs from the plant under control. Figure 7.1 illustrates how biological systems have inspired development of Cognitive Systems culminating in the engineering field of Soft Computing.

By so doing, the controller exhibits human behavior and decision making ability with the expectation of improving closed loop control performance. However, in many practical control problems it is difficult to formulate expert rules for process operation and control. Although experienced plant operators are in charge of process control, their regulating actions are intuitively stimulated based on experience and knowledge of the plant.

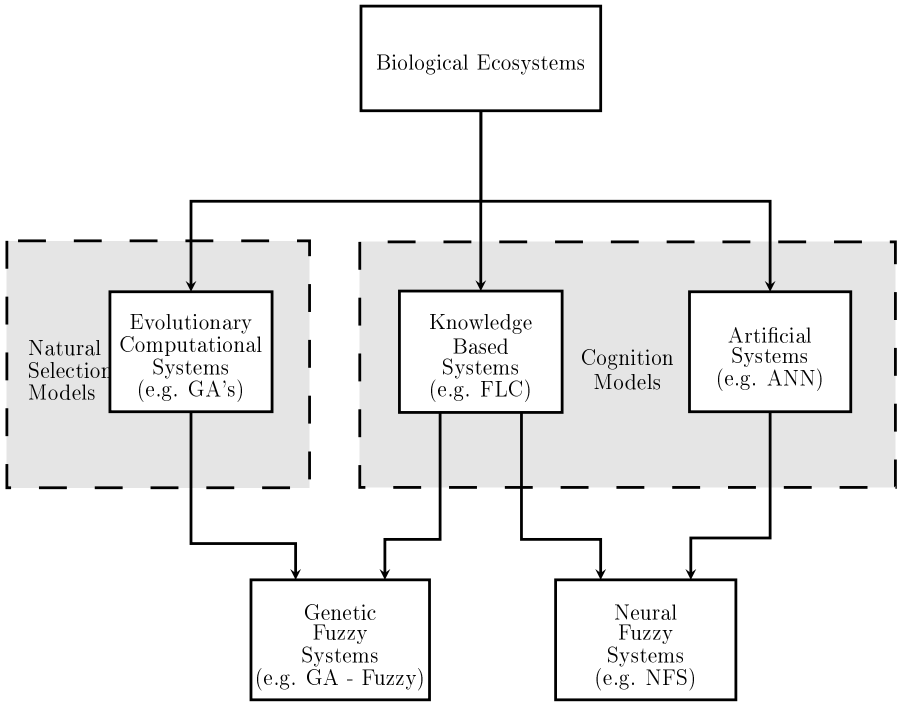

Figure 7.1: Illustration of Biologically inspired Cognitive Systems as applied to Soft Computing.

On the other hand natural processes within biological ecosystems dominate the drive for survival of the fittest individual to propagate to the next generation. The enabling mechanism of how this is achieved within biological ecosystems is through reproduction, namely genetic crossover and gene mutation. This process is encapsulated under the umbrella of Evolutionary Computational Systems (ECS) of which Genetic Algorithms forms but one such technique.

Therefore, the amalgamation of ECS systems such as Genetic Algorithms and Fuzzy Logic Controller design leads to a branch of Soft Computing known as Genetic Fuzzy Systems. This is graphically illustrated by Figure 7.1. The central idea behind Genetic Fuzzy Systems is to use the Genetic Algorithm for the automatic learning and adaptation for the fuzzy rule base and to ensure the optimal utilization of the respective membership functions and scaling parameters.

7.2 Evolution and Adaptation of Fuzzy Systems

Real complex systems enforce the realization that not all processes can be modeled or controlled by a set of exact differential equations such as Laplace transfer function models. This stems from their parametric nature of where unknown or neglected system dynamics prove to be a challenge for ensuring robust controller performance. Thus, Fuzzy Systems provide a convenient mechanism by which unknown or neglected dynamics can be modeled.

Within large interconnected power systems it is not possible to model all system dynamics because the network is just too large and due to its dynamic nature the AGC controller is required to provide adequate regulating performance.Therefore advances in controller design techniques encourages the following desirable controller attributes (Kaya and Tan (2005)).

1. Effectively modeling unknown or neglected system dynamics.
2. Robust performance amidst parameter variations.
3. Optimal control throughout all possible operating regimes, within minimal structural or parametric changes.
4. Encouraging adaptation and learning of the controller through performance evaluation.
5. Modifying the internal structure of the controller to yield improved controller performance.

Each of the aforementioned attributes are achieved by applying genetic crossover and gene mutation as the evolutionary processes to modify the internal structure of the Fuzzy System. This section describes how this is achieved, through Genetic Algorithms and describes some of pivotal aspects of Genetic Fuzzy controller design.

7.2.1 Genetic Tuning and Learning of Fuzzy Systems

Chapter 5 examined both the theoretical and practical aspects of Fuzzy Logic Controllers (FLC), where FLC design was based on expert knowledge of both the Knowledge Base (KB) and the Rule Base (RB). The design of the KB, is examined within this subsection while the RB is described in the subsequent subsection.

The KB is typically designed by expert knowledge of the process, where the expert has a detailed knowledge of the operational and control aspects of the plant. Within the KB, the control and manipulated variable search spaces are classified according to linguistic terms. These are selected based on expert design experience and the specific control objectives of the problem.

With reference to AGC, the control objectives are to improve the frequency control performance of the electrical network, thereby minimizing the ACE error of the respective control area and its interconnections. Therefore, the tuning of the FLC-AGC controller is to effectively manage the real power output of all generating units within the control area, maintaining total Generation (Figure 7.2).

Figure 7.2 illustrates the mechanism of KB tuning and optimization by means of expert analysis. To a large extent, this mechanism of tuning is by trial and error techniques, in which the performance of the overall closed loop system is assessed and minor adjustments are made to the input - output scaling parameters, and similarly to the membership functions. By repeated analytical observation and parameter adjustment, the performance of the controller is improved for optimum controller response over all operating regimes.

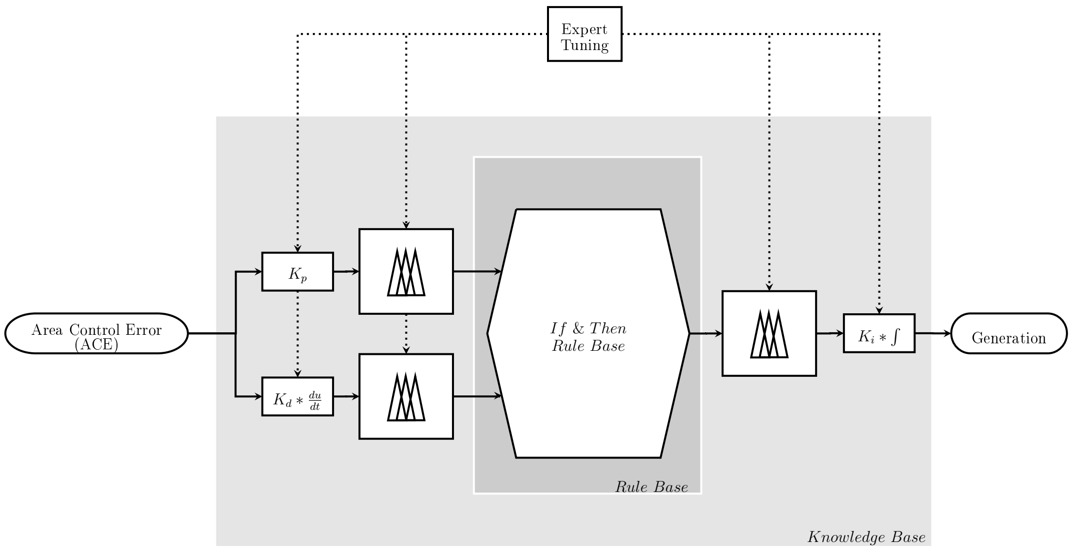

Figure 7.2: Illustration of Expert Tuning of the Knowledge Base

7.2.2 On Using the Genetic Algorithm for Tuning Fuzzy Systems

Fuzzy Systems are typically designed and optimized manually by an iterative process by the control designer. This typically takes the form of adjusting the controller PI gains (assuming that a PI controller structure is chosen) to yield optimal closed loop performance. The tuning of the controller can be made via the adjustment of input and output scaling gains, the tuning of input and output membership functions and the optimization of the Fuzzy Rule Base.

In contrast to tuning by trial and error methods, learning is a cognitive process by which experience of system behaviors are incorporated into the design process.

For the expert plant operator, this is an intuitive mechanism of learning and builds on established operational experiences. In order for learning to be encapsulated within FLC design, a mechanism of introducing novel control operation within the controller is required, and is typically performed by GA. The next section highlights this idea (Figure 7.3).

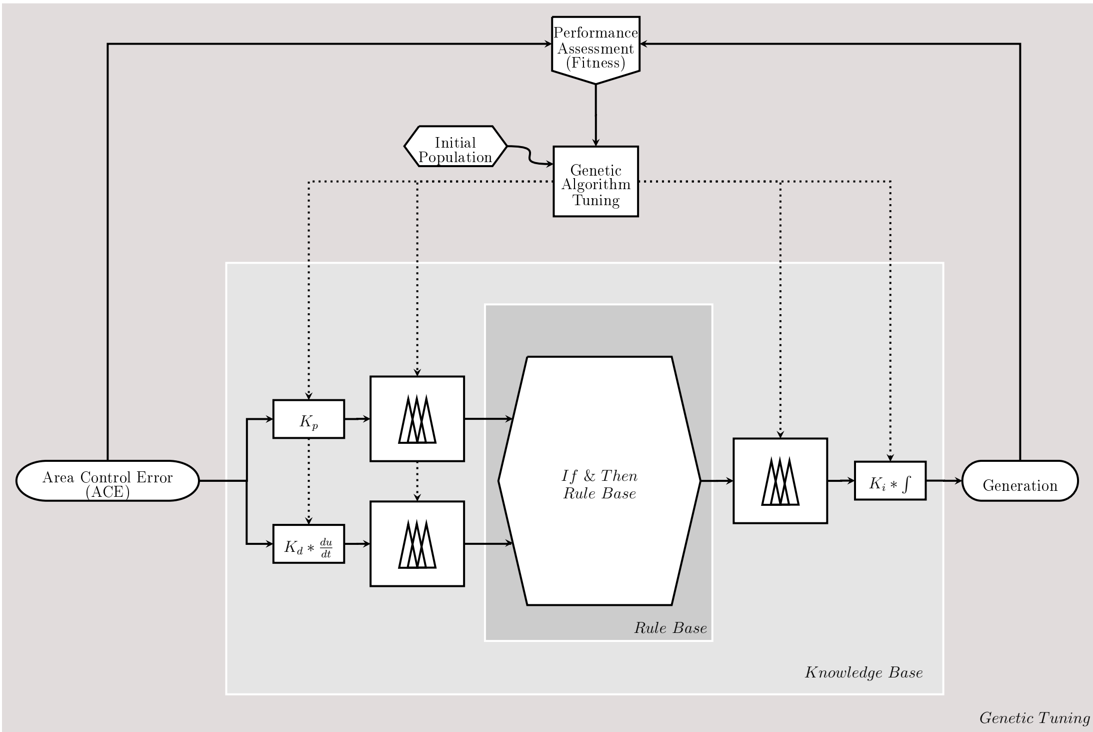

Figure 7.3: Illustration of Genetic Algorithm Tuning of the Knowledge Base

Therefore, fundamental to the design of FLC controllers by means of evolutionary strategies is the encoding of the design problem into genetically tunable parameters. Conventional FLC design uses expert knowledge for designing both the KB and the RB as described in Section 7.2.1. Thus both the KB and the RB need to be formulated as genetic chromosomes.

Each of the FLC tunable parameters as shown in Figure 7.3, namely the scalable input error proportional gain K_p, the scalable input rate of change gain K_d and the scalable output integral gain K_i as well as each of the respective membership functions are encoded as binary chromosomes. This ensures that genetic operators such as crossover and mutation can be performed on the parent chromosomes, yielding a prospectively enhanced offspring with improved performance attributes.

7.2.3 Membership Function Adjustment

Chapter 5 described Fuzzy Logic Control and discussed the role of Fuzzification and membership function selection for effective closed loop control. This section looks at how membership functions can be appropriately encoded for optimization by GA.

Two important factors in GA - Fuzzy design is the encoding of the chromosome and the definition of the fitness function. Encoding of the solution space is one of the more critical aspects of formulating the problem as a Genetic optimization problem.

In this application, symmetrical encoding of triangular membership functions are chosen, since this considerably reduces the GA search space and the number of parametric variables for optimization. As the number of parametric variables increase to define the membership function, the search space increases as well.

In addition, selection of more mathematically complicated encoding schemes for membership functions does not necessarily yield better performance attributes, and is left to the control system designer for appropriate selection.

$$Triangular \qquad \mu(x,a,b,c) = \begin{cases} 0 & x \le a \\ \frac{(x-a)}{(b-a)} & a \le x \le b \\ \frac{(c-x)}{(c-b)} & b \le x \le c \\ 0 & x \ge c \end{cases} \tag{7.1}$$

$$Trapezoidal \qquad \mu(x,a,b,c,d) = \begin{cases} 0 & x \le a \\ \frac{(x-a)}{(b-a)} & a \le x \le b \\ 1 & b \le x \le c \\ \frac{(d-x)}{(d-c)} & c \le x \le d \\ 0 & x \ge d \end{cases} \tag{7.2}$$

$$Gaussian \qquad \mu(x,a,b) = e^{\frac{-1*(x-a)^2}{2*b^2}} \tag{7.3}$$

$$Bell \qquad \mu(x,a,b,c) = \frac{1}{1+ \| \frac{(x-c)}{a} \|^{2*b}} \tag{7.4}$$

Figure 7.4 illustrates the encoding of the membership function. As can be seen symmetrical triangular membership functions are selected. Parameters a and b represent the tunable parameters over the Universe of Discourse (UoD). Therefore for use within GA, the tunable parameters are encoded as either binary chromosomes or as real valued encoding schemes and then concatenated to form one coherent chromosome string to allow for genetic operations.

As genetic operators through GA evolve the membership function sets, the

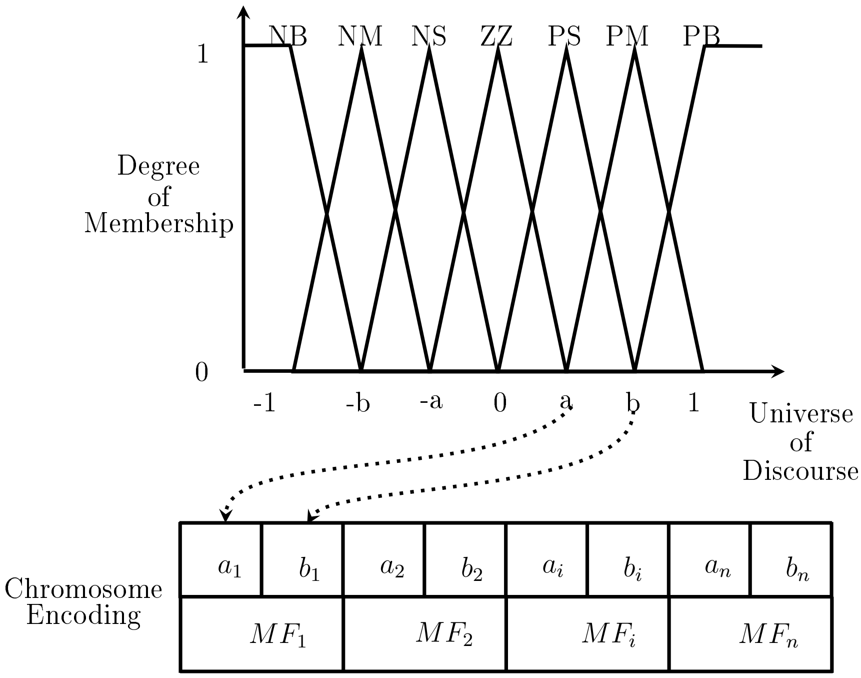

Figure 7.4: Chromosome Encoding of the Membership Function

Knowledge Base is improved to meet the stated performance criteria, requiring limited or no domain expert intervention during the design process. In some contexts, it may be required that the length of the chromosome be changed dynamically in response to the GA process (i.e. variable length chromosome string), however, this increases the size of the GA search space. For this reason, we have applied fixed chromosome length according to the design variables and the characteristic properties of the problem to be solved.

It should be noted that the tuning of the Scaling Gains, Membership Functions and the Rule Base cannot be performed independently of each other, since to a certain extent, each influences the other in measure. Therefore, due to complexity and size of the problem (number of input and output membership functions, size of input output variables and the size of the rules), it is important to appropriately select the methods of interactions during encoding in such a manner that adjustment influences does not counter the effect of the other variables.

Table 7.1: Linguistic term encoding and representation within the chromosome

#	Linguistic Term	Abbreviation	Binary Encoding	Integer Representation
1	Negative Big	NB	001	1
2	Negative Medium	NM	010	2
3	Negative Small	NS	011	3
4	Zero	ZZ	100	4
5	Positive Small	PS	101	5
6	Positive Medium	PM	110	6
7	Positive Big	PB	111	7

As an example, the selection of the membership functions are closely related to the fuzzy rules. A change in membership function definition would characteristically also change the response of the rule base and similarly changes in the rule base definition would change the interpretation of the membership functions (see Figures 7.5 and 7.6). However, this to the GA process is trivial, but it does increase the computational time of the Genetic run since complexity increases as more parameters become available for optimization.

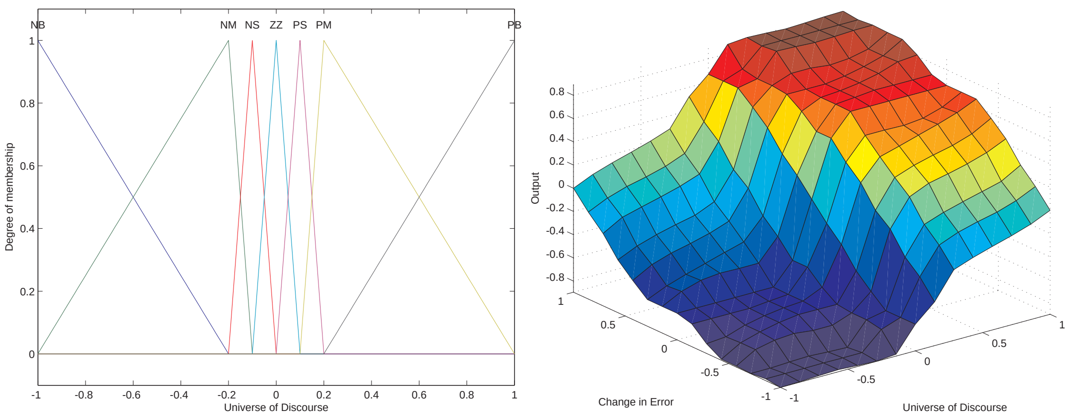

Figure 7.5: Influence of Tunable Parameter Variation of Membership Functions on Rule Surface ($a = 0.1$, $b = 0.2$)

As can be seen (Figures 7.5 and 7.6) , with only a few parameters available, in this case two for tuning, namely a and b, many permutation possibilities for solutions exist. The figures show a fixed Rule Base. Each of these variations would lead to different dynamical closed loop responses.

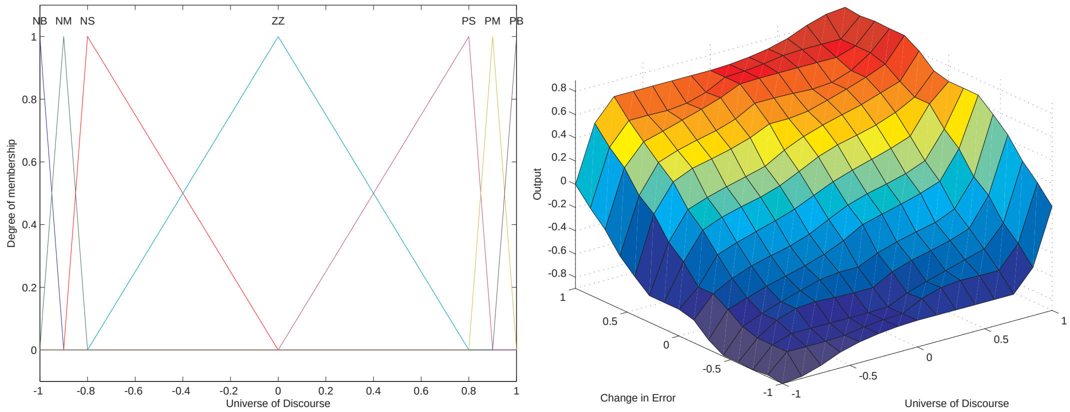

Figure 7.6: Influence of Tunable Parameter Variation of Membership Functions on Rule Surface ($a = 0.8$, $b = 0.9$)

Therefore, any classical membership function can be used, given that an appropriate encoding strategy can be formulated as part of the optimization routine.

7.2.4 Fuzzy Rule Base Generation by Genetic Algorithms

Fuzzy Rule Based Systems (FRBS) have been increasingly applied to automatic control systems, especially in power systems engineering, and in this context, to Automatic Generation Control (AGC). Recently there have been developments in the automatic adaptation of FRBS and Fuzzy Logic Controllers to account for unknown system dynamics due to dynamic process variation over time.

With present uncertainty, the performance of the controller deteriorates which is an inherently undesirable characteristic. Within the power system context, there is continual power system growth, increasing load conditions, increasing interconnections within neighboring control areas and also new electrical generators being connected to the power grid. All of these factors have a profound effect on the performance of the AGC controller. It is for this reason that FRBS, because of their inherent ability to embrace uncertainty, has found an attractive appeal for power system application.

However, one of the difficulties in FRBS design is the development of the fuzzy system to account for these dynamic variations. Genetic Algorithms have been successfully applied as a search algorithm for Fuzzy Rule Base design. Thus evolutionary genetics provide a convenient mechanism for adaptation and learning. This is particularly achieved by means of genetic operators such as crossover and mutation, in which new genetic material is created with the intent of creating better offspring.

This evolutionary process can be used as a means for providing population diversity and can be employed as a rule discovery mechanism for FLC's (Figure 6.2). This approach to FLC controller design has proved valuable in instances where expert knowledge of the process under control is not well known, in Multiple Input Multiple Output (MIMO) FLC controller design where it is difficult to formulate control rules and in instances where complex dynamical systems are applicable.

In addition, in instances where detailed process models are not available or proves difficult to obtain, evolutionary optimization is plausible. This is especially relevant in situations where it is difficult to obtain process models, either due to the restrictions in plant testing for model parameter estimation. It is often the case that testing of certain process plants cannot be implemented due to the inherent risks associated with such testing. If this is the case, alternative methods based on online process data and correlating the input and output data characteristics may be required. In this manner, evolutionary optimization is one method of obtaining process models for complex dynamical systems.

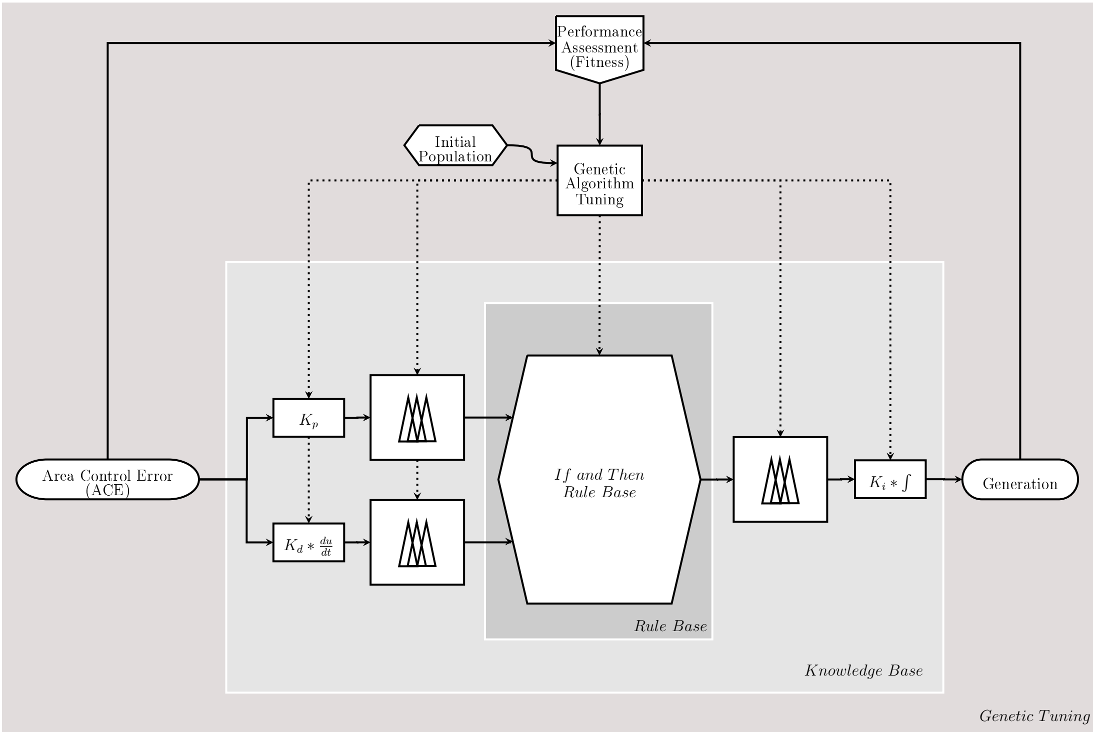

Figure 7.7: Genetic Tuning of the Rule Base and the Knowledge Base

Therefore, fundamental to the design of Fuzzy Logic Controllers by means evolutionary strategies is the encoding of the design problem into genetically tunable parameters. Conventional FLC design uses expert knowledge for designing the knowledge base (KB) and the rule base (RB).

Therefore, the application of genetic algorithms to FLC design, both the KB and RB needs to be formulated as genetic chromosomes where genetic operators such as crossover and mutation can be applied. The chromosomes are either formulated as a binary string or as a real valued chromosome depending upon the nature of the problem to be solved. This is graphically illustrated in Figure 7.2.

Depending upon the nature of the control problem, its complexity and respective encoding mechanisms for the Knowledge Base (KB), the selection between binary string and real valued chromosome encoding is dependent upon the desired convergence properties of the GA. For certain problems, binary string encoding provides limitations in that its mutation characteristics being the binary complement of the respective Bit, potentially slows down convergence rates. Alternatively, real valued chromosome encoding provides alternative more methods for achieving chromosome mutation and thus improves the convergence properties of the Genetic Algorithm.

Table 7.2: Encoding of the Rule Base as a Genetic Chromosome

Rule Base (RB)

	Error $e(t)$						
Change $\dot{e}(t)$	R_{11}	R_{12}	$\cdots$				
		$\cdots$	$R_{i(j-1)}$	R_{ij}	$R_{i(j+1)}$	$\cdots$	
					$\cdots$	$R_{m(n-1)}$	R_{mn}

RB Chromosome Representation

R_{11}	R_{12}	$\cdots$	$R_{i(j-1)}$	R_{ij}	$R_{i(j+1)}$	$\cdots$	$R_{m(n-1)}$	R_{mn}

where, $1 \leq i \leq m$, $1 \leq j \leq n$.

$$R_{ij} : If\ \dot{e}(t)\ is\ CE_i\ and\ e(t)\ is\ E_j\ Then\ u(t)\ is\ R_{ij} \tag{7.5}$$

In (7.5) CE_i is the input linguistic membership function for the change in input error ($\frac{de(t)}{dt}$). E_j is the input linguistic membership function for the input error ($e(t)$). R_{ij} is the output linguistic membership function for the output ($u(t)$). i & j are integer indices ($i, j \in 1, 2, 3, 4, 5, 6, 7$).

A static structure of the FLC RB is chosen in which the length of the chromosome is fixed and each entry is a binary representation of $n = 3$ bits, representing a linguistic term (i.e. NB = 1, NM = 2, NS = 3, ZZ = 4, PS = 5, PM = 6 and PB = 7). The $n = 3$ bits represents an integer. The length of the rule base chromosome is 147 bits long. Additional bits are added to represent the scaling gains on the FLC controller and the input and output membership functions respectively.

7.3 On the Selection of the Fitness Function for Controller Design

Assessing the performance of the control loop and the effectiveness with which the control strategy regulates the process forms an important design consideration. This is particularly important in the design of the GA - Fuzzy controller, since the evaluation of system performance in the form of the fitness function defines and directs the success of the genetic algorithm. In some cases, this may prove to be a non-trivial task and careful selection of the fitness function may be needed.

Automatic generation of fuzzy logic controllers by means of genetic algorithms is largely dependent upon the choice of the fitness function. Improper selection of the fitness function would mean that the performance of the system would not lead to optimal results. It should also be noted that the fitness function is problem dependent and is chosen in line with the objectives of the design criteria.

$$\begin{aligned} Fitness_{min} &= \frac{ITAE}{ITAE+1} \\ where, \quad ITAE &= \sum_{IC=1}^{N} \sum_{t=0}^{T} t|ACE_1| + t|ACE_2| \end{aligned} \tag{7.6}$$

In (7.6), IC is the Initial Conditions chosen for the design, where $N = 8$ is the number of initial conditions and IC $\in$ (-0.01, -0.01) (-0.01, 0) (-0.01, 0.01) (0, -0.01) (0, 0.01) (0.01, -0.01) (0.01, 0) (0.01, 0.01) are symmetrical load disturbances in each control area of the interconnected power system (See Figure (7.8)). ACE is the Area Control Error.

In conventional GA optimization routines, the GA algorithm maximizes the fitness function as to propagate the survival of the fittest individual, therefore in equation (7.6) the minimization of the cost function $ITAE$ is chosen. In control theory we are interested in the minimization of control system errors, to maintain good set-point regulation and good disturbances rejection properties. This is achieved by the former construction of the fitness function.

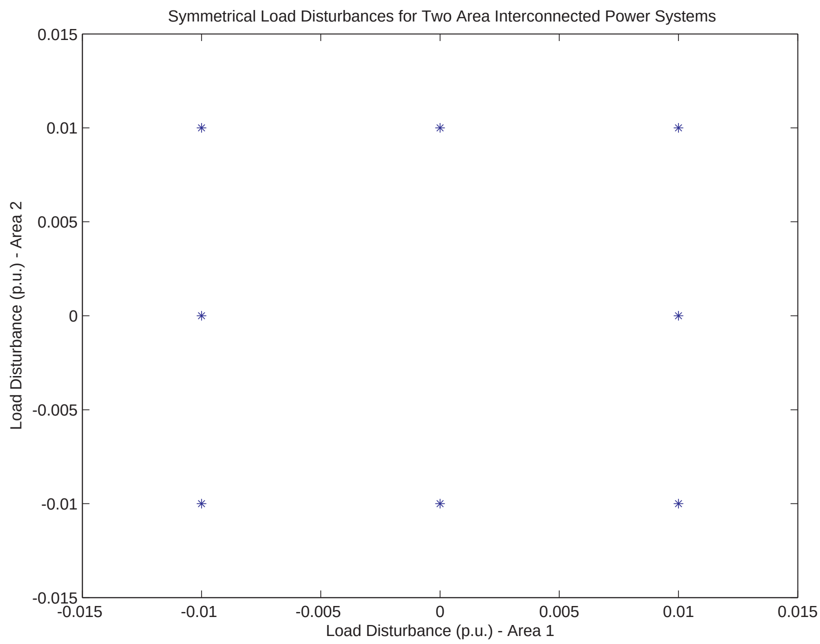

Figure 7.8: Symmetrical Load Disturbances for Initial Load Conditions

7.4 AGC Controller Design

Automatic Generation Control is described in section 2.2 as a closed loop real time controller where the aim is to ensure that the control area's generation matches the demand for load. In addition, it also endeavors to maintain Tie -

Line power flow and system frequency at its nominal value, while also minimizing a cost objective, known as Economic Dispatch (ED).

Not only limited to this, AGC regulates all power generators to minimize frequency changes, firstly by Primary Frequency Control or speed governing and then by Secondary Frequency Control (or AGC). The latter is comparably slower than Primary Frequency Control, which operates on the order of seconds while AGC only responds to persistent frequency deviations over a period of minutes.

Figure 7.9 illustrates the operation of Primary Frequency Control and Secondary Frequency Control. As can be seen the Speed Controller performs the speed regulation function of the turbine during run ups.

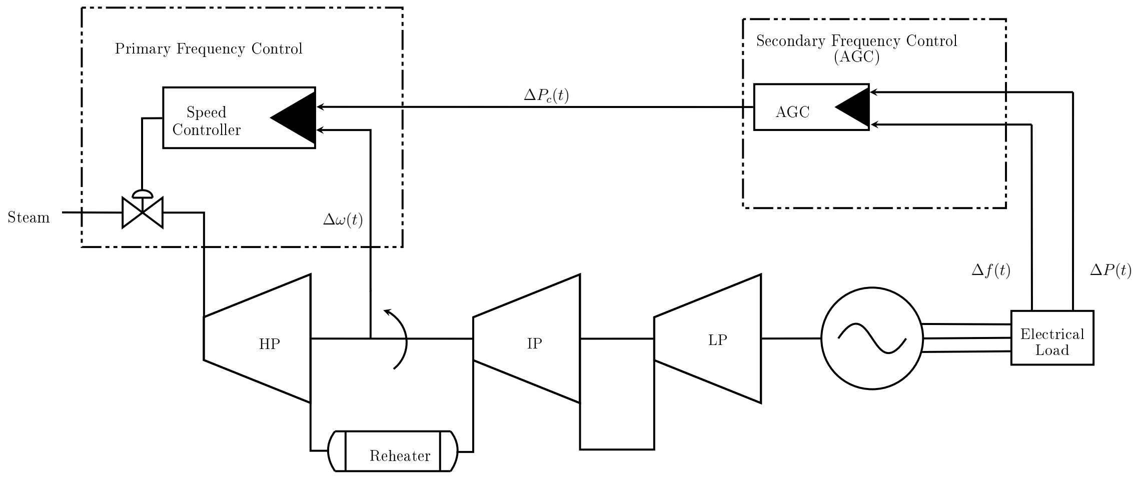

Figure 7.9: A Simplified Illustration of Primary Frequency Control and Relation to Secondary Frequency Control

Therefore, the AGC performance is dependent upon how fast the generating units can respond to AGC commands, in terms of Raise and Lower commands from Central Dispatch, and also upon the health of the particular generating unit. This would include, coal quality for coal powered stations, type of unit, whether it is a Drum or Bension type boiler, the respective control strategy used for coordinated control of boiler and turbine control system and also on the general health state of the unit.

At synchronized speed, the Load Controller becomes the active control agent of the control system. It accepts a load reference signal $\Delta P_c(t)$ from the AGC controller, to control the ramping ability of the machine according to frequency deviations $\Delta f(t)$ and power deviations $\Delta P(t)$.

The load reference $\Delta P_c(t)$ signal is sent from National Dispatch, who monitors the control areas inter area power flows and network frequency, these quantities are collated to form the Area Control Error (ACE) as described by Section 2.3.2.1, Equation 2.1. It is the ACE error which gives an indication of the energy balance contained within the electrical network. A positive ACE indicates over generation, while a negative ACE indicates under generation.

7.4.1 Conventional PI and PID AGC Control

Within an AGC context, PI and PID AGC controllers are typically tuned by either classical design approaches or more generally by trial and error techniques (Khodabakhshian and Edrisi (2008); Sinha et al. (2008); Tan (2009)), and thus closed loop performance deteriorates when nonlinearities are present and does not offer good dynamic performance over all operating regimes and loading conditions.

Therefore, PI and PID type AGC controllers require continual tuning and optimization throughout the operational life of the controller. This is primarily due to variations in network conditions over time, increasing load demands, additional generators being connected to the electrical grid, deteriorating performance of generating units and other unknown dynamic influences which affect the performance of the control system.

Nonetheless, amidst these shortcomings, PI and PID type AGC control laws are the more frequently applied AGC controllers used within industry today (Ramakrishna and Bhatti (2008); Anand and Jeyakumar (2009a)). This stems primarily from its ease of implementation, it is well understood and it provides a platform for nominal performance.

Tables 7.3, 7.4 and 7.5 clearly illustrate the design of the PI and PID type controller as applied to the AGC control problem for various closed loop performance criteria.

Table 7.3: Nominal PI Controller Gains Optimized by GA

	IAE	ISE	$ITAE$	$ITSE$
K_P	0.2218	0.1221	0.0812	0.0194
K_I	0.0548	0.0567	0.0711	0.0881

It is seen that the controller performs well amidst nonlinearities such as governor Deadband (DB) and Generation Rate Constraint (GRC), see sections 2.4.2 and 2.4.4 respectively.

Table 7.4: Nominal PID Controller Gains Optimized by GA

	IAE	ISE	$ITAE$	$ITSE$
K_P	1.1353	0.1226	1.1333	0.2755
K_I	0.0740	0.1124	0.1196	0.0748
K_D	1.3787	1.4758	1.3525	1.3688

Observation of the performance values (Table 7.5) and comparison of the transient responses (Figure 7.10) confirms that the selection of the performance criteria plays an important role in the optimal transient response characteristic for AGC control of Interconnected Power Systems (Sinha et al. (2008); Patel (2007)).

It is also noted that in the presence of GRC, the performance of the system tends to be oscillatory in nature. From a practical perspective this is also confirmed by the fact that the rate of change limits on Generation (especially by the Generating Unit) has a significant impact on network performance. Therefore Generation rate limits imposes a limit on response and because the AGC controller over compensates, a slightly oscillatory response is seen. This is mitigated by slightly de-tuning the AGC controller be a certain margin.

Table 7.5: Performance Indices for PI and PID type Control Laws

	IAE	ISE	$ITAE$	$ITSE$
PI	0.2208	0.9370	0.0319	0.5950
PID	0.2208	0.9370	0.0319	0.7646

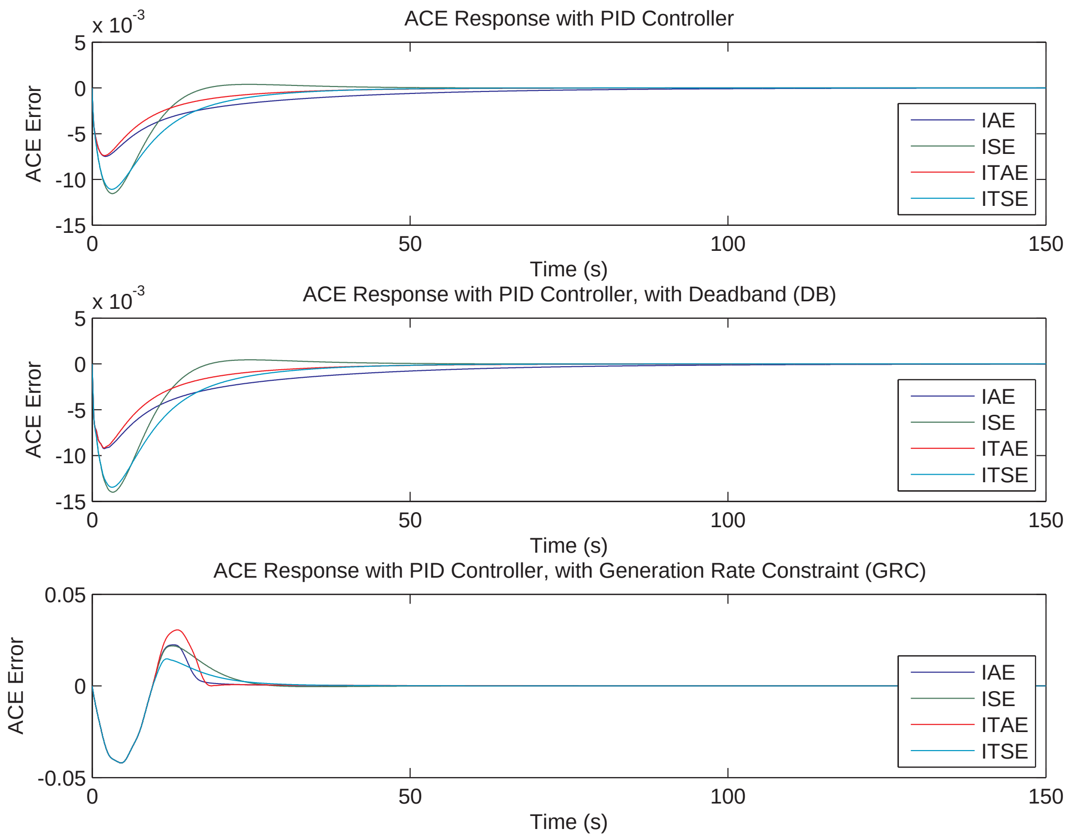

Figure 7.10: PI/PID Controller Response For Various Performance Indices With Nonlinearities, such as Deadband and Generation Rate Constraint

7.4.2 GA Fuzzy Controller Design

Chapter 5 introduced FLC controller design, highlighting certain fundamental aspects of controller design and optimization by expert knowledge. This section expounds further on FLC design and presents GA-Fuzzy controller design, by means of a multi - objective optimization problem where evolutionary strategies are employed within the design.

Equation 7.7 illustrates the optimization problem as an objective (fitness) function ($f(x)$) minimization problem subjected to optimization constraints ($g(x)$). The decision for Minimization or Maximization is dependent upon the nature and attributes of the problem, however within a Genetic sense, the objective is to maximize the fitness function (Bodenhofer (2004); Ji-lin et al. (2006)).

$$\begin{gathered} Minimize\ (or\ Maximize) \\ f(x) = \{f_1(x),\ f_2(x),\ \cdots\ f_i(x),\ \cdots\ f_N(x)\} \\ Subject\ to\ Constraints \\ A(x) \leq g(x) = \{g_1(x),\ g_2(x),\ \cdots g_i(x),\ \cdots\ g_N(x)\} \leq B(x) \end{gathered} \tag{7.7}$$

In equation 7.7, $f(x)$ is the objective function, x is representative of the search variables, $g(x)$ is the set of objective constraints, i is the sequential objective function index and N is the total number of objectives present in the problem. $A(x)$ and $B(x)$ is lower and upper bounds respectively, and is problem specific according to the nature of the problem being solved.

Typically within control system design, there exists a conflict between objective functions and their respective constraints and as such a compromise in performance is usually deemed necessary. This inherently implies that there exists invariably many solutions to the problem as the search space increases and thus the solution is not unique. However, analysis of the solutions would indicate that acceptable solutions would lie within certain boundaries of performance and robustness characteristics, this typically provides for sufficient engineering decision ability to select the most appropriate solution.

By its application, GA's are well suited for multi - optimization control problems and several approaches to control and AGC design alike by GA have been proposed in the literature (Golden (2003); Garduno-Ramirez and Lee (2002); Ghoshal (2005); Du and Li (2006); Chen and Cartmell (2007); Ishibuchi (2007); Eksin (2008)).

Firstly from an AGC perspective, generating units are required to respond to random load fluctuations and to cycle from minimum generation through to maximum generation as the demand for energy dictates according to strict time schedules. Although most generating units are designed for a base load type operation, cycling of generating units imposes rigorous wear and tear on the mechanical components of the unit, and thus as part of the AGC performance objectives, it is required to maximize equipment operational life cycle expectations.

There may also be objectives for the minimizing of fuel consumption, environmental objectives such as emissions control, reducing thermal stress on the machine due to cycling and for the life extension of metal components by effective AGC regulation and control. In order to meet these objectives, AGC typically is tuned very conservatively to meet all the operational objectives throughout a wide range of operating modes.

Secondly, GA's operates on a population of solutions and thus they are well suited for multi - objective search problems. Hence this is conveniently encoded within the Pittsburgh approach to GA-Fuzzy design, where the entire solution is encapsulated within the encoding framework (Ishibuchi (2007)).

7.4.2.1 Chromosome Encoding and Problem Formulation

For the application of GA's in the design of GA-Fuzzy controller design, an effective mechanism of representing knowledge is required. In traditional FLC methods, experience and operating control knowledge is formulated as a set of rules. However, this may be a time consuming and an expensive exercise (Park and Lee-Kwang (2000); Kim et al. (2008b)) and much of the controller tuning depends on trial and error methods. Therefore automatic methods of designing FLC controllers, in their Knowledge Base and Rules Bases are required and have seen increasingly more research interest (Makrehchi (1995); Peng et al. (2001); Surmann et al. (2002); Castro and Camargo (2004); Li et al. (2005); Li and Du (2006); Czekalski (2006); Sánchez et al. (2009)).

Figure 7.4 and Table 7.2 illustrated the encoding mechanisms for the membership functions and the rule base respectively. In fact there is no globally prescribed mechanisms of encoding, suffice to say that it adequately represents the problem to be solved and that each of the tunable parameters are represented within the encoding process.

Shown in Table 7.6 is a representation of the encoding scheme used in the AGC design process, where the chromosome length increases with the magnitude of the problem and hence the encoding process varies. In some contexts, a variable chromosome length could also be used (Park and Lee-Kwang (2000)), which dynamically changes as the GA process continues, however, we have used a fixed total chromosome length in response to the dictates of the problem re-

Table 7.6: GA-Fuzzy Controller Encoding as applied to AGC Design

No.	Description of Encoding	Parameters	Encoding	Bits	Total Bits
1.	FLC Scaling Gains (K_P, K_I, K_D)	3	Binary	$24X3$	72
2.	Membership Functions (a_i, b_i)	$i = 3$	Binary	$24X6$	144
3.	Rule Base ($e(t)$, $\frac{d}{dt}e(t)$)	$7X7$	Binary	$3X49$	147
4.	Chromosome Length ($Chromo_{Length}$)	1	Binary	363	363

quirements.

7.4.2.2 Genetic Parameters for Optimization

One of the problems associated with genetic algorithms is of early convergence where the Genetic process "stalls" in finding solutions, and prematurely returns a result. This may be overcome by dynamically changing the Genetic Parameters (Table 7.7) as the genetic generation continues (Adriansyah and Amin (2005); Kaya and Alhajj (2006)).

Increasing the Mutation Probability (P_m) would reduce the optimization routine to a random search. This is important to realize since it provides information into the selection of the P_m. Typically, P_m is selected relatively small and contributes to maintaining adequate genetic material within the Population. This provides guidelines into dynamically changing the genetic parameters. In addition, by observing the rate of convergence, additional guidelines are provided for genetic parameter selection.

Table 7.7: Genetic Optimization Parameters for GA-Fuzzy Controller Design as applied to AGC

No.	Parameter	Value
1.	Number of Generations ($nGen$)	50
2.	Population Size ($nPop$)	60
3.	Mutation Probability (P_m)	0.02
4.	Crossover Probability (P_c)	0.75
5.	Number of Bit for Reals ($nBits$)	24
6.	Elitism	$True$
7.	Chromosome Length (in Bits)	363

This is achieved by modifying either the Mutation Probability (P_m) or the Crossover Probability (P_c) or both according to a prescribed path. Increasing P_m increases population diversity, while P_c adds genetic material through reproduction.

7.4.3 Discussion

The dynamic frequency response model for a two area interconnected power system is studied and is shown in Figure 7.11 below.

Each of the major components of the model is defined in section 2.4, where the major non linear components such as Deadband (DB) and Generation Rate Constraint (GRC) is described.

Each interconnected control area contributes to the control of system frequency, in response to its own random load variations. The ACE_i error of the area is used as a performance measure where the objective is to maintain the ACE_i error at zero (i.e. $ACE_i = 0$).

ACE and Frequency Control (FC) of Interconnected Power Systems is closely

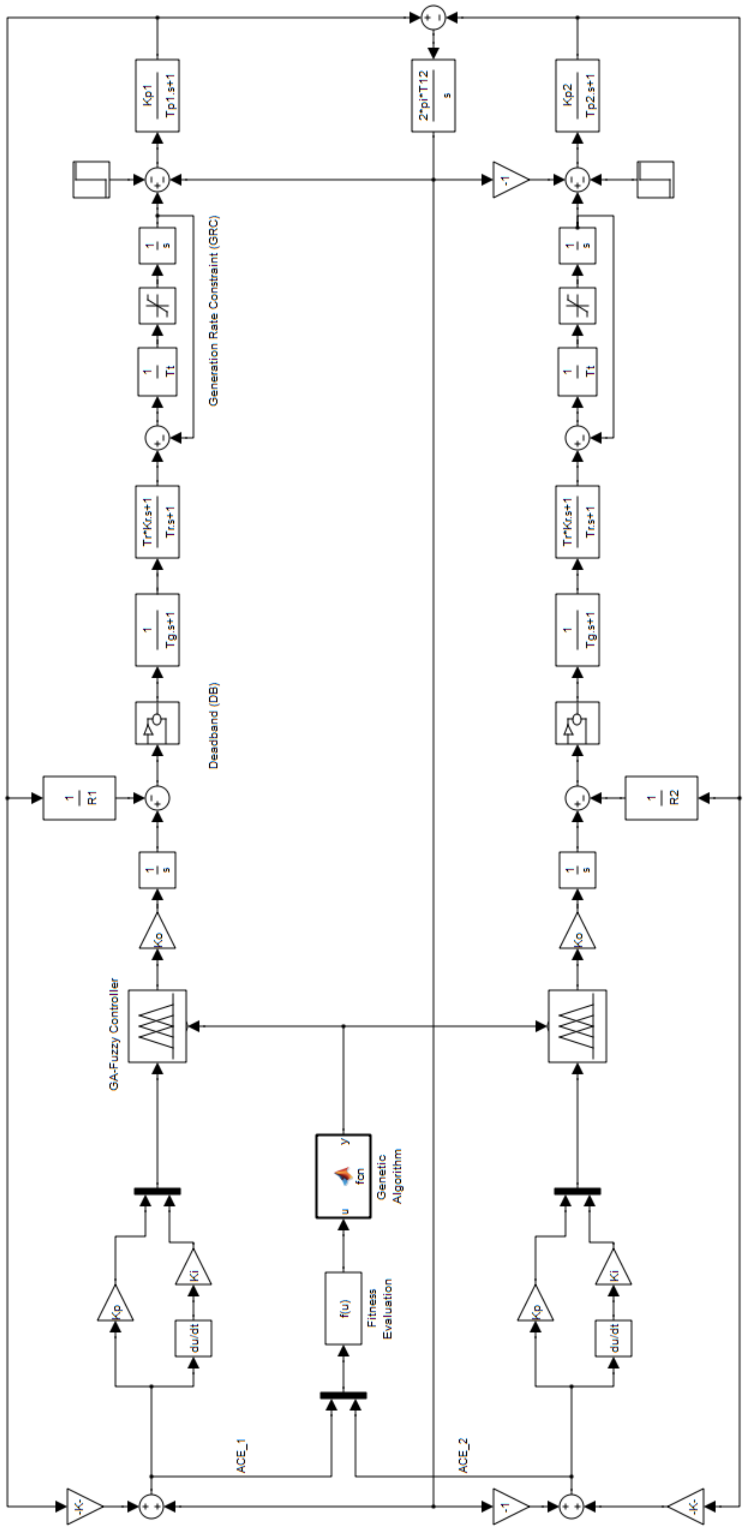

Figure 7.11: Two Area Interconnected Power System, with GA Fuzzy Controller and Non Linear Components such as Deadband and Generation Rate Constraints

related to the regulation of power, and within a multiarea power system it is important to control Tie - Line power exchanges, Power Scheduling and Load Following ability of the power utility. In order to achieve these performance demands, Frequency Control as has been noted in Chapter 2 responds to load variations on the order of a few seconds to about a few minutes in response time, while load following is of the order of a few minutes to about an hour.

Therefore initial control affect is realized by governor control within the first few seconds, AGC control within the first few minutes and models for economic dispatch and scheduling over minutes through to hours. Thus within multiarea systems, the control of Tie - Line power flows is of paramount importance, since it has an encapsulated financial objective associated with it in terms of bilateral trade agreements with neighboring control areas.

Therefore, with this in mind, the GA-Fuzzy AGC controller is to be robust to parametric changes, representative of actual power system uncertainties.

7.4.3.1 GA Tuning and Optimization for AGC Systems

Power system operation and control as applied to AGC systems play an important role in the regulation of real power, for frequency control and for the maintenance of AGC systems within optimal performance criteria. This has played a dominant role in the control of interconnected power systems by controlling Tie - Line Power flow and the control of system frequency (see section 2), both from a primary and tertiary frequency control perspective.

This is important since it lends itself to the support of neighboring control areas in the event of any load variations. Thus the goal of electrical power systems is to match system generation to the instantaneous load requirement of the interconnected electrical grid. In addition, any ill tuned control areas, in terms of AGC performance, adversely affects the performance of large interconnected power systems.

Thus, within AGC systems the health of network frequency is the primary indicator of network performance and forms the measure by which system generation performance is analyzed. Since frequency is the major common factor within the interconnection, any frequency deviation from its designated nominal operating frequency is a measure of network health. Typically the integral of frequency over time is a measure of performance.

Figure 7.12 illustrates typical performance measures as the integral of frequency and its variants evolves over a number of genetic generations. Although the performance measure is problem specific, its selection is often by design where the one main requirement for effective performance measure selection is that it uniquely represents the problem by ensuring a clear distinction between solutions, reflecting the relative strengths and weaknesses of each possible solution. By using GA for tuning, optimization and learning, the objective in AGC studies is to find a plausible AGC controller for maintaining frequency deviations close to zero as is practically possible.

Therefore this section presents results on GA tuning of AGC systems and its optimization by means of GA heuristics as applied to Fuzzy rule based systems.

7.4.3.2 AGC Simulation of GA Fuzzy Controller

Due to the heuristic nature of genetic algorithms, a feasible solution cannot always be guaranteed. This in part is motivated by the convergence properties of

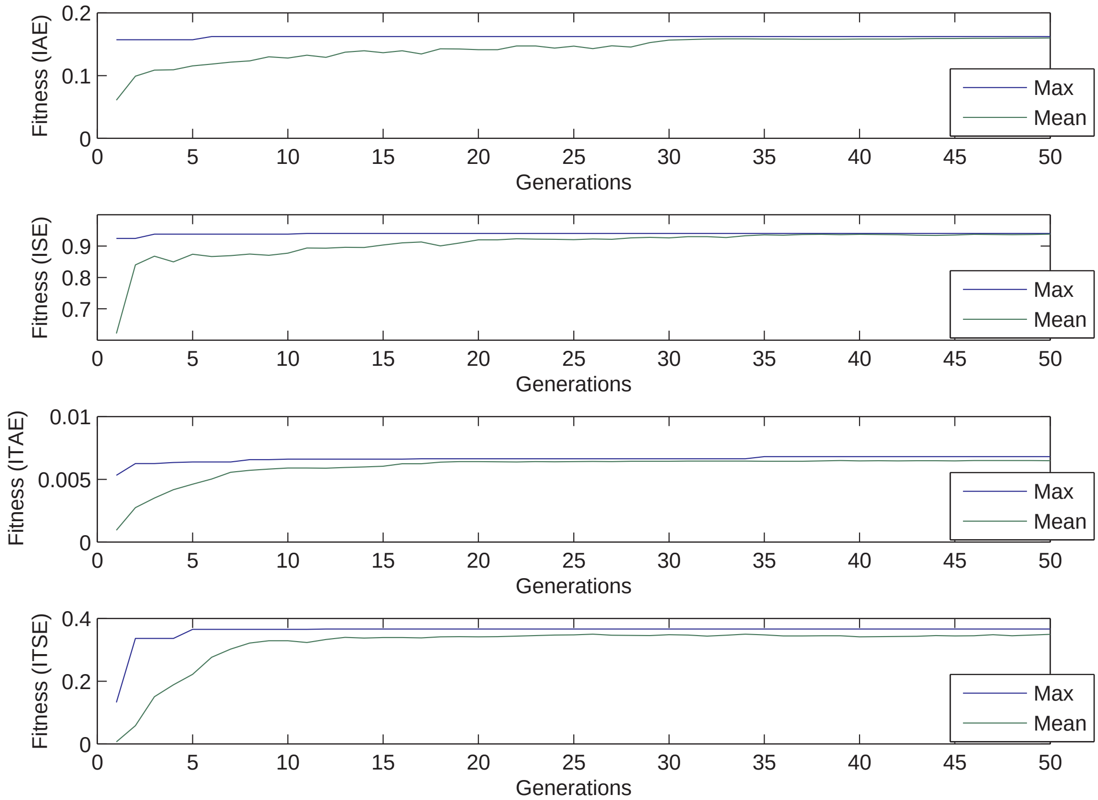

Figure 7.12: Typical Genetic Comparison of Performance Indices

the genetic algorithm, whereby a particular solution dominates the population, contributing to premature convergence and in most cases does not yield the best solution.

Therefore, in order to minimize this effect, a number of genetic runs are performed in the design of the GA - Fuzzy controller, where, in essence a number of multiple populations are maintained, and facilitates a semi parallel population of solutions (Pulido and Coello Coello (2003); Herrera (2005)). This ensures that the designed GA - Fuzzy controller performs robustly and that the final solution adequately controls the AGC process. This is illustrated in Figure 7.13, where a number of GA - Fuzzy controllers have been designed and compared to the conventional AGC controller.

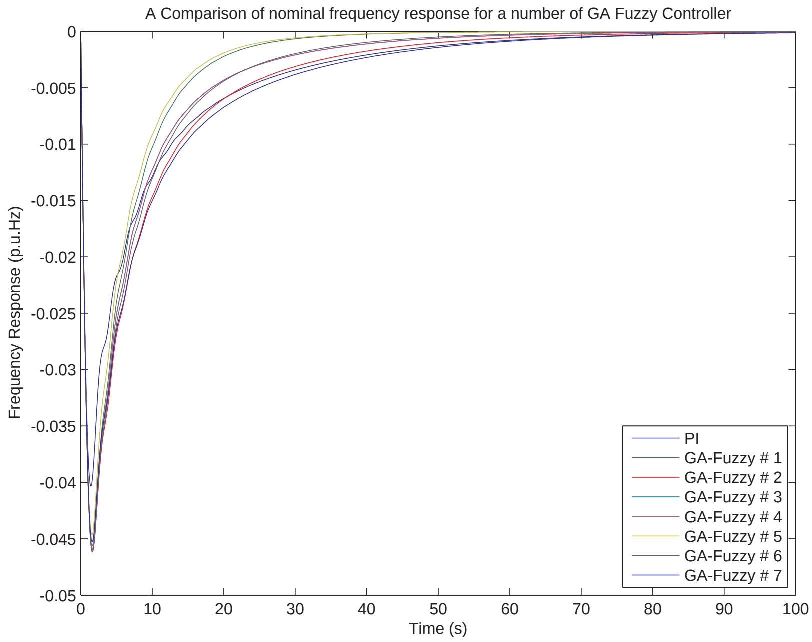

Figure 7.13: A comparison of a number of GA - Fuzzy Controllers showing the frequency response characteristic due to a load disturbance in Area 1 without DB and GRC.

It is clearly seen that favourable performances are obtained when compared with conventional PI AGC methodologies. It is immediately evident from Figure 7.13 that the performance of the GA - Fuzzy controller to load disturbances (0.01 p.u.MW) yield satisfactory transient response performance. GA - Fuzzy # 5 compares favorably in that it provides for faster zero steady state error when compared with the PI and adequately maintains good disturbance rejection properties.

Dynamic frequency response curves are shown in Figure 7.14 due to a load disturbance in control area 1 of (0.01, 0) p.u. MW, with frequency deadband. As can be seen from the transient response curves, comparing the PI controller response to that of the GA Fuzzy controller, both controllers respond in a similar fashion, ensuring that the ACE error is zero, with the GA Fuzzy controller performing favorably.

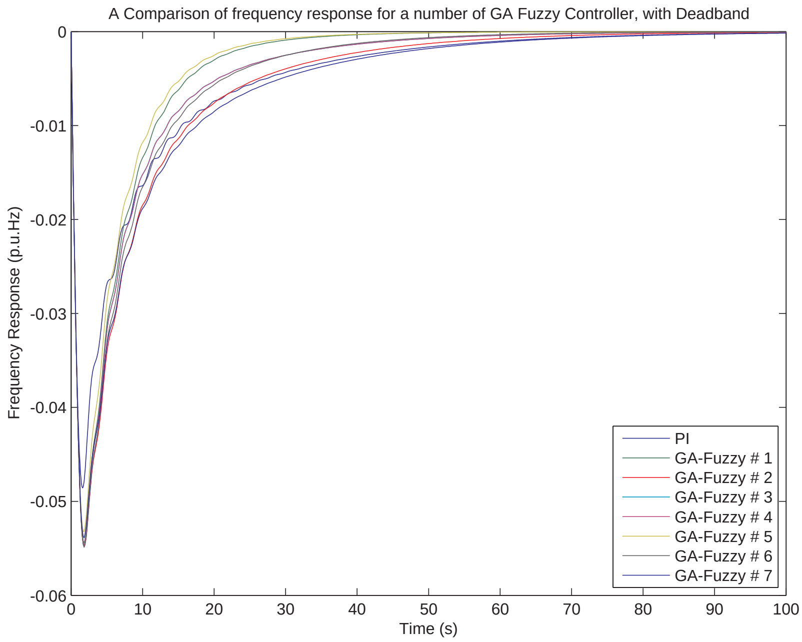

Figure 7.14: A comparison of a number of GA Fuzzy Controller showing the frequency response characteristic due to a load disturbance in Area 1, and considering governor deadband.

It is important that the response tends towards zero as quickly as possible, being robust against random load disturbances and growing power system complexity. As the complexity of the electrical network grows over time, the performance of the AGC controller deteriorates and requires continual optimization and tuning for best performance. However, the important attributes of the controller is to guarantee robust performance within the operating region of Secondary Frequency Control.

Table 7.8 tabulates the designed GA - Fuzzy controller rules (GA - Fuzzy # 5), where each row and column entry is representative of the linguistic term forming part of the encoding strategy (i.e. NB = 1, NM = 2, NS = 3, ZZ = 4, PS = 5, PM = 6 and PB = 7). The method of how the Rule Base is encoded forms an important part of how the optimized Rule Base is structured. Therefore, it is proposed to first design the rule base, then to tune the respective membership functions and then the respective scaling gains. Encoding strategies which include all components of the Rule Base system, namely the Rule Base and the Knowledge Base also exist.

Table 7.8: Optimized GA Fuzzy Rules Table (GA - Fuzzy # 5)

$\frac{d}{dt}e(t)$ \ $e(t)$	NB	NM	NS	ZZ	PS	PM	PB
NB	6	3	6	7	2	1	1
NM	3	7	1	6	2	1	3
NS	4	1	3	6	7	3	4
ZZ	1	2	4	4	4	7	4
PS	1	4	1	2	5	2	2
PM	4	3	5	7	6	6	5
PB	1	4	3	5	3	7	7

It is clearly seen from the transient response curves (Figure 7.15) that GRC has a destabilizing effect on the AGC control system (Panda et al. (2009b)). In practice, AGC controllers are typically detuned with lower overall process gain to manage GRC, however this sacrifices AGC speed of response, which forms an important component for good load disturbance rejection properties.

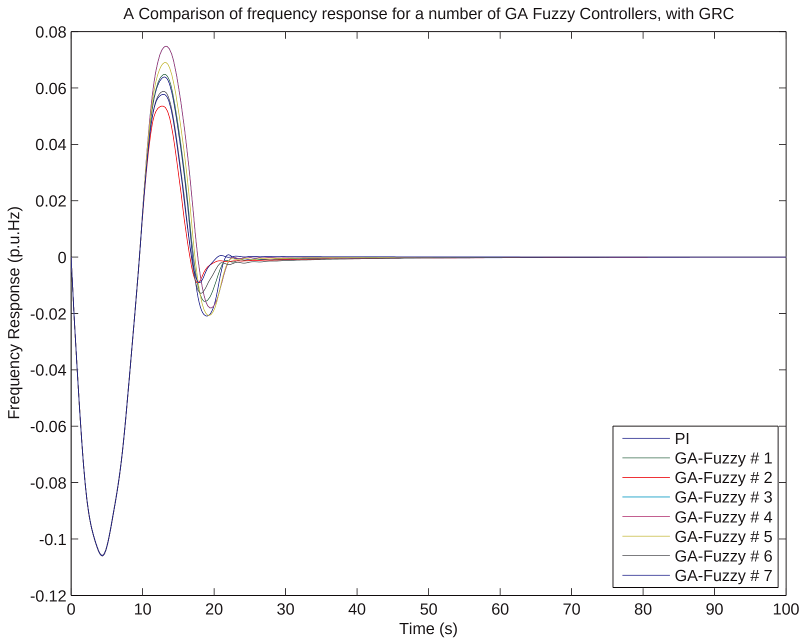

Figure 7.15: A comparison of a number of GA Fuzzy controller showing the frequency response characteristic due to a load disturbance in Area 1, and considering Generation Rate Constraint.

In addition, Figure 7.15 illustrates the performance of a number of GA - Fuzzy controllers and their influence in the presence of GRC. It is seen that the GA - Fuzzy controller consistently regulates the system frequency with zero steady state error and compares favorably with the conventional PI controller strategy. Since all GA - Fuzzy controllers (GA - Fuzzy # 1 through to 7), although different in KB and DB, their transient performances are similar, thus making them all plausible solutions. It is interesting to note, that if the GA problem is formulated correctly with an appropriate encoding strategy, the GA consistently provides plausible solutions.

7.4.3.3 GA - Fuzzy Controller Robustness and Parametric Model Variation

Over the past few decades, continual research has been focused on robust AGC control methodologies (Shayeghi et al. (2009); Bevrani (2011)) and has been applied to various technical areas for power plant control and operation. In conventional AGC controller design techniques, a model based approach has typically been the industrial norm and is based on human experience and mathematical modeling techniques (Peet and Leung (1995); Egido et al. (2004); Barbieri and Lastra (2007)).

However, AGC controllers based emphatically on mathematical modeling does not provide adequate solutions for real world application, where power systems and electrical networks are continuously increasing in size and where the complexity of electrical interconnections are changing (Taher and Hematti (2008); Taher et al. (2008)). This is particularly motivated by insufficient technical information of process dynamics, limited or simplified process models and unknown or neglected system modes (Tan and Xu (2009)). Hence the performance of the AGC controller is evaluated in the presence of parametric uncertainty as a measure to contrast controller performance.

Figures 7.16 and 7.18 shows the performance of the GA - Fuzzy controller for parametric model variations, where it is immediately apparent that the GA - Fuzzy controller is more robust to model uncertainty. This is inline with the expectation of advanced techniques such as GA - Fuzzy AGC control methodologies, where evolutionary methods of optimization proves beneficial for controller design. Conventional PI methods are unstable as the uncertainty grows and requires continual controller tuning to maintain performance requirements.

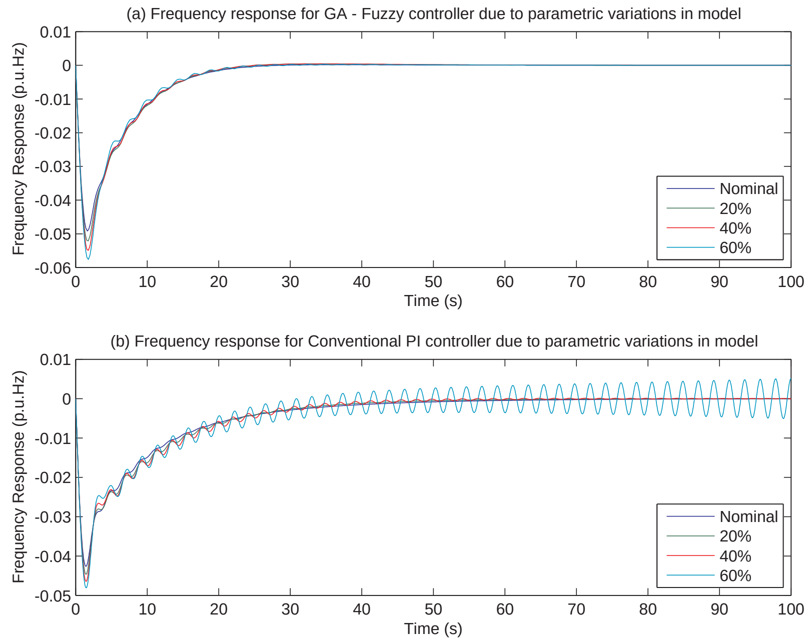

Figure 7.16: Nominal performance due to Model Parametric Variation for various uncertainty values, (a) GA - Fuzzy Controller response, (b) Conventional PI Controller response.

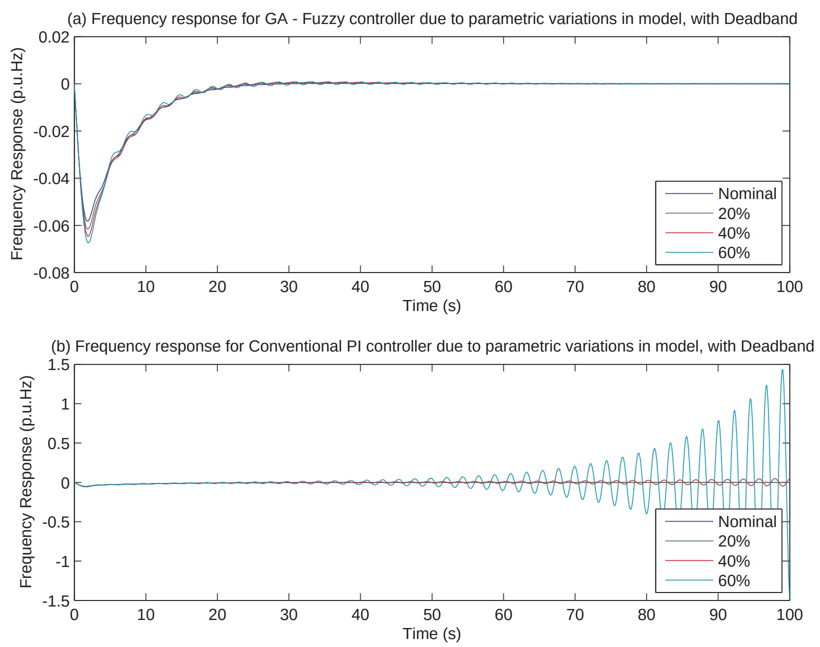

Figure 7.17: Frequency response comparison due to Model Parametric Variation for various uncertainty values considering deadband, (a) GA - Fuzzy Controller response, (b) Conventional PI Controller response.

Figure 7.18 shows the GA - Fuzzy controller's performance due to an electrical load disturbance in presence of generation rate constraint. Generation rate constraint is one of the important limiting factors in the transient response of the generating unit and have a significant impact on AGC controller performance and for frequency response studies. The figure (7.18) illustrates that GRC has a destabilizing effect on the system, and both AGC controllers, namely PI and GA - Fuzzy controller are sensitive to GRC variations (Panda et al. (2009b); Anand and Jeyakumar (2009a)).

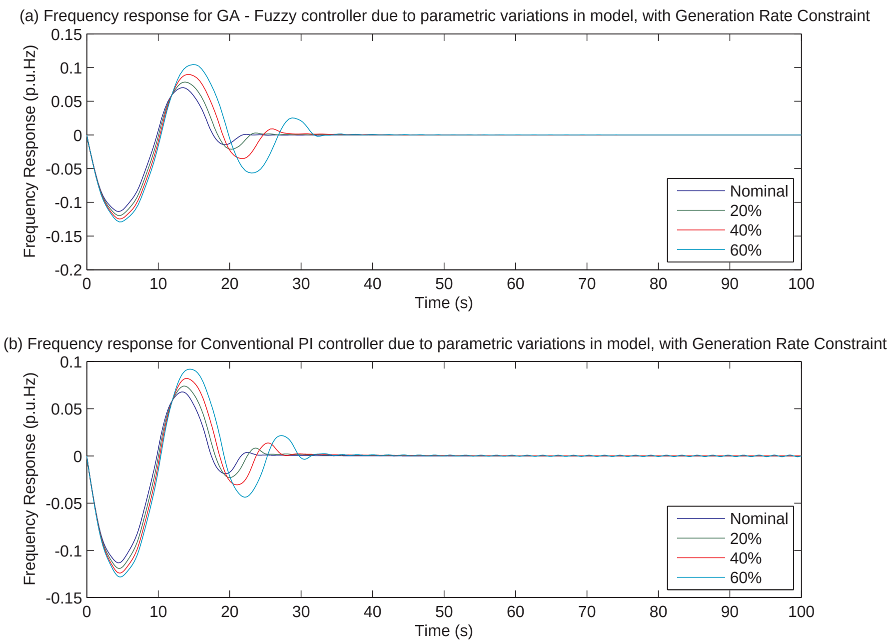

Figure 7.18: Frequency response comparison due to Model Parametric Variation for various uncertainty values considering Generation Rate Constraint, (a) GA Fuzzy Controller response, (b) Conventional PI Controller response.

7.4.3.4 Exploration versus Exploitation of Search Space

Exploration and Exploitation are two of the main focus areas of GFRBS. In Exploration, the adaptation and learning abilities of the genetic algorithm are effectively harnessed in the pursuit of finding new solutions to the problem (Ng and Lim (2002)). This is typically achieved by adjustment of the mutation genetic operator in the GA.

Exploitation on the other hand refers to the ability of the heuristic algorithm to improved on genetic offspring through reproduction primarily and selection of the strongest individual, to dominate the direction of the search results. Both methods, namely Exploration and Exploitation are fundamental concepts in GRBS (Lin and Jou (2000); Ji-lin et al. (2006)).

This has invariably lead to modifications to the typical implementations of evolutionary algorithms (GA's), to enhance the characteristic traits of the GA in finding solutions. In order to achieve these enhancements, there are primarily two areas of greatest influence of where this can be achieved.

7.5 On Using Bezier Surface Encoding for GFRBS

One of the most fundamental functions in GA-Fuzzy controller design is the rationalization of the chromosome encoding. This typically has followed a structure where each fuzzy rule is coded sequentially as a binary string, where genetic operators such as crossover and mutation would perform its reproductive functions (Janabi-Sharifi (2002); Adriansyah and Amin (2005); Bousserhane et al. (2006); Cai and Rad (2007)).

However, one of the drawbacks of this technique is that it is dependent upon the number of rules, which when there is a substantial number of rules, the genetic search space would increase accordingly (Magdalena (1997); Sharkawy and Others (2010)). In addition the size of the binary chromosome would also increase requiring increased computational time and encoding complexity.

Therefore, this work focuses on applying Bezier Surfaces as a means of representing the fuzzy control surface directly. This is particularly motivated by the ease by which Bezier Surfaces are represented and secondly by the relatively small number of control points used to represent the Bezier Surface in contrast to the number of fuzzy rules (Zhuang and Wongsoontorn (2006)).

By means of illustration, a fuzzy controller with 49 fuzzy rules would require a binary string representation of the 49 rules, whereas a Bezier Surface represented by 16 control points would require a binary string representative of these 16 control points. The Bezier Surface and the Fuzzy Control Surface is synonymous in that the Bezier Surface is the representation of the control surface.

7.5.1 Chromosome Encoding by means of the Bezier Surface

Parametric curves or surfaces such as Bezier Surfaces is an extension of Bezier Curves which was invented specifically for the car manufacturing industry by Pierre Bezier in the early 1960s for the development of curves for shape design (Zhuang and Wongsoontorn (2006)). These curves are intuitive and lend itself to a large variety of curves or surface shapes based on the manipulation of only a few control points. In addition, these curves are smooth and have an aesthetic appeal which may be of benefit to Fuzzy Logic controller design from a surface perspective, ensuring that control functions are not erratic. By definition a Bezier Surface $S(u, v)$ is as shown in Equation 7.8.

$$S(u, v) = \sum_{i=0}^{m} \sum_{j=0}^{n} P_{ij} * B_i^m(u) * B_j^n(v) \tag{7.8}$$

Where $B_i^m(u)$ and $B_j^n(v)$ represent the Bernstein polynomials with degree m and n in the variables of u and v respectively. P_{ij} is an m by n matrix of control points $P_{ij} \in \Re^3$ with $i = 0, 1, , m$ and $j = 0, 1, , n$. As can be seen, the Bezier Surface is a combination of the control points and the product of the Bernstein polynomials; this creates the terms of the surface. Thus the Bezier Surface is a parametric surface based on the control points.

The Bernstein polynomials are defined as is shown in Equation 7.9. Figure 7.19 illustrates the encoding of the FLC including is scaling gains and fuzzy control surface. Each allele is represented a binary string.

$$B_i^m(u) = \begin{pmatrix} m \\ i \end{pmatrix} (1-u)^{(m-i)} * u^i \tag{7.9}$$

In Equation 7.9, $\begin{pmatrix} m \\ i \end{pmatrix} = \frac{m!}{i!(m-i)!}$.

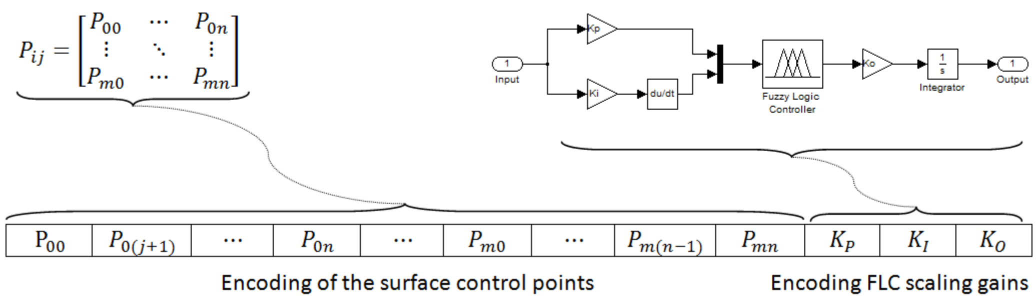

Figure 7.19: Illustration of the Chromosome Encoding of the Bezier Polynomial Coefficients, Control Points and Scaling Gains

The optimal control points matrix P_{ij} is shown below (Equation 7.10), manipulating the control points would adjust the fuzzy control surface accordingly, this indirectly modifies the Rule Base as well.

$$P_{ij} = \begin{bmatrix} 0.8571 & 0.4386 & -1.1868 & -0.8933 \\ 1.3188 & 0.1876 & -0.1465 & -0.4923 \\ 0.7555 & 0.0411 & 0.1055 & -0.6919 \\ 0.0154 & -1.2106 & 0.1221 & 0.7656 \end{bmatrix} \tag{7.10}$$

As can be seen from the transient response curves (Figure 7.20), comparing the PI controller response to that the GA Fuzzy controller, both controllers perform similarly, however, the GA Fuzzy controller is more robust in the presence of Generation Rate Constraint (GRC).

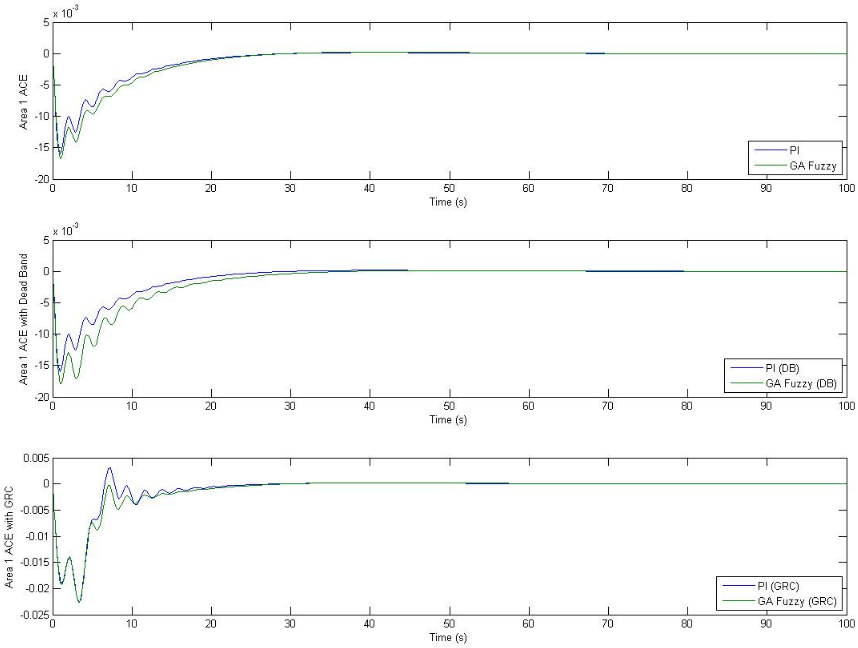

Figure 7.20: Transient Response Curves for Optimized GA-Fuzzy Controller with Encoding by a Bezier Surface, showing Area frequency response to load disturbance.

It is an important characteristic for controllers to be robust in the presence of parametric variation and model uncertainty. In the case of AGC, power system dynamics are constantly changing, loads are changed randomly, requiring robust AGC performance. With GRC, each generating unit forming part of the network has physical rate limits and thus the ramping of the machine is limited.

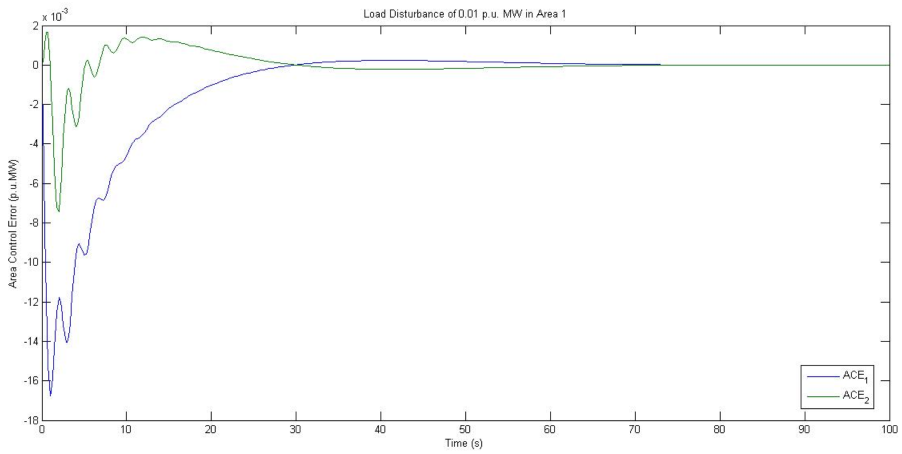

Figure 7.21: Area Control Error response to load disturbance using Bezier Surface Encoding

7.6 Summary of Chapter 7

Chapter 7 focused on the design and analysis of a GA - Fuzzy AGC controller for a large interconnected power system. The chapter described the genetic tuning and learning of Fuzzy Rule Based systems by means of Genetic Algorithms, and how GA's can be used as a good global near minimum optimization and learning tool.

The chapter highlighted the importance of chromosome encoding and emphasized the need for effective fitness function selection. This plays a significant role in GA - Fuzzy controller design.

The chapter concludes by illustrating transient response curves and shows that comparably favourable results are obtained, when compared to conventional AGC controller design strategies. The chapter finally discusses concepts such as Exploration and Exploitation and how these can be of benefit to GA - Fuzzy

Controller design.

This chapter has also illustrated the application of Bezier Surfaces as an encoding mechanism for GA - Fuzzy Controller design. Results show that fuzzy control rules can be considerably reduced by this encoding mechanism, and hence simplifies the search space for controller optimization. Transient performance characteristics are favourable.

Chapter 8

Conclusions and Future Work

The Automatic Generation Control (AGC) problem of large Interconnected Power Systems is discussed in this thesis, especially the design of AGC controllers and how Soft Computing as applied under the auspices of GA Fuzzy Controller design techniques can be applied as a viable AGC control strategy.

Therefore, in this research, emphasis has been placed on understanding the interactions of GFRBS, their specific methods for encoding a problem and on how these techniques can be effectively applied to the study of Secondary Frequency Control for dynamic frequency response studies.

Although AGC has a relatively long history of application and have been part of power system technology since the design of centrally controlled power systems, there is a continual need for improved AGC performance, especially when conventional methods fail or deteriorating performance is observed by prevailing control strategies. It is for this reason that modern controller design techniques are relevant and applicable for the closed loop design of AGC systems.

It was noted in Chapter 1 that AGC control is a challenging problem for modern power utilities, firstly from a performance perspective to guarantee a reliable supply and quality of electrical energy but more importantly as well to ensure robustness of performance amidst the changing dynamic environment of electrical power networks and systems.

The dynamic changes experienced throughout the life cycle of power systems have many contributing factors, in part attributed to unknown knowledge of system behavior, neglected process dynamics and a limited knowledge of system interactions, which makes modeling for AGC systems particularly trying.

This invariably introduces the notion of vagueness and imprecision and how best these concepts can be modeled within modern AGC design. Although modern practice for AGC control rests strongly upon the shoulders of the classical PI or PID type control law, modern techniques for AGC design which encapsulates imprecision and uncertainty is gaining continual support.

One technique as contained and described within this thesis is GFRBS and is hereafter described with key observations and how best it can be applied for AGC.

8.1 General Discussion on GFRBS

In order to appreciate GFRBS, an in depth knowledge of Rule Based Systems is needed, in particular the merits of Heuristic Search methods and its variants are investigated in Chapter 4, while Fuzzy Logic Control and knowledge based systems are examined in Chapter 5. These Chapters have formed the foundation for discussions on Soft Computing and Genetic Fuzzy Systems as contained within Chapter 6.

8.1.1 Genetic Algorithms

From within an engineering context and a systems design application perspective, Genetic Algorithms have been proven to be a reliable and robust method of Heuristic Search (Chapter 4) for finding solutions based on population dynamics.

In particular the learning ability of Genetic Algorithms and applied to GFRBS is marked by great success and widespread application. However, one attribute as described in Chapter 4 and reaffirmed by Chapter 7 which decreases the algorithm's convergence to a global optimal solution, is that GAs does not always guarantee an appropriate solution.

This invariably then requires problem re-formulation and adjustment, either by changing Crossover and Mutation probabilities P_C and P_M respectively or modifying the fitness function to represent the problem performance criteria more holistically. In some cases it may be necessary to rerun the algorithm until an acceptable solution is found.

In addition, GAs utilize huge amounts of computational resources, especially by the calculation of the fitness function. However, modern computational systems with embedded multiprocessor platforms substantially reduce computational time for algorithm execution. This may warrant more effective methods of fitness function evaluation, especially when the problem under investigation is complex, requiring rigorous mathematical calculation or simulation.

Nonetheless, Genetic Algorithms in the form of the Simple Genetic Algorithm (SGA) has performed very well in finding solutions for the GA - Fuzzy AGC controller.

8.1.2 Strengths and Weaknesses of GFRBS

As described by Chapter 6, especially Section 6.3, there are conventionally three approaches to GFRBS, namely the Michigan, the Pittsburgh and the Iterative Approaches to Genetic Fuzzy Rule Base Systems. All other GFRBS are either variants of the three main categories, or employ different encoding mechanisms for improved performance.

The strength of the Michigan Approach is that it is iterative (similar to the Iterative GFRBS) and lends itself to online or real time application for control or problem solving. However, the coding of the Michigan Approach can be a daunting task when started from the beginning, and is prone to error, without substantial debugging. Therefore, for the application of the Michigan Approach application use of commercial implementations of the algorithm would be beneficial in order to save programming time.

In addition to this, because the Michigan Approach is online and because of genetic evolution and learning, stricter control of the Effector control actions are warranted, especially for real time control of AGC systems. Although there are control strategies which mitigates this effect, additional control algorithms may be required for this to be effectively realized in practice. This stems primarily from the fact that learning occurs over time, where weaker individuals are penalized and receive an equivalent reward.

Therefore, being an offline learning method, the Pittsburgh GFRBS approach is more attractive and allows for designed intervention in finding and validation of controller actions. This is particularly important in AGC controller design, where it is mandatory to ensure that all control actions distributed to generating units under control of AGC are well within operational boundaries.

Furthermore, the Pittsburgh Approach more directly employs the standard SGA algorithm structure, making the algorithm very versatile with minimal modification, and can be applied to a wide spectrum of control problems, where the problem is appropriately formulated according to the dictates of the design objective.

8.1.3 GA - Fuzzy AGC Controller Design

The premise of the thesis as described by Section 1.2 and further detailed in Chapter 7 is to show the plausibility of GA - Fuzzy Controller design for AGC control systems. Because the process of control optimization and tuning is iterative and continual evaluation of closed performance is required, the application of GFRBS is an attractive method for controller design.

When considering Fuzzy Logic Controllers, human knowledge of the process is tabulated as a set of Rules which governs a set of control actions, however finding the specific control rules which globally optimizes closed loop performance can be difficult to obtain. This is especially difficult when expert knowledge of the system is not known.

Therefore GA - Fuzzy AGC systems have been investigated. It is found that GA - Fuzzy AGC systems are comparable to conventional controller methods, both in terms of robust performance and nominally returning the Area Control Error to zero following significant load variations. However, it is also found that the GA - Fuzzy AGC controller is more robust to nonlinearities such as Generation Rate Constraint (GRC).

This is an important finding, since Generation Rate Constraint tends to destabilize frequency performance and has a negative effect on network performance as a whole, both in terms of scheduled power exchanges and generating unit response.

Problem formulation and chromosome encoding is probably one of the most important factors to be considered in any GA - Fuzzy Controller design exercise, since this to a large extent defines the measure of success of the design. Various encoding methods can be used, with no prescribed directive of how the encoding should be performed, suffice to say that it needs to be representative of the controller structure, its internal functioning and and that it sufficiently describes the control problem.

The extension and application of Genetic Fuzzy Rule Based Systems (GFRBS) to all spheres of engineering analysis and design can be accomplished fairly readily by appropriate problem formulation and design of the problem specific objective function. The methods and techniques discussed within this document outlines minimal processes for GFRBS design and future work will be focused on more generalized formulations for more global application.

8.2 Summary of Contributions

This work made contributions to the international literary community by the acceptance of three (3) technical papers accepted for publication, as summarized below. Each of the papers contain certain aspects of the contents of this thesis and have contributed to the body knowledge on GFRBS, specifically applied to the Automatic Generation Control problem of large interconnected power systems.

8.2.1 Application of GA-Fuzzy Controller Design to Automatic Generation Control

Portions of Chapters 1, 2, 4, 5, 6 and 7 have appeared in the following paper:

> Application of GA-Fuzzy Controller Design to Automatic Generation Control, Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, Third International Workshop On Advanced Computational Intelligence (IWACI2010).

8.2.2 A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems

Large portions of Chapters 2, 6 and 7 have appeared in the following paper:

> "A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems", Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, Fourth International Workshop On Advanced Computational Intelligence (IWACI2011).

8.2.3 On the application of Bezier Surfaces for GA - Fuzzy controller design for use in Automatic Generation Control

Large portions of Chapters 2, 6 and 7 have appeared in the following paper:

> "On the application of Bezier Surfaces for GA - Fuzzy controller design for use in Automatic Generation Control", Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, 2nd International Conference on Advances in Energy Engineering (ICAEE2011).

8.2.4 Dynamic governor model development for grid code compliance in South Africa

"Dynamic governor model development for grid code compliance in South Africa", Graeme Chown, Craig Lucas, Mike Coker and Rahul Desai - PPA Energy, Jean vd Merwe and Christelle - MTech, Bunty Kiremire, Craig Boesack, Preshen Moodley and Albert Smit - Eskom. To be submitted to Energize 2012.

8.3 Future Work

The field of GFRBS, its methods and application is of relevance to modern power systems today, both from a regulation perspective of generating units and for supervisory control and monitoring of secondary control loops. Its application is widespread and continues to grow through the application of new technology. However, there are areas of research which have not matured and would form an area for future work and basis for further study.

8.3.1 Exploring Alternative Methods of Chromosome Encoding

Different methods of chromosome encoding for Genetic Algorithms have a direct impact on the performance of the GA - Fuzzy system. A problem that is poorly encoded, or does not adequately reflect the controller structure would lead to a poorly designed controller. Therefore, a comparative analysis of different techniques for chromosome encoding could lead to a more generally accepted guideline for GFRBS system design. It would highlight the advantages and disadvantages of each encoding method and its respective impact on overall system performance.

8.3.2 Evaluate Alternative Heuristic Search Methods

There are a number heuristic search methods which could be employed as a learning and adaptation tool for GFRBS, each with their peculiar strengths and weakness. Since Genetic Algorithms perform well in general, it does suffer from premature convergence in certain instances and on occasion does not yield satisfactory results. This motivates the need for more advanced GA algorithms, such Niching GAs which could be applied to multi-modal problems. In addition, a comparative analysis of other heuristic search methods, such as Particle Swarm Optimization, Ant Colony Optimization and Simulated Annealing as applied to GFRBS may be of interest.

8.3.3 Influences of Renewable Energy Sources on AGC Performance

Although this thesis focused specifically on a two area interconnection, it neglected the influence of renewable energy sources such as Solar and Wind energy on AGC Systems. Since the electrical network is constrained and because there is an ever increasing requirement for more energy efficient systems, Renewable Energy Sources play a more dominate role in power regulation, since more renewable energy sources are being connected to the electrical grid. However, this form of energy is highly dependent upon natural elements such as sunlight and wind, which varies randomly throughout the day and hence have a significant effect on AGC controller performance.

It would therefore be beneficial to analyze this performance and to determine what the new guidelines for AGC controller design in such cases would be.

Appendices

Appendix A

Previously Published Work

A.1 Application of GA-Fuzzy Controller Design to Automatic Generation Control

This is the Citations section of the document. Large portions of Chapters 1 and 2 have appeared in the following papers:

> Application of GA-Fuzzy Controller Design to Automatic Generation Control, Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, Third International Workshop On Advanced Computational Intelligence (IWACI2010).

Application of GA-Fuzzy Controller Design to Automatic Generation Control

Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo

Abstract— **The design of fuzzy logic controllers involves the rationalization of the Fuzzy Inferencing Rules and the appropriate selection of the input and output membership functions. This typically have been achieved by the application of expert knowledge of plant operation and by the appropriate selection of weighting gains. This paper presents the fuzzy logic controller with certain parameters which can be optimized to suite the specific application under control. Traditionally, this has been performed manually by design. However, contained within this study, Genetic Algorithms are applied as a plausible fuzzy logic controller optimizer (Genetic - Fuzzy Controller), and is applied to the Automatic Generation Control problem of large interconnected power systems.**

I. Introduction

CONVENTIONAL Proportional and Integral (PI) controllers as applied to Automatic Generation Control (AGC) have been studied extensively as contained within the literature and have been successfully applied to many large scale interconnected power systems [1], [2], [3]. In this paper, the design of Automatic Generation Controllers are studied and evaluated, in particular the control methodology employed is that of Genetic - Fuzzy Control.

The reliability and availability of large interconnected power systems are crucial to national infrastructure, both in terms of meeting quality of supply demands and on ensuring that the load demand balance is maintained at all times. Especially when considering that quality of electrical supply, which is viewed primarily by the stability of system frequency and by maintaining electrical power, it is paramount, that power utilities achieve good control of their generating units. This multi-objective control function is achieved by AGC, which forms a supervisory controller on all generating units contained within the power utility.

In this research, we take a deeper look into AGC and the application of Genetic - Fuzzy Control system technology as a viable control strategy for large interconnected power systems. The attraction of Genetic - Fuzzy Control technology for this application stems from the fact that Genetic based adaptation and robustness properties, which is an inherent characteristic of this method, may prove beneficial for generation control purposes.

Modern power systems are typically controlled by a proportional and integral type control law, which aims at minimizing the Area Control Error (ACE) of the power system, thereby maintaining system frequency and tie - line power exchanges. Recent research effort have focused on the application of fuzzy logic control [4], hybrid artificial neural network control strategies [5] for the application of AGC, in which, improvements in control strategy and control system performance is reported.

Therefore, the present study focuses on applying GA-Fuzzy controller design techniques as applied to modern AGC of large interconnected power systems. The main contribution of this work is to review current literature and to analyze the performance of the designed controller by means of simulation. Section 2 presents the literature review, followed by a discussion on GA-Fuzzy design (Section 3). In Section 4 simulation results are presented.

Craig D. Boesack is with the School of Electrical & Information Engineering, University of the Witwatersrand, Johannesburg, South Africa (email: craig.boesack@tiscali.co.za).

Tshilidzi Marwala is with the School of Electrical Engineering, University of Johannesburg, Johannesburg, South Africa (email: tmarwala@uj.co.za).

Fulufhelo V. Nelwamondo is with the CSIR Modelling and Digital Science Department, CSIR, Pretoria, South Africa (email: fnelwamondo@csir.co.za).

II. A Literature Review

In this section, a review of the current literature is performed. It focuses primarily on AGC and the application of Genetic - Fuzzy Controller design techniques as contained within the literature. The primary research methodology employed is that of answering the following questions which forms part of the key design objectives for the design rationale.

1) What is AGC and why is it an important function for large interconnected power systems?
2) What are the key associated problems with AGC as found within industry?
3) What are the design objectives for AGC?
4) In terms of controller design, it is proposed to apply Genetic - Fuzzy controller design methodologies as a proposed solution to the AGC problem. Fundamental questions are as follows.
   a) How are Genetic - Fuzzy controllers designed and what are the key design considerations?
   b) Since Genetic Algorithms are based on random selection and probabilistic search methods, how is the stability of the system guaranteed especially when Genetic - Fuzzy controllers are applied?
5) How does Genetic Fuzzy controllers compare with conventional controller techniques in terms of performance and robustness, what is its advantages and limitations when applied to AGC?

These questions forms the basis of the literature review section and is aimed at establishing the required theoretical and practical knowledge for applying Genetic - Fuzzy controllers to AGC. Therefore, the discussion begins by describing AGC, followed by an account of fuzzy logic controllers and the operation of Genetic Algorithms.

A. Automatic Generation Control

Automatic Generation Control (AGC) can be considered as a supervisory control strategy for large interconnected power systems, with the express aim to regulate system frequency and tie-line interchange power [1]. This forms an important function within modern power utilities and forms a primary business objective, especially when viewed from a power regulatory perspective.

Interconnected power systems can be divided in sections known as control areas which represents a coherent group of electrical Generating Units operating under synchronized frequency conditions. In each control area, the AGC controller strives to meet its scheduled demand by regulating each Generating Unit up or down (controlled by raise or lower pulses) according to its scheduled load demand. The load demand depends upon the system frequency Δf and its relative power exchange deviations ΔP_{Tie} with its neighboring control areas [6]. This is graphically illustrated in figure 1.

The dynamic behavior of large interconnected power systems is dependent upon system disturbances, uncertainties due to loading requirements and upon the need to supply electricity of good quality in terms frequency control [1]. Therefore, within an interconnected power system, the network frequency is an important indication of the power mismatch between energy demand and supply. This inherently places strict performance demands upon the AGC controller, not only to maintain good disturbance rejection properties, but also to be robust in terms of controller design and also to exhibit good regulatory performance [7].

1) Generating Unit Governing and Control: By considering typical Generating Units which are controlled by turbine governing systems upon load disturbances does not yield a zero steady state error for system frequency. In fact, as the loading on the electrical network increases, the frequency tends to decrease, due to the increased energy demand and vice versa (as the loading decreases the frequency tends to increase). This implies that there needs to be a continuous energy balance in terms electrical demand and supply.

Therefore, due to governor action there is an immediate governing response to frequency deviations, however, this does not return the system frequency to its nominal value. This is known as primary frequency control. However, in order to return the frequency to its nominal value, secondary frequency control is required or AGC.

2) Conventional AGC Control: Conventional control approaches to solving the AGC problem has been based on tie-line bias control [8], [1] and by making use of the classical PI controller strategy. In this approach, corrections due to frequency deviations Δf are made via the area frequency response characteristic β. This is in turn used to form the the Area Control Error (ACE) as described by the equation 1 below, where ΔP_{Tie} represents the tie-line interchange power. The subscript i denotes the i^{th} control area within the interconnected power system.

The equation,

$$ACE_i = \Delta P_{Tie_i} + \beta_i * \Delta f_i \tag{1}$$

is the Area Control Error (ACE) where, $\Delta P_{Tie_i} = P_{Tie_i} - P_{Tie_0}$ and $\Delta f_i = f_i - f_0$.

Effectively the ACE manages the power frequency balance in order to maintain system frequency by manipulating system power. The Frequency Bias factor $-10B$ depends upon the system capacity and size of the generating electrical network, and is synonymous to the area frequency response characteristic β. In conventional Tie-Line Bias Control it is recommended that $-10B = \beta$ [8], in that it would tend to reject internal area disturbances.

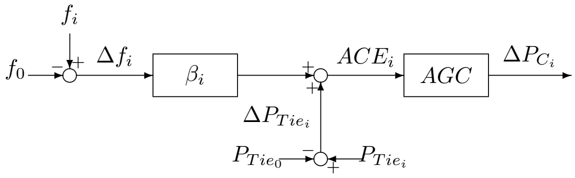

Fig. 1. Conventional Tie-Line Bias Control for AGC

The term ΔP_{C_i} represents the power demand required by all Generating Units participating within AGC control. This signal is proportioned accordingly by means of the capabilities of the Units in terms of power generation limits and are proportioned by means of participation factors.

3) AGC Controller Design Approaches: Contained within the literature there are many controller design methodologies which have been applied to the Automatic Generation Control problem [1]. The studies presented have focused on classical approaches such as the PI controller design methods to the application of more robust controller design theories, such as H_{inf} Optimal Control. The present study will therefore highlight a few of these design methods and will expound on their application to AGC.

The conventional AGC controller is based on the classical Proportional and Integral (PI) controller structure. This can be written as follows, where K_P and K_I represent the Proportional and Integral controller gains respectively.

$$\Delta P_{C_i} = K_P * ACE_i + K_I * \int ACE_i dt \tag{2}$$

Typically, the controller parameters (K_P and K_I) are designed conservatively to meet the stated performance objectives in terms of robustness and system stability. This is of importance to the interconnected power system since it ensures good quality of frequency and power supply to the grid.

More recently, fuzzy logic controller design techniques have been applied [9] and [10]. These techniques provides superior performance as stated within the literature in terms of robust performance, particularly because the nature of these techniques considers design uncertainty.

Moreover, robust controller design techniques have also been applied to the AGC control problem. These include Variable Structure Control [2], [11], Genetic Fuzzy Gain Scheduling [6], [9], techniques based on evolutionary optimization [11], [12].

Apart from the conventional controller design criteria (such as robust performance and stability), the AGC controller design aims at maintaining adequate load rejection regulation, as well as minimizing the Generating Units movement to the control demand.This minimizes production costs. In addition, the importance of this to power utilities is that it guarantees substantial production cost savings, reducing routine maintenance due to wear and tear (caused by Unit cycling) but more importantly it aims at meeting the business objectives of the power utility.

B. The Design of Fuzzy Logic Controllers

The design of feedback controllers are aimed at controlling a plant process at its nominal process parameters. Typically these controllers are in the form of a mathematical equation which categorically depends upon a known process plant model, which calculates the desired control action.

Fuzzy logic controllers on the contrary apply expert knowledge of the plant dynamics and formulates control action in the form of linguistic terms. This technique of control was first introduced by Lofti A. Zadeh [13] and have found wide spread industrial application. Figure 2 shows the structure of the fuzzy logic controller.

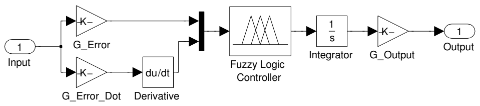

Fig. 2. Fuzzy Logic Controller

Fuzzy logic controllers (FLC) are based on the following elements:

- Fuzzification, fuzzification is the process of converting crisp process variables into linguistic variables.
- Rule Base & Inference Engine, the rule base (a set of if and then statements) and the inference engine is the processing engine for interpreting expert knowledge and is thus the decision making mechanism.
- Defuzzification, defuzzification is the process of converting linguistic variables into crisp process variables.

It is interesting to note that FLC controller design tries to express human behavior and human knowledge of the plant, transcribing it into a control signal for process control. This provides a design methodology available to the control engineer for design versatility, bringing about robustness of control.

1) On the Design of Fuzzy Logic Controllers: The process of fuzzy logic controller design involves the following basic procedural steps. These steps typically are iterated a few times in order to optimize the performance of the controller, for stated performance criteria.

2) Input Membership Functions and Fuzzification: The translation of crisp process variables into linguistic terms is known as Fuzzification. In this process, Input Membership functions are used to convert the crisp variable into a parameter over the range 0 to 1 which is known as the universe of discourse. Typically, the functions are described as triangular functions, in part due to its simplicity of design. However, more complex functions can also be chosen.

3) Fuzzy Inferencing Rules and Engine: The Fuzzy inferencing rules and engine is the decision making engine of the fuzzy logic controller. The operation of the fuzzy inference engine is well documented within the literature [14], [15]. However, the description given below focuses on the basic principles of the fuzzy logic controller. The fuzzy decision making process typically involves expressing the control problem in the form IF and Then statements. This is illustrated by expressing the Rule as,

IF Error is Zero ***And*** Change In Error is Zero ***Then*** Output Is Zero.

Typically there would be a number of Rules each describing the required control action for given set of input (process) conditions. In addition, there are also Fuzzy operators such as Or and And functions, Min and Max functions for enhancing the control operation.

4) Output Membership Functions and Defuzzification: The process of Defuzzification is the process of converting the required control as determined by the inferencing engine into crisp controller outputs. Defuzzification could therefore be described as a translation from a Fuzzy description of the process control into a crisp representation for control.

C. The Theory of Genetic Algorithms

Genetic Algorithms are based on Darwins theory of natural selection and survival of the fittest. Primarily a heuristic optimization technique, it has found application within a wide area of industry [16], [17]. This is in part due to the fact that Genetic Algorithms search for the most optimal solution (fittest individual) from a global perspective but more importantly, it provides a mechanism by which solutions can be found to complex optimization problems fairly quickly and reliably.

Shown in Figure 3 is a flow chart of a typical Genetic Algorithm. As can be seen, the Genetic Algorithm is an iterative process whereby the fittest individuals are selected from the population, sacrificing the weaker individuals. This process attempts to emulate the natural environment where only the fittest individuals survive and is propagated through to the next population via Reproduction.

The genetic algorithm starts by initializing a population of candidate solutions to the optimization problem, these are typically initialized randomly. It then follows by evaluating the fitness of the population, which is equivalent to the objective function within standard optimization routines. This is then followed by individual selection, reproduction by means of genetic crossover and mutation.

Within the natural reproduction process, genetic information is transferred from the parent individuals to the offspring via a process known as Crossover. Under certain conditions, the offspring undergoes a genetic mutation which influences the phenotype characteristic of the individual. It is this adaptation behavior which ensures the versatility of the Genetic Algorithm. Each of these processes are described below [6], [18], [12].

1) Individual Selection: The reproduction process as found within nature occurs between two individuals composed of the same genetic make-up (i.e. the same species). There can be found a strong competitive drive to find a suitable mate, and often nature competes with itself and only the strongest survive. This process of finding a mate and reproducing is initiated by means of individual selection.

Within the context of Genetic Algorithms, individual selection is performed by means the Roulette Wheel method, which most often is the commonly applied method of selection. There are other means of selection as well, such

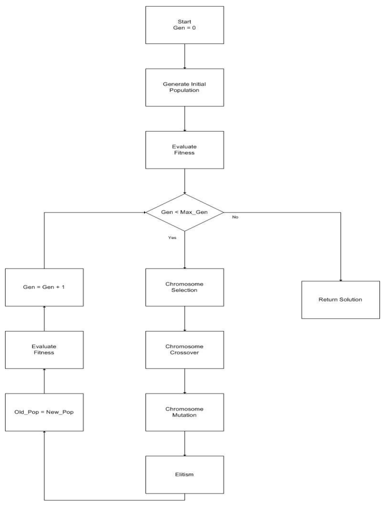

Fig. 3. Flow Chart for a Typical Genetic Algorithm

as Stochastic Sampling, Stochastic Universal Sampling and Remainder Stochastic Sampling with Replacement. However, the Roulette wheel method is the common.

2) Chromosome Reproduction and Crossover: In nature, during reproduction the genetic material of the parents are transferred to the offspring, with inherited characteristics. Each genotype of the chromosome relates to an associated characteristic in the phenotype.

Therefore, the genetic algorithm emulates this process by Crossover. During Crossover, a random position within the chromosome is selected. The bits of the parents between the crossover position are exchanged to form two offspring. The figure illustrates the crossover principle.

The pairs of individual selected for crossover are selected with a probability P_c. A random number R_c is generated between 0 - 1, where the parent individual undergo crossover only if the random number $R_c \leq P_c$. Natural processes for crossover includes multiple points for crossover, which can also be emulated by the algorithm.

3) Chromosome Mutation and Adaptation: The natural world has processes in place for the adaptation of systems to meet the demands of present survival situations over time. As more constraints are experienced by the organism, a method for ensuring survival is to adapt to changes quickly and robustly. Within the genotype of the individuals genetic breakdown, variations within the genetic code are activated, with characteristic attributes for ensuring organism survival. This is classified as Mutation.

It should be noted as well, that not all mutation has a positive impact on the organism, typically, mutation is destructive in its effects on the phenotype and occurs seldom within nature. However, since the genetic code contained within the chromosome allows for a wide spectrum of attributes, Mutation is vital to the survival of the individual.

Therefore, within the genetic algorithm it is the algorithms ability to mutate its individuals that leads to the finding of solutions heuristically. The mutation function is performed by means of probability P_m. A random bit within the chromosome length is chosen and bitwise inverted. Typically, this probability value is chosen very small, typically of the order 0.001 or thereabouts.

4) Elitism: Within each generation of the population, superior genetic material and the fittest individual may be lost due the functions of Selections (where fit individuals are not chosen) Crossover and Mutation may lead to the deterioration of fittest individuals. Therefore, to preserve the good character traits of the population, good genetic material needs to be preserved within the algorithm. This function is known as Elitism.

Fuzzy logic controllers are typically designed and optimized manually by an iterative process from the control designer. This typically takes the form of adjusting the controller PI gains (assuming that a PI controller structure is chosen) to yield optimal closed loop performance. The tuning of the controller can be made via the adjustment of input and output gains, the tuning of input and output membership functions and the optimization of the Fuzzy Rule Base. These techniques are expounded upon as described below.

D. Tuning Methods

In order for the controller to meet stated performance requirements for closed loop regulatory and disturbance performance demands, optimization of the controller to the plant process needs to be performed. This process is typically performed iteratively by trial and error methods, or in the form of analytical design and via control system simulation.

1) Tuning the FLC via Input and Output Scaling: Scaling of the inputs and outputs of the fuzzy logic controller are added to the controller structure to improve on its performance dynamics and to allow for a method of controller tuning.

2) Tuning the FLC via Membership Functions: The tuning of the Fuzzy Set membership functions can be performed by the application of Genetic Algorithm optimizations. The Fuzzy Set is defined by parametrized membership functions. The optimization of fuzzy logic controllers be means of GA's have found widespread application within industry [9], [1].

III. AGC Controller Design

Automatic Generation Control (also called Load Frequency Control - LFC) is paramount to meeting the energy balance between electrical demand and supply. The performance requirement for the Automatic Generation Controller is to,

- Minimize the frequency deviations $\Delta f(t)$ within an electrical control area due to load disturbances.
- To ensure that Tie-Line power $\Delta P_{Tie}(t)$ exchanges are maintained according to their scheduled demand.
- To maintain zero steady state error of the controlled variables ($\Delta f(t)$ and $\Delta P_{Tie}(t)$).

Typically, the Automatic Generation Controller takes the form of the standard PI controller structure. This is in part motivated by the its ease of implementation and by the fact that conventional AGC techniques have been based on this approach (Tie-Line Bias Control).

Therefore, in order to assess the performance of the designed controller, simulation studies are required to optimize and to obtain an in depth appreciation of the dynamic behavior of the controller and its impact on the plant under control

A. AGC Model Description

The system model which forms the focus of this present study is the two area control model for interconnected power systems. The model is a linearized model, encapsulating the plant dynamics sufficiently well to enable control system design studies as well as analyzing the transient performance of the power system. (Nominal parameters are R1 = 3; R2 = 2.4; Tg = 0.08; Tr = 10; Kr = 0.5; Tt = 0.3; Kp = 120; Tp = 20; T12 = 0.0867 or 2*pi()*T12 = 0.545 p.u.MW).

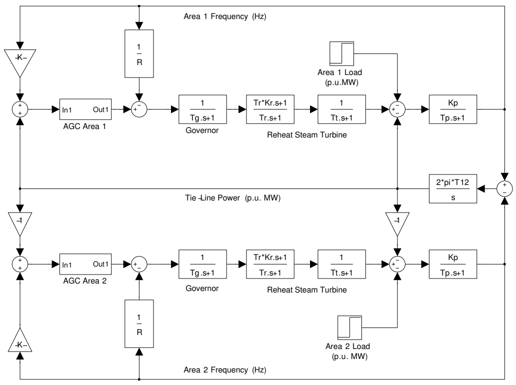

Fig. 4. A Two Area Interconnected Power System Model

The model consists of a governor, turbine and an electrical power system, interconnected by means of the synchronising coefficient.

B. GA-Fuzzy Controller Design

Two important factors in GA-design is the coding of the chromosome and the definition of the fitness function. Coding of the solution space is one of the more critical aspects of formulating the problem as a Genetic Optimization problem, in which it is paramount to encode the binary chromosomes accordingly [17]. In this application, symmetric coding of the membership function is chosen, since this considerably reduces the GA search space (shown in figure 5).

The fitness function (Integral Time Squared Error - ITSE) chosen for the system is shown in equation 3. The attractiveness of using this function is that it minimizes the ACE error as a function of time (t), which adheres to the ACE and AGC objectives. It is noted as well, that there are additional performance indices for closed loop control systems (ISE, IAE and ITAE), which are not discussed presently.

$$Fitness = \frac{1}{\int t.ACE_1(t)^2 + \int t.ACE_2(t)^2 + 1} \quad (3)$$

Figure 5 also illustrates the Fuzzification process. The linguistic terms Negative Big (NB), Negative Small (NS), Zero (ZZ), Positive Small (PS) and Positive Big (PB) are used to describe the input over its input range. This allows for human thinking to express the physical process in a manner relating to human thinking, and thus provides a means for the subject control expert to rationalize the control decision process.

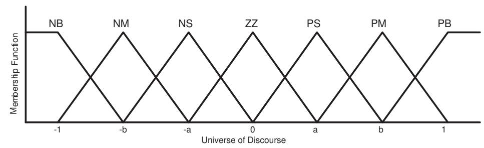

Fig. 5. Symmetric Coding of the Membership Functions

In addition, each of the fuzzy logic controller tunable parameters as shown in figure 6 (scalable input error gain K_p, scalable input change in error gain K_d, output gain K_{out} as well as each of the input and output membership functions according to figure 5) are coded as a binary chromosome of length 108 bits, with each parameter represented by a 12 bit string. Each 12 bit string is then decoded into an equivalent integer and then scaled to a real valued parameter used during optimization and design.

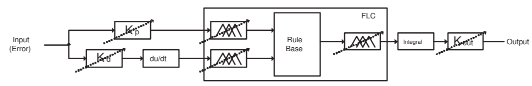

Fig. 6. Fuzzy Logic Tunable Parameters

The performance of the genetic algorithm is shown in figure 7. As can be seen, the algorithm converges toward an optimal solution acceptably for all the tunable parameters.

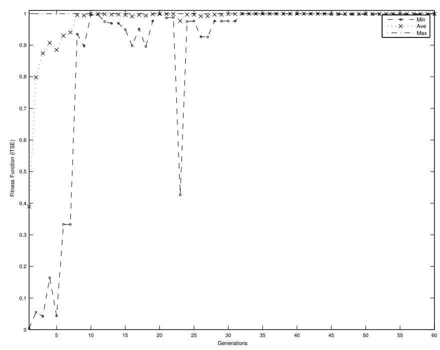

Fig. 7. Performance of the Genetic Optimization

In the GA-Fuzzy controller design, the fuzzy logic controller rules are given as shown in Table 1. Typically, the rules are designed symmetrically, converging toward zero to ensure control system stability. These rules are designed by expert knowledge, however, it should also be noted that the fuzzy rules could be optimized by means of GA.

IV. Simulation Results

The chosen system for study is that of a two-area interconnected power system, motivated by the fact that before we can progress to multi-area systems, we have to understand the dynamics of a two-area system. For this reason, simulation results are shown below (Table 2 shows the optimized controller parameters).

TABLE I
FUZZY LOGIC CONTROLLER RULES.

		e(t)						
		NB	**NM**	**NS**	**ZZ**	**PS**	**PM**	**PB**
$\dot{e}(t)$	NB	NB	NB	NB	NM	NM	NS	ZZ
	NM	NB	NB	NM	NM	NS	ZZ	PS
	NS	NB	NM	NM	NS	ZZ	PS	PM
	ZZ	NM	NM	NS	ZZ	PS	PM	PM
	PS	NM	NS	ZZ	PS	PM	PM	PB
	PM	NS	ZZ	PS	PM	PM	PB	PB
	PB	ZZ	PS	PM	PM	PB	PB	PB

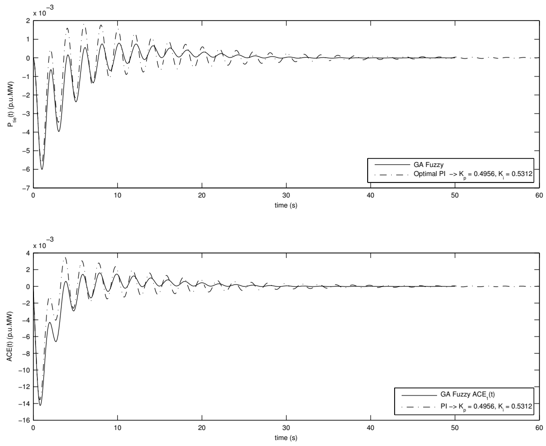

Fig. 8. Comparison between GA-Fuzzy AGC and Conventional PI ACE

It is observed via the transient response curves (Figure 8) that the GA-Fuzzy controller performs favorably with conventional Tie-Line Bias control methods and PI based AGC controllers. The PI controller was optimized by genetic algorithm based on the performance index shown in equation 3. It is noted that the transient responses for the GA-Fuzzy controller is less oscillatory, converging to its set point more quickly, thus an improvement in power system quality and reliability is achieved. Not considered within this simulation study are the effects of boiler dynamics and non-linear effects such as governor dead-band and generating ramp limits, which are of relevance to industrial applications. These properties are studied in a subsequent analysis, and is therefore not presented in this study.

TABLE II
GA-OPTIMIZED MEMBERSHIP FUNCTIONS AND GAINS.

		MF Parameters		
		e(t)	**e(t)**	**u(t)**
Optim	**a**	0.4973	0.2453	0.2779
	b	0.5761	0.9032	0.7803
	k	1.0043	0.4087	0.2860

V. CONCLUSION

In this paper the application of GA-Fuzzy controller design is presented and applied to the Automatic Generation Control problem of large interconnected power systems. It is shown via simulation results that the controller compares favourably with conventional AGC approaches, not only in terms of transient performances, but also by ensuring and maintaining system stability during load disturbances.

It is additionally shown that the multi-control objective of AGC is obtained by the optimization of the controller by genetic algorithms. Although conventional genetic algorithms are applied to off-line optimization, future research would investigate its on-line application and its learning ability in the presence of dynamic power system uncertainty.

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A.2 A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems

This is the Citations section of the document. Large portions of Chapters 1 and 2have appeared in the following papers:

> "A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems", Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, Fourth International Workshop On Advanced Computational Intelligence (IWACI2011).

A GA-Fuzzy Automatic Generation Controller for Interconnected Power Systems

Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo

***Abstract*—This paper presents a GA-Fuzzy Automatic Generation Controller for large interconnected power systems. The design of Fuzzy Logic Controllers by means of expert knowledge have typically been the traditional design norm, however, this may not yield optimal performance. Therefore, genetic algorithms are used to design and optimize the fuzzy controller as applied to the Automatic Generation Control problem of large power systems.**

***Index Terms*—Automatic generation control, interconnected power systems, genetic algorithms.**

I. Introduction

THE network frequency of interconnected power systems is a primary indication of the health of the electrical grid. It's not only a measure of network stability, but also provides a mechanism by which the generating supply and demand energy balance is assessed. An increase in frequency indicates an energy surplus while a decrease in frequency is indicative of under generation. Therefore, control of network frequency by means of increasing or decreasing generation is known as Automatic Generation Control (AGC).

Conventional approaches to the AGC control problem have been based on Tie-Line Bias control, where a proportional and integral type control strategy is employed [1]. Since during normal electrical load variations, AGC provides a convenient means by which frequency deviations are returned to nominal parameters. This maintains frequency deviations and tie line power exchanges at zero steady state error values.

However, Tie-Line Bias control does not lead to optimal closed loop control performance, which tend to be more oscillatory in nature, especially when considering modeling uncertainties, unknown non-linear plant characteristics and the complex behavioral interactions of large interconnected power systems [1]. For this reason, much research effect have been focused on the development of AGC controller design methodologies for good robustness performance objectives as well as maintaining good load disturbance rejection properties.

Contained within the literature, various AGC controller design methodologies have been proposed in response to unknown process dynamics, with improvements in performance being cited when compared to established AGC techniques. These can be summarized as follows. Conventional PID approaches are considered in [2], where a new design approach to PID tuning is detailed based on maximum peak resonance specification (MPRS), citing improvements in control system performance and improved robustness properties [3]. MPRS is a frequency domain loop shaping controller design method.

In addition to conventional I, PI and PID controller design strategies [4], the application of optimal control [5], variable structure control, model predictive control [6] and the application of linear matrix inequalities [7]–[9] to the AGC control problem of interconnected power systems have found widespread research interest and application [10]. This is particularly motivated by the fact that the aforementioned controller design strategies are inherently robust to model uncertainty, and when applied to AGC yield desirable closed loop characteristics. This would include robustness against network growth and complexity, unknown non-linear dynamics and complicated network interactions.

However, the former controller design techniques are model dependent and may prove to be a challenge to obtain especially when dynamics are not well known nor accurately modeled or when system identification is not readily available, limiting the performance of the controller. This inadvertently led to the application of more intelligent design methods, including fuzzy logic control [11], [12], fuzzy gain scheduling [13], [14], artificial neural networks [15] and fuzzy neural networks [16] to name by a few. These techniques are founded upon expert knowledge and human reasoning, taking into account system unknowns from a linguistic perspective.

In view of this, one of the main aspects which makes intelligent control methods such as fuzzy logic control (FLC) and artificial neural networks (ANN) a non trivial task is that of rationalization and neural network training. Fuzzy systems depend upon expert knowledge, however, an expert may not always be available [17], making the fuzzy logic controller design and rule base generation non trivial. In addition, when considering multiple input or output systems and their respective interactions, large number of fuzzy rules are involved and the parametrization of the membership functions including its scaling gains, FLC design can become overwhelming. In the case of ANN, especially large networks, training and optimization can become an issue. For this reason, it is proposed to use genetic algorithms for the optimization of fuzzy controllers.

With application to control systems and power systems, genetic algorithms have found universal application [18], [19]. Their heuristic search characteristics makes genetic algorithms suitable for finding appropriate solutions to complex control problems via optimization methods. In this research, we apply genetic algorithms to the optimization of a fuzzy logic controller, applying them to the Automatic Generation Control problem of interconnected power systems.

Craig D. Boesack is with the School of Electrical & Information Engineering, University of the Witwatersrand, Johannesburg, South Africa (email: craig.boesack@tiscali.co.za).

Tshilidzi Marwala is with the School of Electrical Engineering, University of Johannesburg, Johannesburg, South Africa (email: tmarwala@uj.co.za).

Fulufhelo V. Nelwamondo is with the CSIR Modeling and Digital Science Department, CSIR, Pretoria, South Africa (email: fnelwamondo@csir.co.za).

II. Automatic Generation Control

Electric power systems constitutes a vital role within society today, amid national growth in electrical demand and the need for reliable electrical networks have placed strict demands upon Power Utilities to provide sustainable energy as well as to adhere to the performance standards of the National Grid. In order to achieve this, Power Utilities have implemented various controlling strategies aimed at providing network stability, assurance in terms of meeting energy demand versus energy supply and on enabling that systems are in place for the recovery of system frequency upon any external network disturbances. This regulatory process is known as Automatic Generation Control.

In general, frequency control of power systems are governed by what is known as primary speed (or frequency) governing, secondary frequency control (or Automatic Generation Control) and should the frequency continue deviate to beyond operational limits, tertiary control (or load shedding) becomes effective. Each of these control mechanisms has a stabilizing effect on the frequency.

A. Primary Governing Of Turbo-Generators

Turbine Governing control systems forms a critical component for modern rotating machinery, such as turbo-generating systems. This is necessary to perform fast turbine speed regulation and once the turbo-generator is synchronized to the national electrical grid, it provides a means by which the loading on the generator is varied. Opening or closing of the main steam admission control valves to the turbine (water gate valves in the case of a hydro turbine), leads to an increase in generated energy. However, it should be noted the primary governing on its own does not lead to zero steady state error.

B. Automatic Generation Control

Therefore, to drive the network frequency to zero steady state error, AGC is employed. It forms a load reference input to the turbine governor control system of Generation Units. Its primary objectives are to,

- Maintain frequency deviations $\Delta f(t)$ at zero in the presence of electrical load disturbances.
- Maintain Tie-Line power $\Delta P_{Tie}(t)$ exchange deviations at zero with all neighboring control areas contracted for AGC.
- Maintain the Area Control Error (ACE) $ACE(t)$ at zero. Both the frequency and the ACE can be considered as a health measure for the interconnected power system.

III. Modeling Of Interconnected Power Systems

Interconnected Power Systems (IPS) consists of a number of generating units operating in synchronization, supplying electrical energy to various resistive, inductive or capacitive loads connected to the electrical grid via transmission lines. Invariably, any variation in loading has a direct impact on the frequency of the electrical system. This places strict demands upon the properties of the AGC controller to maintain frequency stability throughout a wide operating region, given increasing electrical network size and complexity.

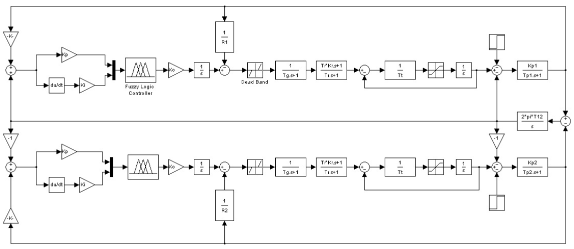

Fig. 1. An Interconnected Power System

Figure 1 shows a two area interconnected power system, with governor dead band and generation rate constraint. The system is controlled by a Fuzzy Logic AGC controller.

A. Governor Dead Band

In practice, governor dead-band forms part of the Turbine Governor. In effect dead-band eliminates governor movement over the dead-band range but could also contribute to low frequency oscillation of the system.

B. Generation Rate Constraints

Generation Rate Constraints (GRC) is imposed on real power systems, limiting the rate of change of generation. In this study, GRC of 0.1 p.u. per minute is considered, as shown in equation (1).

$$\Delta \dot{P}_g \leqslant \delta = 0.0017\, p.u.\, MW/s \tag{1}$$

IV. Genetic Fuzzy Controller Design

The application of genetic algorithms to Fuzzy Logic Controller (FLC) design has seen widespread application and interest. This stems primarily from the fact that as process complexity increases and as knowledge of the system decreases it becomes increasingly more difficult to formulate fuzzy rule bases for optimal FLC design.

Traditional expert systems (FLCs) are formulated by knowledge engineers (or plant operators) who are responsible for the compilation and design of the fuzzy rules of the controller. However, in GA Fuzzy systems genetic algorithms are used as a means of learning the rules for optimal control. It is the aim of the learning facet of the controller design to change the inherent characteristics of the system to improve on performance. Figure 2 below illustrates the genetic evolutionary process of the FLC.

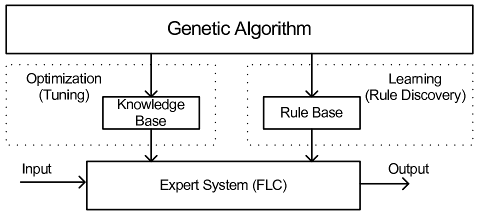

Fig. 2. Genetic Fuzzy Controller

V. Evolution of Fuzzy Systems

Evolutionary genetics provides a convenient mechanism for adaptation and learning. This is particularly achieved by means of genetic operators such as crossover and mutation, in which new genetic material is created with the intent of creating better offspring.

This evolutionary process can be used as a means for providing population diversity and can be employed as a rule discovery mechanism for FLC's (Figure 2). This approach to FLC controller design has proved valuable in instances where expert knowledge of the process under control is not well known, in Multiple Input Multiple Output (MIMO) FLC controller design where it is difficult to formulate control rules and in instances where complex dynamical systems are applicable. In addition, in instances where detailed process models are not available or proves difficult to obtain, evolutionary optimization is plausible.

A. GA Encoding of the FLC

Fundamental to the design of Fuzzy Logic Controllers by means evolutionary strategies is the encoding of the design problem into genetically tunable parameters. Conventional FLC design uses expert knowledge for designing the knowledge base (KB) and the rule base (RB).

Therefore, the application of genetic algorithms to FLC design, both the KB and RB needs to be formulated as genetic chromosomes where genetic operators such as crossover and mutation can be applied. The chromosomes are either formulated as a binary string or as a real valued chromosome depending upon the nature of the problem to be solved. This is graphically illustrated in Figure 3.

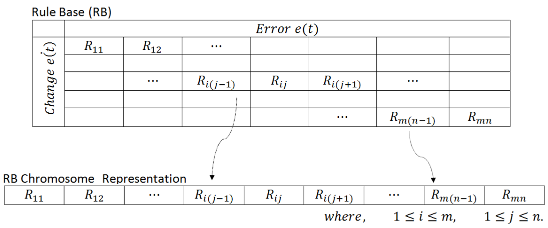

Fig. 3. Illustration of Coding the Rule Base

In (2) CE_i is the input linguistic membership function for the change in input error ($\frac{de(t)}{dt}$). E_j is the input linguistic membership function for the input error ($e(t)$). R_{ij} is the output linguistic membership function for the output ($u(t)$). i & j are integer indices ($i, j \in 1, 2, 3, 4, 5, 6, 7$).

$$R_{ij} : If\ \dot{e(t)}\ is\ CE_i\ and\ e(t)\ is\ E_j\ Then\ u(t)\ is\ R_{ij} \quad (2)$$

A static structure of the FLC RB is chosen in which the length of the chromosome is fixed and each entry is a binary representation of $n = 3$ bits, representing a linguistic term (i.e. NB = 1, NM = 2, NS = 3, ZZ = 4, PS = 5, PM = 6 and PB = 7). The $n = 3$ bits represents an integer. The length of the rule base chromosome is 147 bits long. Additional bits are added to represent the scaling gains on the FLC controller and the input and output membership functions respectively.

B. Selection of the Fitness Function

Automatic generation of fuzzy logic controllers by means of genetic algorithms is largely dependent upon the choice of the fitness function. Improper selection of the fitness function would mean that the performance of the system would not lead to optimal results. It should also be noted the fitness function is problem dependent and is chosen in line with the objectives of the design criteria.

$$\begin{aligned} Fitness_{min} &= \frac{ITAE}{ITAE + 1} \\ ITAE &= \sum_{IC=1}^{N} \sum_{t=0}^{T} t|ACE_1| + t|ACE_2| \end{aligned} \quad (3)$$

In (3), IC is the Initial Conditions chosen for the design, where $N = 8$ is the number of initial conditions and IC $\in$ (-0.01, -0.01) (-0.01, 0) (-0.01, 0.01) (0, -0.01) (0, 0.01) (0.01, -0.01) (0.01, 0) (0.01, 0.01) are symetrical load disctubances in each control area of the interconnected power system. ACE is the Area Control Error.

C. Generation of the Fuzzy Rule Base

The Genetic Algorithm (GA) used during the discovery of the FLC scaling gains, membership functions and rule base was the Simple Genetic Algorithm (SGA), using the Elitist strategy, two point crossover and a mutation rate of $P_m = 0.2$. The Population size is 60 and the total Generations are 150. Figure 4 shows the evolution of the fitness score.

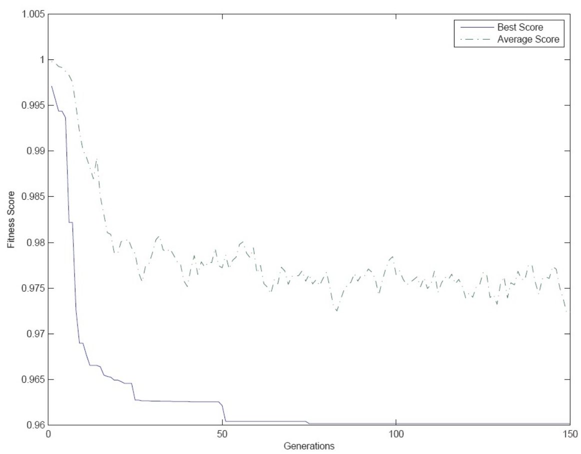

Fig. 4. Evolution Of The Fitness Score

VI. Simulation Results and Discussion

Dynamic frequency response curves are shown in 5 due to a load disturbance in both control areas of (0.01, 0,01) p.u. MW.

As can be seen from the transient response curves, comparing the PI controller response to that of the GA Fuzzy controller, both controllers respond in a similar fashion, with the GA Fuzzy controller being slightly more robust in the presence of GRC.

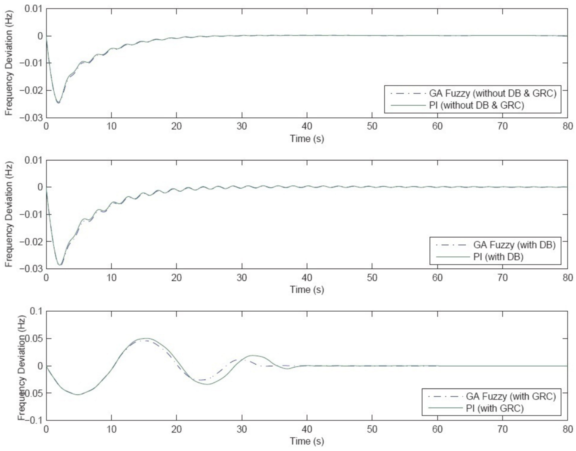

Fig. 5. Frequency Response Due To A Load Disturbance $\Delta P_{Load} = 0.01 p.u.MW.$ in both areas

Figures 6, 7, 8 and 9 shows the evolved Rule Based and the final optimized input and output membership functions respectively.

Error Error	NB	NM	NS	ZZ	PS	PM	PB
NB	PM	NS	NB	ZZ	PM	PS	PM
NM	PB	NS	PM	PM	PM	NB	PB
NS	PS	PB	NB	NB	NS	NM	PM
ZZ	PM	NB	PM	ZZ	NM	PB	NM
PS	NB	ZZ	PM	PB	NB	NB	NM
PM	PS	PS	NM	ZZ	NS	PS	NM
PB	NM	PB	PB	NS	PB	NB	NB

Fig. 6. GA Fuzzy Rules Table

VII. Conclusion

This paper illustrated the design of a Genetic Fuzzy controller as applied to the Automatic Generation Control problem of large interconnected power plants. It illustrated that the automatic FLC design by GA is greatly dependent upon the selection of the fitness function and on the objectives of the design problem. In addition, similar transient response curves between the conventional PI AGC controller and the GA Fuzzy controller is observed, with the GA Fuzzy being slightly more robust in the presence of Generation Rate Constraint.

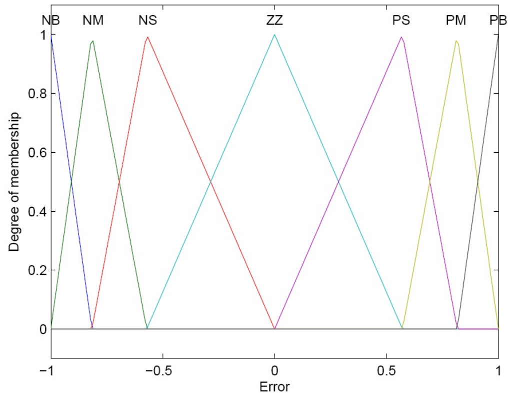

Fig. 7. Error Membership Function

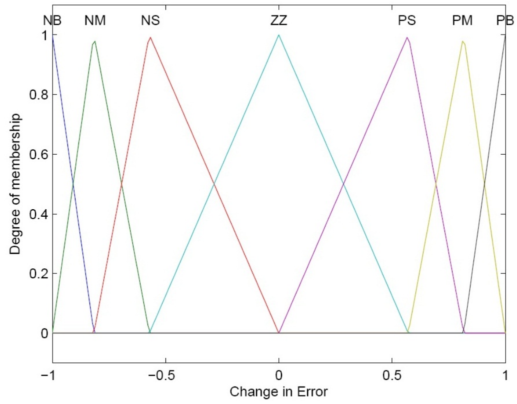

Fig. 8. Change In Error Membership Function

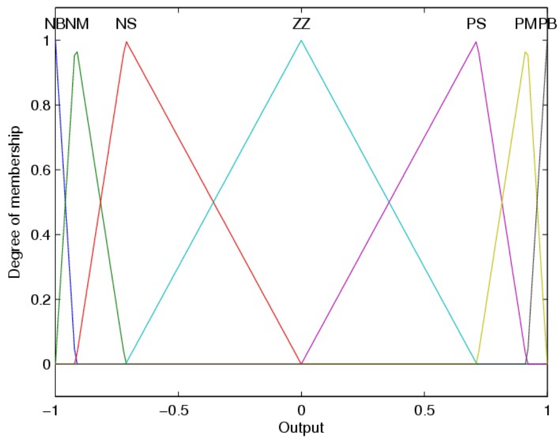

Fig. 9. Output Membership Function

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A.3 On the application of Bezier Surfaces for GA - Fuzzy controller design for use in Automatic Generation Control

"On the application of Bezier Surfaces for GA - Fuzzy controller design for use in Automatic Generation Control", Craig D. Boesack, Tshilidzi Marwala and Fulufhelo V. Nelwamondo, 2nd International Conference on Advances in Energy Engineering (ICAEE2011).

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2nd International Conference on Advances in Energy Engineering

On the application of Bezier Surfaces for GA-Fuzzy controller design for use in Automatic Generation Control

Craig D. Boesack[a], Tshilidzi Marwala[b], Fulufhelo V. Nelwamondo[c]a*

[a]School of Electrical & Information Engineering, University of the Witswaterand, Johannesburg, South Africa
[b]School of Electrical Engineering, University of Johannesburg, Johannesburg, South Africa
[c]CSIR Modeling and Digital Science Department, CSIR, Pretoria, South Africa

Abstract

Automatic Generation Control (AGC) of large interconnected power systems are typically controlled by a PI or PID type control law. Recently intelligent control techniques such as GA-Fuzzy controllers have been widely applied within the power industry. This work presents a comparative study of conventional AGC control with that of a GA-Fuzzy controller. In particular this work focuses on the application of Bezier Surfaces in encoding the genetic problem for the Rule Base (RB) representing the fuzzy control surface. It is shown that favorable performance is obtained in the presence of power plant nonlinearities and Generation Rate Constraint (GRC).

Keywords: Automatic Generation Control; GA-Fuzzy Control System; Rule Based Systems.

1. Introduction

Automatic Generation Control of large Interconnected Power Systems (IPS) form an important function for modern power utilities and thus the quality of frequency control forms a basic performance measure. In order to achieve satisfactory frequency control performance, closed loop control of all power generators forming part of AGC is warranted. This closed loop control function is realized by Automatic Generation Control [1].

In addition, frequency also indicates the health of the electrical network in terms of over generation and under generation. Any excess of frequency above its nominal value would indicate a surplus of energy and likewise any deficiency of frequency below is nominal value would indicate an energy demand.

The dynamic behavior of large Interconnected Power Systems is dependent upon system disturbances, uncertainties due to loading requirements and upon the need to supply electricity of good quality in terms of frequency control. Therefore, within an IPS the network frequency is an important indication of the power mismatch between energy demand and supply. This inherently places strict performance demands

* Corresponding author. Tel.: +27 (0)79 753 2674; fax: +27 (0)86 689 0864.
E-mail address: craig.boesack@tiscali.co.za

upon the AGC controller, not only to maintain good disturbance rejection properties, but also to be robust and to exhibit good regulatory performance [2].

Conventional AGC control laws are of the Proportional and Integral (PI) type control strategy. However, more recently, intelligent controller strategies such Artificial Neural Networks (ANN) [3], Neural Fuzzy (NF) approaches [4], Fuzzy Logic Controllers (FLC) [5], [6] and the use of Genetic Algorithms (GA) [7] have found application within the power industry and also within AGC controller design.

The successes of the aforementioned control strategies are that they provide performance robustness in the presence of parametric model uncertainties when compared with conventional AGC design techniques. The objectives of the AGC controller are threefold:

- To maintain the frequency deviations $\Delta f(t)$ at zero in the presence of electrical load disturbances.
- To minimize Tie-Line power $\Delta P_{Tie}(t)$ exchange deviations with all neighboring control areas contracted for AGC.
- To maintain the Area Control Error (ACE) $ACE(t)$ at zero.

These objectives form the main criteria for assessing the control performance of the AGC controller and are combined in the form as illustrated by equations (1) and (2) respectively to form conventional Tie-Line bias control,

$$\Delta ACE_i(t) = \Delta P_{Tie\,i}(t) + \beta_i * \Delta f_i(t) \tag{1}$$

where the subscript i denotes the i[th] control area within the IPS and β_i is synonymous to the area frequency response characteristic. K_p and K_i represent the proportional and integral gains of the AGC controller respectively. $\Delta P_{Ci}(t)$ is the load reference.

$$\Delta P_{Ci}(t) = K_p * ACE_i(t) + K_I * \int ACE_i(t)dt \tag{2}$$

In this work a GA – Fuzzy controller is designed by means of Genetic Algorithms. In particular during the encoding of the chromosome the control points of the Bezier Surface are used as alleles. In applying this control strategy to the Automatic Generation Control problem of large interconnected power systems, favorable results are obtained in comparison with conventional AGC approaches. Key observation points are that for successful GA – Fuzzy approaches the selection of the fitness function is vital for control strategy formulation. In addition, the selection initial conditions for evaluating the fitness functions are also pivotal.

2. GA – Fuzzy Control Systems

Fuzzy Logic Control (FLC) systems have found widespread industrial application [8], [9], [8]. This is particularly motivated by the fact that FLC controllers can intuitively represent expert knowledge for solving complex control problems. However, if expert knowledge of processes are not fully known, or if there are situations where the number of control rules are large, conventional FLC controller design methods by expert knowledge could be limiting.

Therefore, in order to optimize and learn the fuzzy control rules, automatic generation of fuzzy rules by Genetic Algorithms have been proposed [10]. This is known as GA – Fuzzy Control Systems (GAFCS). Figure 1 illustrates the GA – Fuzzy Controller. As shown, the genetic algorithm is used to optimize the knowledge base consisting of the scaling gains and the membership functions and secondly to learn the fuzzy logic control rules.

In review of Genetic Algorithms (GA), these are heuristic search techniques based on the principles of natural selection and survival of the fittest. GA’s forms the guiding mechanism in GA – Fuzzy controllers to finding optimal solutions.

One of the most fundamental functions in GA-Fuzzy controller design is the rationalization of the chromosome encoding. This typically has followed a structure where each fuzzy rule is coded sequentially as a binary string, where genetic operators such as crossover and mutation would perform its reproductive functions. However, one of the drawbacks of this technique is that it is dependent upon the number of rules, which when there is a substantial number of rules, the genetic search space would increase accordingly. In addition the size of the binary chromosome would also increase requiring increased computational time and encoding complexity.

Therefore, this work focuses on applying Bezier Surfaces as a means of representing the fuzzy control surface. This is particularly motivated by the ease by which Bezier Surfaces are represented and secondly by the relatively small number of control points used to represent the Bezier Surface in contrast to the number of fuzzy rules. By means of illustration, a fuzzy controller with 49 fuzzy rules would require a binary string representation of the 49 rules, whereas a Bezier Surface represented by 16 control points would require a binary string representative of these 16 control points. The Bezier Surface and the Fuzzy Control Surface is synonymous in that the Bezier Surface is the representation of the control surface.

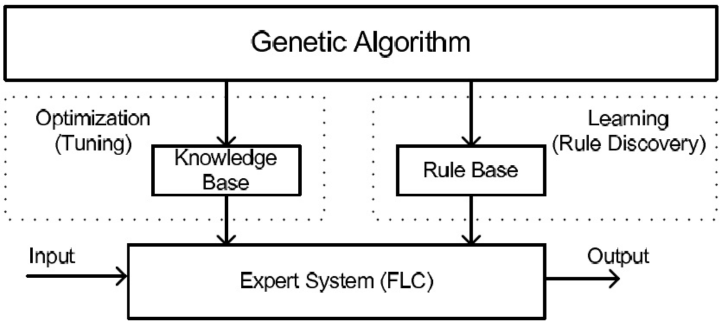


Fig. 1. Genetic Fuzzy Controller.

2.1. Chromosome Encoding by means of the Bezier Surface

Parametric curves or surfaces such as Bezier Surfaces is an extension of Bezier Curves which was invented specifically for the car manufacturing industry by Pierre Bezier in the early 1960's for the development of curves for shape design [11]. These curves are intuitive and lend itself to a large variety of curves or surface shapes based on the manipulation of only a few control points. In addition, these curves are smooth and have an aesthetic appeal which may be of benefit to Fuzzy Logic controller design from a surface perspective, ensuring that control functions are not erratic.

By definition a Bezier Surface $S(u, v)$ is as shown in equation (3).

$$S(u,v) = \sum_{i=0}^{m} \sum_{j=0}^{n} P_{ij} * B_i^m(u) * B_j^n(v) \quad (3)$$

Where $B_i^m(u)$ and $B_j^n(v)$ represent the Bernstein polynomials with degree m and n in the variables of u and v respectively. P_{ij} is an m by n matrix of control points ($P_{ij} \in R^3$) with $i = 0, 1, \dots, m$ and $j = 0,1, \dots, n$. As can be seen, the Bezier Surface is a combination of the control points and the product of the Bernstein polynomials; this creates the terms of the surface. Thus the Bezier Surface is a parametric surface based on the control points.

The Bernstein polynomials are defined as is shown in equation 4. Figure 2 illustrates the encoding of the FLC including is scaling gains and fuzzy control surface. Each allele is represented a binary string.

$$B_i^m(u) = \binom{m}{i}(1-u)^{(m-i)}u^i \; where \binom{m}{i} = \frac{m!}{i!(m-i)!} \quad (4)$$

Standard symmetrical triangular membership functions are used for both the input and output member functions of the FLC controller (Fig. 2).

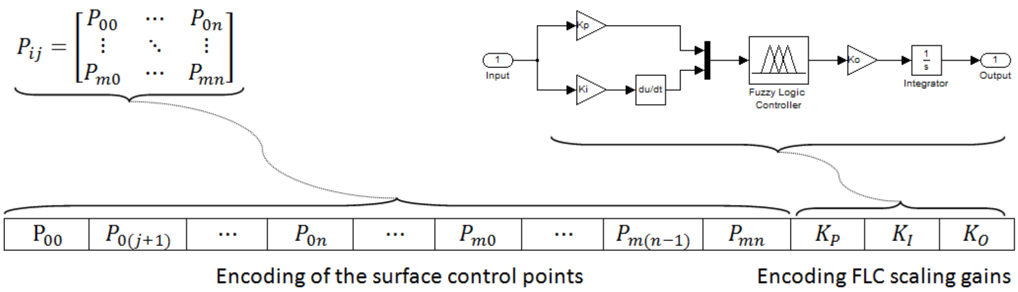


Fig. 2. Illustration of the Chromosome encoding showing the control points and the scaling gains.

2.2. Fitness Function Selection and its Importance

One of the main decisions to be made in applying Genetic Algorithms to problem solving is the selection of the fitness function. It forms the criteria by which the suitability of the solutions are accessed and evaluated for the specific problem at hand [12], [13]. Improper selection of the fitness function would lead to deteriorating controller performance. It should be noted that the fitness function is problem dependant and should be chosen in line with the objectives of the control system design. Equation 5 illustrates the fitness function selection consider in this study, namely the Integral of the Absolute Error (IAE) as defined by (5).

$$Fitness = \frac{IAE}{IAE+1}$$

$$IAE = \sum_{\mathrm{IC}=0}^{\mathrm{N}} \left(\int_0^{\mathrm{T}} |\Delta \mathrm{f}_1(\mathrm{t})| + |\Delta \mathrm{f}_2(\mathrm{t})| + |\Delta \mathrm{P}_{\mathrm{Tie}}(\mathrm{t})| \mathrm{dt} \right) \tag{5}$$

$$IC \in (-0.01, -0.01)\ (-0.01, 0)\ (-0.01, 0.01)\ (0, -0.01)\ (0, 0.01)\ (0.01, -0.01)\ (0.01, 0)\ (0.01, 0.01)$$

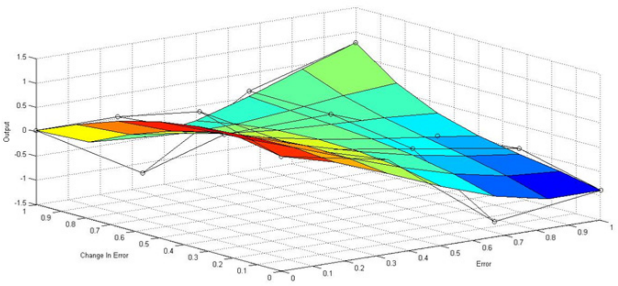
In (5), IC is the initial conditions chosen for the design and represents the load disturbances for each control area, where N = 8 is the number of initial conditions considered. Symmetrical load disturbances are chosen for each of the initial conditions. It is paramount that the IC's consider every possible load disturbance scenario for effective GA design to ensure that the dynamic performance of the controller meets the stated design criteria.

The genetic algorithm used for the discovery of the Rule and its respective scaling gains is the Simple Genetic Algorithm (SGA), using the Elitist strategy with two point crossover. A mutation rate of Pm = 0.2 and a population size of 100 chromosomes. A total Generation of 130 is chosen.

3. Simulation Results and Discussion

This section presents simulation results of the dynamic frequency responses and illustrates the performance of the design GA – Fuzzy controller. Although not illustrated in this work, the power system model analyzed is a two area AGC problem as contained within the literature, using governor dead band and considering Generation Rate Constraint (GRC) [4], [14].

Shown in Fig. 3 is the optimized Bezier Surface representing the control surface. From the Bezier Surface an equivalent Rule Base is generated as shown.



Change in Error $e(t)$ \ Error $e(t)$	NB	NM	NS	ZZ	PS	PM	PB
NB	PB	PM	PS	NS	NM	NB	NB
NM	PB	PM	PS	ZZ	NM	NM	NB
NS	PB	PM	PS	ZZ	NS	NM	NM
ZZ	PB	PM	PS	ZZ	NS	NS	NM
PS	PM	PS	ZZ	ZZ	ZZ	NS	NS
PM	PS	ZZ	NS	NS	ZZ	ZZ	PS
PB	ZZ	NS	NM	NS	ZZ	PS	PB

Fig. 3. Optimized Bezier Surface represents Fuzzy Control Surface by GA, also showing 16 control points and Rules.

The optimal control points matrix P_{ij} is shown below (6), manipulating the control points would adjust the surface accordingly.

$$P_{ij} = \begin{bmatrix} 0.8571 & 0.4386 & -1.1868 & -0.8933 \\ 1.3188 & 0.1876 & -0.1465 & -0.4923 \\ 0.7555 & 0.0411 & 0.1055 & -0.6919 \\ 0.0154 & -1.2106 & 0.1221 & 0.7656 \end{bmatrix} \quad (6)$$

As can be seen from the transient response curves (Fig. 4), comparing the PI controller response to that the GA – Fuzzy controller, both controllers perform similarly, however, the GA – Fuzzy controller is more robust in the presence of Generation Rate Constraint (GRC). It is an important characteristic for controllers to be robust in the presence of parametric variation and model uncertainty. In the case of AGC, power system dynamics are constantly changing, loads are changed randomly, requiring robust AGC performance. With GRC, each generating unit forming part of the network has physical rate limits and thus the ramping of the machine is limited.

4. Conclusion

This paper illustrated the design of a Genetic Fuzzy controller, based on encoding the problem as a Bezier Surface to represent the Rule Base as applied to the Automatic Generation Control problem of large interconnected power systems. It is illustrated that the solution compares favorably with conventional AGC approaches, amidst Generation Rate Constraint.

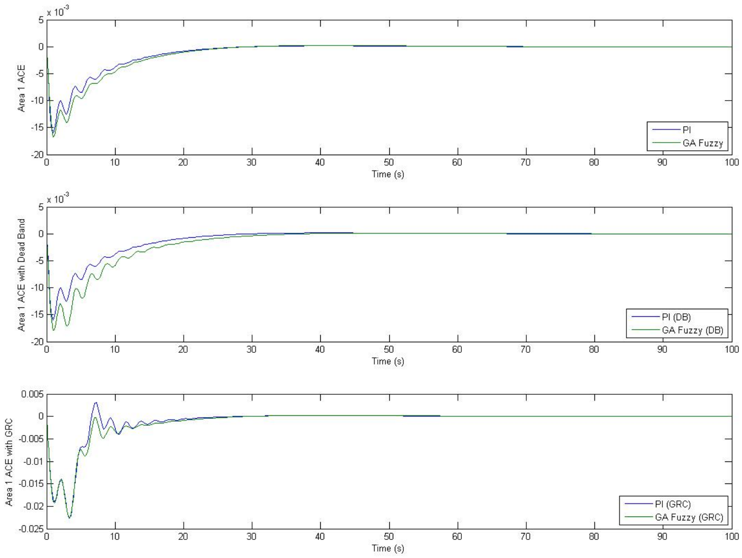


Fig. 4. Area Control Error response for a load disturbance of 0.01 p.u.MW in Area 1.

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A.4 Dynamic governor model development for grid code compliance in South Africa

"Dynamic governor model development for grid code compliance in South Africa", Graeme Chown, Craig Lucas, Mike Coker and Rahul Desai - PPA Energy, Jean vd Merwe and Christelle - MTech, Bunty Kiremire, Craig Boesack, Preshen Moodley and Albert Smit - Eskom. To be submitted to Energize 2012.

Dynamic governor model development for grid code compliance in South Africa

By: Graeme Chown, Craig Lucas, Mike Coker and Rahul Desai – PPA Energy

Jean vd Merwe and Christelle - MTech

Bunty Kiremire, Craig Boesack, Preshen Moodley and Albert Smit - Eskom

Abstract

This paper describes the process followed for the development of governor models for 4 Eskom coal fired power stations. A seven step process was developed to ensure models were developed in the quickest, safest and most accurate manner. This paper describes the process steps.

Introduction

The South African Grid Code requires that accurate models of the power station response to network frequency changes are provided to the Eskom System Operator. These models are required to determine operating reserve requirements and ensure that the balance between supply and demand can be maintained. The ability to balance supply and demand will become more critical as more intermittent generation is added such as wind and solar power. The governor models are further required to study system stability during disturbances, such as loss of one or more generators, and used to determine defence schemes to prevent system blackout such as automatic under frequency load shedding schemes.

The seven step process

A seven step process was developed to ensure that the project is successful as follows:

- Defining the need and explaining need to staff,
- Data Collection,
- Test Planning,
- Testing,
- Modelling,
- System Operator approval, and
- Training

Each of these steps is described further in this paper.

Defining the need and explaining need to staff

Meetings were held at each power station with key stakeholders to describe the need for the models, and outline the information required from the power station and the tests to be performed.

This is vital to ensure that a team of highly skilled staff is developed and is made aware of the tests to be performed and to keep everybody briefed on progress.

Data gathering

Data gathering is a significant step in the process as this identifies the key characteristics of the power station that is to be modelled.

This phase identifies the control system strategy, mechanical plant design and limitations.

A good information gathering exercise reduces the number of tests required to be performed to determine the characteristics.

The data gathering also identifies all the measuring points required.

Test plan

A test plan is developed that will test the unit for the key characteristics required for the development of the governor model. The test plan identifies all the key players, measuring points, and test sequence.

The test plan is refined to ensure that all tests do not stress the unit in any way.

The test plan is then presented to the power station for comment and finally for approval. Test dates are agreed to.

A full risk analysis is done on the test plan to ensure all safety concerns have been addressed. This ensures that all tests to be performed are safe, will not stress the unit and that all possible contingencies are considered.

Testing

Connecting measuring equipment

The strategy followed was to record as much information as possible on from the unit control system. Typically some 100 or more measurements were made with a data sampling rate of 1 second.

In order to have faster measurements of some critical parameters recorders were also attached to measure.

- Three generator phase stator voltages
- Two generator line currents
- Generator field current
- Governor valve position
- Governor valve target setpoint

Figure 1 Measurement equipment used for fast recordings on unit

The measurement equipment required consisted of:

- High speed data acquisition system (100 kHz)
- 1A/5A CT clip-ons
- 400A AC/DC clip-on
- 0-20mA clip-ons
- 1000V Differential Probes
- Linear Potentiometers for governor valve or hydro gate travel
- Portable Oscilloscope
- Handheld Multimeters

Testing boiler and turbine mechanical characteristics

Tests were performed to determine the mechanical characteristics and dynamic time constants of the boiler and turbine. The tests were performed with the controllers on manual and required that key boiler and turbine engineers from the power station were on hand to ensure the boiler and turbine were not stressed. Tests included:

- Step of governor valve
- Step of fuel
- Step of steam flow

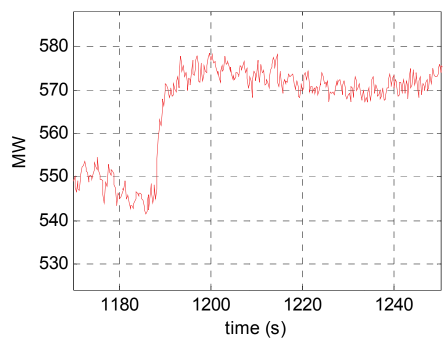

Figure 2 A unit's MW response to step change in governor valve with boiler controls in manual.

Testing unit control system characteristics

The control system tests are summarised as:

- Boiler Pressure controller test
- Unit ramping at maximum rate

- Unit ramping on Automatic Generation Control (AGC)
- Unit's response to changes in system frequency

Model development

The model used by Eskom System Operator for coal fired power stations is the IEE TGOV5 model.

This model has sepate sub models for the turbine, boiler and control system.

The first model parameters developed are the turbine and boiler constants from the mechanical tests performed.

These constants determine fixed characteristics such as the power ratios in the various turbine stages and the delay in the steam flow from one stage to the next.

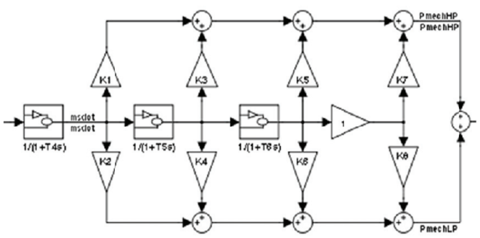

Figure 3 IEEE TGOV5 turbine model

The other characteristics determined are governor valve speed, fuels delays and boiler storage time constants.

The desire was to get the modelled mechanical characteristics as close as possible to the real data, such that in the future different control strategies could be applied with confidence as to how the unit will behave.

The current control system parameters are then calculated from the control system tests. This determines the parameters for the boiler pressure controller, governor valve and overall unit control strategy.

The IEEE model is a generic one, and it was found to be deficient in representing the typical control strategies present on some of the power stations. Some minor modifications to the model are therefore proposed.

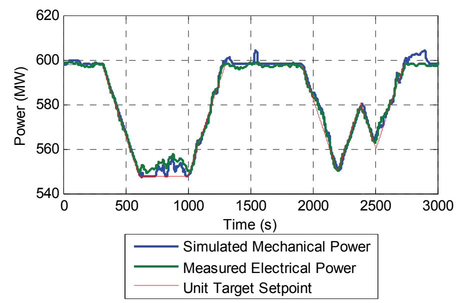

Figure 4 Comparison of measured and simulated MW for unit ramping

System Operator approval

The South African Grid Code requires that the model and parameter development are presented to the System Operator for approval.

A report was also provided which describes how the parameters were developed and the level of accuracy of the model.

Capacity building

The scope of the project was to develop a model for 4 coal fired power stations but also build the capacity within Eskom to be able to develop the models for themselves.

The capacity building consisted of 2 months theory training using the PPA Energy academy and then hands on training.

Acknowledgements

Eskom is thanked for their permission to print this paper.

Contact details: Graeme.chown@ppaenergy.co.za or web site at www.ppaenergy.co.uk

Appendix B

The TGOV05 Unit Model

The TGOV05 unit model as part of the $PSS/E^{©}$ model documentation (PSS/E (2004)) is a simplified boiler and turbine model with associated control systems. It consists of the a turbine model, which can model various turbine configurations including tandem compound and cross compound type turbines. In addition, the turbine model also includes mechanisms for modeling reheater based systems depending upon appropriate selection of modeling parameters.

The boiler model includes the effective fuel and water dynamics, boiler storage as well as the main steam pressure drop model. The boiler controller is a PID type control law with a series lead lag component for pressure error processing. Depending upon the selection of the model parameters, a number of unit control modes, such as boiler follows turbine, fixed pressure and turbine follows boiler control modes can be selected. The model also includes a pressure limiting function and a unit coordinator for effective boiler and turbine control. In addition, the model includes a megawatt set-point formulation function, with associated feed forward components to provide anticipatory control behavior.

For detailed description of all model functions, see PSS/E (2004).

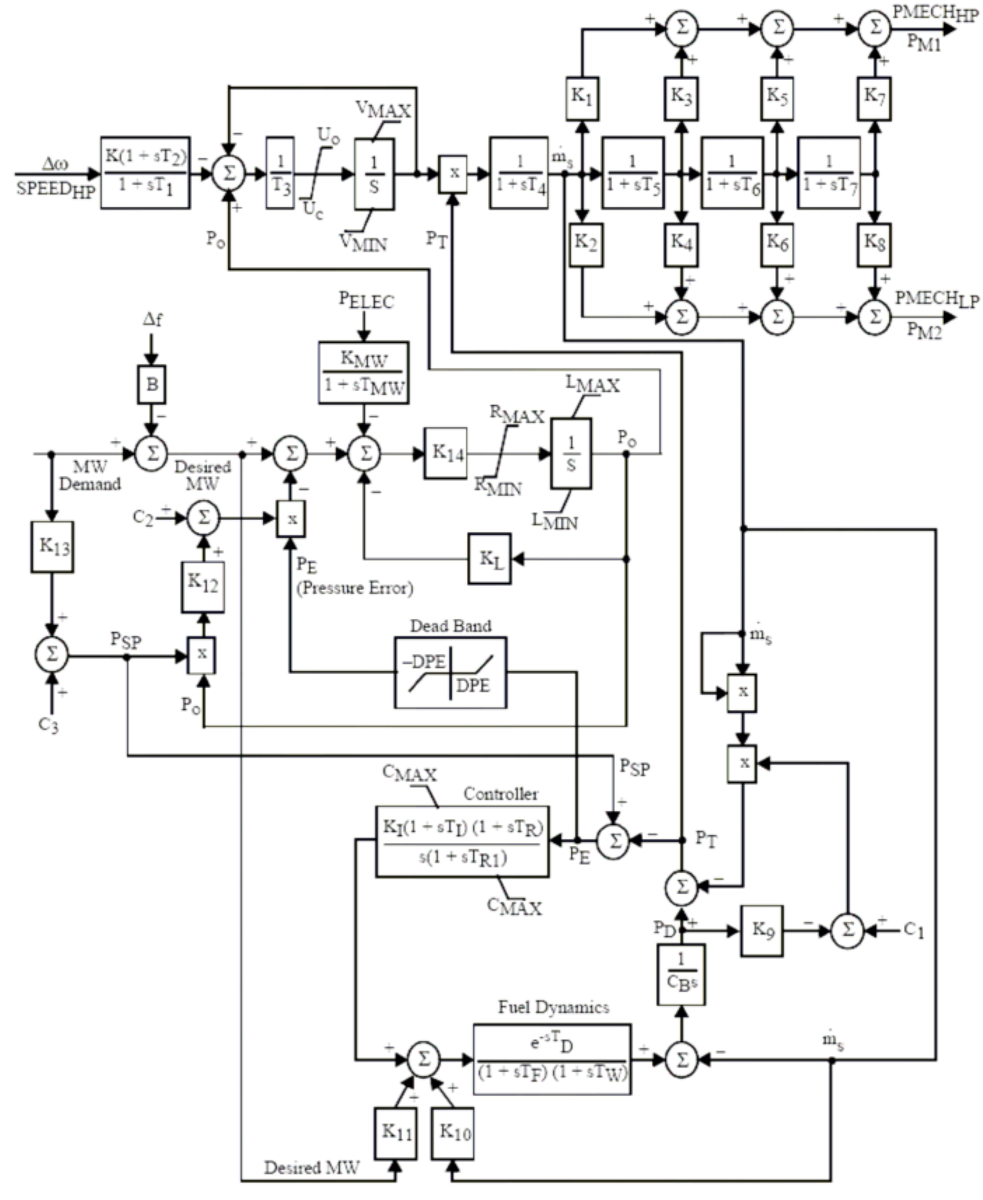

Figure B.1: A Simplified Unit Model ($PSS/E^{©}$), showing steam turbine configurations and associated boiler model and controls, the TGOV05 model (PSS/E (2004))

Appendix C

Matlab Source Code for GA - Fuzzy

This section presents Matlab code for implementing GA - Fuzzy design. The code listed is applied for experimental studies.

1. GeneticAlgorithm - The main loop for the Genetic Algorithm.
2. InitPop - Generates the initial population of binary strings.
3. CalculateReals - Calculates the real values from the binary string.
4. CalculateFitness - Calculates the fitness of the population.
5. RSelection - Performs Roulette wheel selection.
6. Mutation - Performs binary mutation on the population.
7. Crossover - Performs single point crossover.
8. CheckElite - Perform the Elitist strategy.
9. GAModelRun - GA designed FLC controller from the binary string.
10. GenFuzzy - Generates the Fuzzy Controller.

11. PerformIndices - The fitness function.

```
function [Data,String_Population, Fitness] = GeneticAlgorithm()
%% A Simple Genetic Algorithm Implementation (SGA).
% By Craig D. Boesack.
%
% Genetic Algorithms are heuristic search methods based on the principles
% of natural selection and on the survial of the fittest. These algorithms
% have found wide spread application within industry today. It provides for
% a versatile mechanism of find solutions to problems and is a fairly
% robust search method.
%
% Output Variables
%   Data - Holds various data for statistics.
%   String_Population - A binary string of the final solution.
%   Fitness - the final population fitness.

% Declaration of algorithm variables.
nGen = 50;          % Number of Generations
nPop = 100;          % Define the population size.
nVar = 2;            % Number of variables.
nBits = 12;          % Number of bits used per variable.
Pm = 0.02;           % Mutation Probability.
Pc = 0.75;           % Crossover Probability.
Elitism = 1;         % Elitism trus.

% Defining the Upper and Lower Bounds for the problem.
UBound = [2 2];
LBound = [0.01 0.01];
Data = zeros(nPop,4);
PerformanceType = 1;
%% Generate the initial population and Evaluate Population Fitness.
String_Population = InitPop(nPop);
[Fitness] = CalculateFitness(String_Population,nPop,nVar,PerformanceType);

%% Main GA Loop

for Run = 1:nGen

    %% Perform Selection, Crossover and Mutation.
    % Perform Roulette Wheel Selection.
    [Selected_Population, Selected_Fitness] = RSelection(String_Population,
        Fitness,nPop);

    % Perform Single Point Crossover.
    [Crossed_Population] = CrossOver(Selected_Population,Pc);

    % Perform Mutation.
    [Mutated_Population, M,Mcount] = Mutation(Crossed_Population,Pm);

    %% Calculate Fitness of Reproduced Population.
    [MFitness] = CalculateFitness(Mutated_Population,nPop,nVar,PerformanceType);

    %% Perform Elistim.
    if Elitism
        [String_Population,Fitness,MPmax,OldMax] = CheckElite(Mutated_Population
            ,MFitness,String_Population,Fitness);
    else
        String_Population = Mutated_Population;
        Fitness = MFitness;
    end

    % Simply display statistics.
    disp([Run max(Fitness) mean(Fitness) min(Fitness)]);
    Data(Run,:) = [Run max(Fitness) mean(Fitness) min(Fitness)];

end

end
```

```
function iPopulation = InitPop(nPop,InitPop)
% iPopulation = InitPop(nPop,nVar)
%
% InitPop(nPop, nVar) produces an random initial population of nPop, where nPop
    is the
% size of the Population. Chromosome representation is a binary string of 5
% Bits X nVar, where nVar is the number of variables , 4 Bits is the nibble
% respresentation of the number (Example nVar of 3, therefore chromosome
% length is 4*3 = 12).
% iPopulation = matrix of initial chromosomes (nPop By 4*nVar matrix).
%
switch nargin

    case 1

        ChromeSize = 363;
        iPopulation = rand(nPop,ChromeSize)>0.5;

    case 2

        iPopulation = InitPop;

    otherwise

        ChromeSize = 363;
        iPopulation = rand(nPop,ChromeSize)>0.5;
end

end
```

```
function [Integers , Reals] = CalculateReals(Pop,nPop,nVar,nBits,LB,UB)
% Calculates the fitness of the Population.
% (This part of the algirithm is typically problem dependant).
%
% First we need to decode the population of binary strings to real and
% integer values.
%

%% Converting from Binary String to Integers
% Conversion Vectors.
Pow = (nBits - 1):-1:0;
Bin = 2*ones(1,nBits);
Convert = Bin.^Pow;
MaxCon = ones(1,nBits)*Convert';

Integers = zeros(nPop,nVar);
Reals = zeros(nPop,nVar);
for counter = 1:nPop

    index = 1;
    for count = 1:nVar

        % Now calculating the Integer values of the population.
        Integers(counter,count) = Pop(counter,index:index + nBits - 1)*Convert';

        % Converting from Integers to Real (using linear transformation).
        m = (UB(count) - LB(count))/MaxCon;
        c = UB(count) - m*MaxCon;
        Reals(counter,count) = m*Integers(counter,count) + c;

        index = index + nBits;
    end

end

end
```

```
function Fitness = CalculateFitness(Reals_Populations,nPop,nVars,PerformanceType)
% CalculateFitness calculates the fitness of the populsation.
% Reals_Population = Population of real numbers.
% nPop = size of the population.
% nVar = number of variables.

Fitness = zeros(nPop,1);
for ccount = 1:nPop

    Fitness(ccount,:) = Rastrigin(Reals_Populations(ccount,:),nVars,10);
    % Fitness(ccount,:) = RunModel(Reals_Populations(ccount,:),0,PerformanceType);
end

%Fitness = GAModelRunPP(Reals_Populations,PerformanceType);

% Test functions.
    function y = Rastrigin(x,nVars,A) %#ok<INUSL>
        %
        % Rastrigin function.
        % Forms a good test function for evaluating the GA.

        temp = 0;
        for count = 1:nVars
            temp = temp + (x(count)^2 - A*cos(2*pi()*x(count)));
        end
        y = 1/(A*nVars + temp + 1);

    end

end
```

```
function [Selected_Population, Selected_Fitness] = RSelection(Population,Fitness,nPop)
% Implementation of Roulette Wheel Selection.
%
%
Selected_Population = zeros(size(Population));
Fitness_Prob = Fitness./(sum(Fitness));

for counter = 1:nPop

    Prob = rand();
    index = find(cumsum(Fitness_Prob) >= Prob,1,'first');
    Selected_Population(counter,:) = Population(index,:);
    Selected_Fitness(counter,:) = Fitness(index); %#ok<AGROW>

end

end
```

```
function [Mutated_Population,M,Mcount] = Mutation(Population,Pm)
%[Mutated_Population,M,Mcount] = Mutation(Population,Pm)
% where,
% Population = the population.
% Pm = the Mutation probability.
%
% Mutated_Population = the mutated population.
% M = a matrix indicating where the mutations take place.
% Mcount = is a count of the number of mutations for this generation.
Mcount = 0;
[nPop ChromLen] = size(Population);
Mutated_Population = zeros(nPop,ChromLen);
M = zeros(nPop,ChromLen);

for count = 1:nPop

    for counter = 1:ChromLen


        if rand() <= Pm

            Mutated_Population(count,:) = Population(count,:);

            if Mutated_Population(count,counter) == 1

                Mutated_Population(count,counter) = 0;
            else

                Mutated_Population(count,counter) = 1;
            end

            M(count,counter) = 1;
            Mcount = Mcount + 1;

        else

            Mutated_Population(count,:) = Population(count,:);
            M(count,counter) = 0;
        end

    end
end


end
```

```
function [Crossed_Population] = CrossOver(Selected_Population,Pc)

[nPop ChromLen] = size(Selected_Population);
Crossed_Population = zeros(nPop,ChromLen);

for count = 1:2:nPop

    if rand() <= Pc
        CBit = randi([1,ChromLen - 1]);
        Crossed_Population(count,:) = [Selected_Population(count,1:CBit)
            Selected_Population(count + 1,CBit + 1:ChromLen)];
        Crossed_Population(count + 1,:) = [Selected_Population(count + 1,1:CBit)
             Selected_Population(count,CBit + 1:ChromLen)];
    else
        Crossed_Population(count,:) = Selected_Population(count,:);
        Crossed_Population(count + 1,:) = Selected_Population(count + 1,:);
    end


end
end
```

```
function [NPopulation, Fitness,MPmax,OldMax] = CheckElite(Mutated_Population,
    MFitness,Old_Population,OldFitness)

[MPmax, Mindex] = max(MFitness);
[OldMax, Oldindex] = max(OldFitness);

NPopulation = Mutated_Population;
Fitness = MFitness;

if (MPmax < OldMax)

    NPopulation(1,:) = Old_Population(Oldindex,:);
    Fitness(1,:) = OldMax;
    NPopulation(2,:) = Mutated_Population(Mindex,:);
    Fitness(2,:) = MPmax;

else


end


    function CP = CoverConvergence(Population, Fitness)

        [Fit_Sorted, IX] = sort(Fitness,'ascend');
        Pop_Sorted = Population(IX,:);

        nPop = 20;   % select number of replacements.
        String_Population = InitPop(nPop);

        CP = Pop_Sorted;
        CP(1:nPop,:) = String_Population;  % Simply replace the weakest and add
            diversity into population.

    end



end
```

```
function Fitness = GAModelRun(InputMatrix,PerformanceType,Plotting)
% InputMatrix = is the chromosome, partitioned into the following
% FLC_chromosome then followed by the Reals Chromosome.
% [....FLC (IntegerMatrix)..../....Reals (Reals)....]
% The FLC portion of the chromosome (InputMatrix) is converted to integers
% from 1 to 0, representing linguistic terms (NB(0,1),NM(2),NS(3),ZZ(4),PS(5),PM(6),PB(7)).
% nReals = is the number of real values (i.e. the Database (DB), membership functions and scaling gains.

nCount = 1;
nReals = 9; % 9 Reals parameters.
nBit = 3; % is the value of the bit nibble (for FLC controller).
nBitReals = 8;
IntegerMatrix = zeros(1,49); % where 49 is the number of rules. (7 X 7).

ChromoLength = length(InputMatrix); % should be multiples of 3 (since 3 bits represent a value.
ChromoLengthFLC = ChromoLength - nBitReals*(nReals-3);  % less nBit*nReals since nReals are reserved for
                                                         % Reals (coded in the rear of the chromosome.

% Generating the InterMatrix (for Fuzzy Controller).
for Count = 1:nBit:ChromoLengthFLC

    Nibble = InputMatrix(Count:Count + nBit - 1);
    a = ChromosomeToIntegers(Nibble);

    % We do not consider don't cares.
    if a == 0
        IntegerMatrix(nCount) = 1;
    else
        IntegerMatrix(nCount) = a;
    end

    nCount = nCount + 1;
end

% Generating the Reals.
nCount = 1;
%nBit = 24; % for Reals (finer details).
Reals = zeros(1,nReals);
Bounds = [0.01 2]; % Bounds on the Scaling Gains.

for Count = ChromoLengthFLC+1:nBitReals:ChromoLength

    if nCount >= 4
        Bounds = [0.1 1];  % changing the Bounds for the membership functions.

    Nibble = InputMatrix(Count:Count + nBitReals - 1);
    Reals(nCount) = IntegerToReals(ChromosomeToIntegers(Nibble),Bounds,nBitReals);

    Bounds = [Reals(nCount) 1];
    Reals(nCount+1) = IntegerToReals(ChromosomeToIntegers(Nibble),Bounds,nBitReals);
    nCount = nCount + 2;

    else

    Nibble = InputMatrix(Count:Count + nBitReals - 1);
    Reals(nCount) = IntegerToReals(ChromosomeToIntegers(Nibble),Bounds,nBitReals);
    nCount = nCount + 1;

    end
end

InitialiseModelParam; % Initialise the model parameters.
sgReals = Reals(1:3); % sgReals are the reals for the Scaling gains.
mmReals = Reals(4:length(Reals)); % mmReals are the reals for the memebership functions.
[ruleList, Ma] = GenRuleIntegers(IntegerMatrix);
FLC = GenFuzzy(ruleList,mmReals);
ModelName = 'TwoAreaLFCModel';
Fitness = RunModel(ModelName,FLC,sgReals,Plotting,PerformanceType,Ma);
```

```
function FLC = GenFuzzy(ruleList,mmReals)

% Generates the input and output membership functions.
% parameters defines the membership triangular functions paramters.
% Generate FLC over normalised values.

% mmReals
% 3 membership functions (Error, dError, Output).

aError = mmReals(1);
bError = mmReals(2);

adError = mmReals(3);
bdError = mmReals(4);

aOutput = mmReals(5);
bOutput = mmReals(6);

%% Setting up the FIS.
a = newfis('FLC');

%% Creating the input membership function (Error).
a = addvar(a,'input','Error',[-1 1]);
a = addmf(a,'input',1,'NB','trimf', [-1.333 -1 -bError]);
a = addmf(a,'input',1,'NM','trimf', [-1 -bError -aError]);
a = addmf(a,'input',1,'NS','trimf', [-bError -aError 0]);
a = addmf(a,'input',1,'ZZ','trimf', [-aError 0 aError]);
a = addmf(a,'input',1,'PS','trimf', [0 aError bError]);
a = addmf(a,'input',1,'PM','trimf', [aError bError 1]);
a = addmf(a,'input',1,'PB','trimf', [bError 1 1.334]);
%  figure(1);
%  plotmf(a,'input',1);

%% Creating the input membership function (Error_dot).

a = addvar(a,'input','Change␣in␣Error',[-1 1]);
a = addmf(a,'input',2,'NB','trimf', [-1.333 -1 -bdError]);
a = addmf(a,'input',2,'NM','trimf', [-1 -bdError -adError]);
a = addmf(a,'input',2,'NS','trimf', [-bdError -adError 0]);
a = addmf(a,'input',2,'ZZ','trimf', [-adError 0 adError]);
a = addmf(a,'input',2,'PS','trimf', [0 adError bdError]);
a = addmf(a,'input',2,'PM','trimf', [adError bdError 1]);
a = addmf(a,'input',2,'PB','trimf', [bdError 1 1.334]);
%  figure(2);
%  plotmf(a,'input',2);

%% Creating the output membership function (Output).

a = addvar(a,'output','Output',[-1 1]);
a = addmf(a,'output',1,'NB','trimf', [-1.333 -1 -bOutput]);
a = addmf(a,'output',1,'NM','trimf', [-1 -bOutput -aOutput]);
a = addmf(a,'output',1,'NS','trimf', [-bOutput -aOutput 0]);
a = addmf(a,'output',1,'ZZ','trimf', [-aOutput 0 aOutput]);
a = addmf(a,'output',1,'PS','trimf', [0 aOutput bOutput]);
a = addmf(a,'output',1,'PM','trimf', [aOutput bOutput 1]);
a = addmf(a,'output',1,'PB','trimf', [bOutput 1 1.334]);
a = addrule(a,ruleList);

% GA designed FLC Controller.
FLC = a;
```

```
function I = PerformIndices(Time, Error, Alpha, Beta, Control, Type)
% Performance indices function
%I = PerformIndices(Time, Error, alpha, beta, Control, Type)
% Time is a time vector.
% Error is the Error (e(t) or u(t)).
% Alpha used in 6 or IGSE.
% Beta used in 7 or ISECE.
% Type is the type of performance index used.
% Type = 1 or ITE - Integral of total error.
%        2 or IAE - Integral of abosulte error.
%        3 or ISE - Integral of square error.
%        4 or ITAE - Integral of time multiplied by absolute error.
%        5 or ITSE - Integral of time multiplied square error.
%        6 or IGSE - Integral generalized square error.
%        7 or ISECE - Integral of square error and control effort.

switch Type

    case {'ITE',1}
        I = trapz(Time, Error);
    case {'IAE',2}
        Error = abs(Error);
        I = trapz(Time, Error);
    case {'ISE',3}
        Error = Error.^2;
        I = trapz(Time, Error);
    case {'ITAE',4}
        Error = abs(Error);
        Error = Error.*Time;
        I = trapz(Time, Error);
    case {'ITSE',5}
        Error = Error.^2;
        Error = Error.*Time;
        I = trapz(Time, Error);
    case {'IGSE',6}
        a = Error.^2;
        a = a(2:length(a));
        b = diff(Error)./diff(Time);
        b = b.^2;
        I = a + Alpha.*b;
        Time = Time(1:length(Time) - 1);
        I = trapz(Time, I);
    case {'ISECE',7}
        a = Error.^2;
        b = Control.^2;
        I = a + Beta.*b;
        I = trapz(Time, I);
end
```

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