

***FUZZY LOGIC BASED CONTROLLERS
FOR POWER SYSTEMS***

by



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DECLARATION

I declare that this work is the result of my own investigation and that it has not already been accepted in the substance for any degree, nor it is being currently submitted for any degree.

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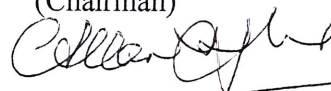


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TO
MY PARENTS
MY WIFE
AND
MY SON HAIDAR

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THESIS ABSTRACT

In this thesis, application of fuzzy logic control to two control problems in electrical power systems have been investigated. To show the effectiveness of the fuzzy based controllers, a comparison is made with other controllers design based on classical and modern control theories.

The first control problem that has been investigated is the low frequency oscillation. Various power system stabilizers (PSS), based on different control methodologies, have been studied for a single machine infinite-bus system to damp the oscillations and to improve the system dynamic performance. These PSS are namely, the conventional lead stabilizer based on classical control theory, linear optimal state regulator, linear suboptimal output regulator, rule-based stabilizers, and various types of fuzzy logic stabilizers. All of these stabilizers have been designed at the same operating condition and their performance has been evaluated at nominal and off-nominal operating condition when the system is subjected to small disturbance of terminal voltage or mechanical torque. In addition, the effect of variation of some system parameters on the performance of the stabilizers have been investigated. The digital computer simulation results shows the effectiveness of the fuzzy logic based stabilizers over the others.

The second control problem that has been studied is the load frequency control of interconnected systems. Different load frequency controllers (LFC) have been designed for the two area power system to maintain the frequency and power exchange over interarea tie-line at scheduled values. The load frequency controllers that have been investigated are the conventional integral LFC, the linear optimal state regulator LFC, and four other new proposed fuzzy based LFC. The first proposed fuzzy controller has been constructed using 49 rules with area control error (ACE) and its rate as input signals while the second proposed fuzzy controller was built using only 9 rules with area frequency deviation and tie-line power deviation as input signals. The other two new proposed LFC are a conventional integral controller with fuzzy gain

scheduling and optimal state regulator with fuzzy gain scheduling. The fuzzy scheduling is done using sugeno-type of fuzzy rules each of which represents a particular operating condition. These two proposed controllers are adaptive with respect to the system operating condition characterised by power system time constant, tie-line synchronising coefficient and the frequency bias setting. All of these LFC's are compared in terms of their performance and effectiveness in maintaining the two area frequency as well as the tie-line power exchange at their scheduled values following a step load disturbance in area demand at nominal and off-nominal operating system conditions. Simulation results show that the proposed LFC with fuzzy gain scheduling yield better dynamic performance than the other LFC's particularly at off-nominal system operating conditions.

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LIST OF SYMBOLS

Δ	Change from nominal value.
0	Subscript to denotes the value at the operating point.
t	Time in sec.
ω_b	Base angular speed (rad/sec)
ω	Angular speed (p.u.)
δ	Torque angle (rad)
E_{fd}	Field voltage (p.u.)
e'_q	Quadrature (q) axis transient voltage (p.u.)
d, q	Direct and quadrature axes
P_e	Electrical power output of machine (p.u.)
Q_e	Electrical reactive power of machine (p.u.)
P_m	Mechanical power on the shaft of machine (p.u.)
T_e	Electrical Toque.
T_m	Mechanical torque.
V_t	terminal voltage
V_{ref}	Reference input voltage.
u	Control signal
M	Machine inertia constant.
T_A	Time constant of excitation system.
K_A	Gain of excitation system.
T_{do}'	d-axis transient open circuit field time constant (sec)
f	system frequency (Hz)
P_g	Turbine output.
P_c	Command signal.
ΔP_d	Incremental load power
P_{tie}	Tie-line power flow.
T_g	Speed governor time constant.
T_P	Power system time constant.
T_t	Turbine time constant.
K_P	Power system gain, Hz/p.u.MW.
T_{12}	Synchronising coefficient.
R	Speed regulation of governor, Hz/p.u. MW.
b	Frequency bias, p.u. MW/Hz.
P_r	Area active power.
β	Frequency response characteristic
T_s	Sampling period.
s	Laplace operator

ABBREVIATIONS

ACE	Area control error.
AFRC	Area Frequency Response Characteristic
CLFC	Conventional Load Frequency Controller.
CLFCGS	Conventional Load Frequency Controller with fuzzy Gain Scheduling.
FLC	Fuzzy Logic Control/Controller.
FLFC	Fuzzy Load Frequency Controller.
FLPSS	Fuzzy Logic Power System Stabilizer.
LFC	Load Frequency Control.
LQR	Linear Quadratic Regulator.
NC	Nominal operating Condition.
NERC	North American Electric Reliability.
OC	Off-Nominal operating Condition
OPTLFC	Optimal Load Frequency Controller.
OPTLFCGS	Optimal Load Frequency Controller with fuzzy Gain Scheduling.
OPTPSS	Optimal PSS.
PID	Proportional, Integral, and Derivative Controller.
PSS	Power System Stabilizer.
RPSS	Rule-Based PSS.
SCR	System Response to frequency deviation Characteristic
SUBPSS	Suboptimal PSS.

CHAPTER 1

INTRODUCTION

1.1 ELECTRICAL POWER SYSTEM CONTROL

Electrical power systems nowadays are highly interconnected, very complex and vulnerable to disturbances which may cause unacceptable system operation. Continuous delivering of electric power to users to maintain their electricity demand with high quality (steady voltage and frequency) are two main requirements in power system control. Blackouts are very costly to all industrial societies, and the lack of quality can result in damage to expensive equipment, or malfunctioning.

Over the past decades, a number of challenging control problems have been reported [18], which include the low-frequency oscillations of interconnected large electric power systems, the subsynchronous resonance and torsional oscillations of turbines in steam-electric power plants with capacitor-compensated transmission lines, automatic generation control problems, and many others. This leads to the development of various control devices to enhance the power system performance such as power system stabilisers (PSS), fast valving governor and fast acting exciters, static VAR compensators, HVDC links, FACTS devices and so many others. In addition, since the need of fast and robust control system in power systems is desired, various control methods have been proposed to control such devices ranging from classical control and modern control theory to artificial intelligence (AI) and expert systems (ES).

1.2 BASIC POWER PLANT COMPONENTS

The basic components of an electric power system is shown in Fig. 1.1. In the figure, the turbine and governor with a speed deviation feedback $\Delta\omega$ are shown in the left, the synchronous generator (SG), exciter and automatic voltage regulator (AVR) with terminal voltage deviation ΔV_t are shown in the middle, and the transformer and transmission line by which the generated electrical energy is transmitted to the load centres and possibly neighbouring power areas, are shown in the right. From the figure, there are two control loops, the governor control loop and the excitation control loop. The main rule of the governor control loop is to maintain the frequency and power output levels. This is accomplished by the turbine governor which will sense the speed deviation from set point and acts accordingly. This control loop is also referred to as the Real power/frequency control loop. On the other hand, the main rule of the excitation control loop is to respond to the deviation of the terminal voltage from its reference value and contribute accordingly to maintain the terminal voltage. This control loop is also referred to as the Reactive power/voltage control loop. The response of the excitation control loop is very fast as compared to the governor control loop, but to be able to control the transient behaviour of the generator satisfactory, a PSS is needed.

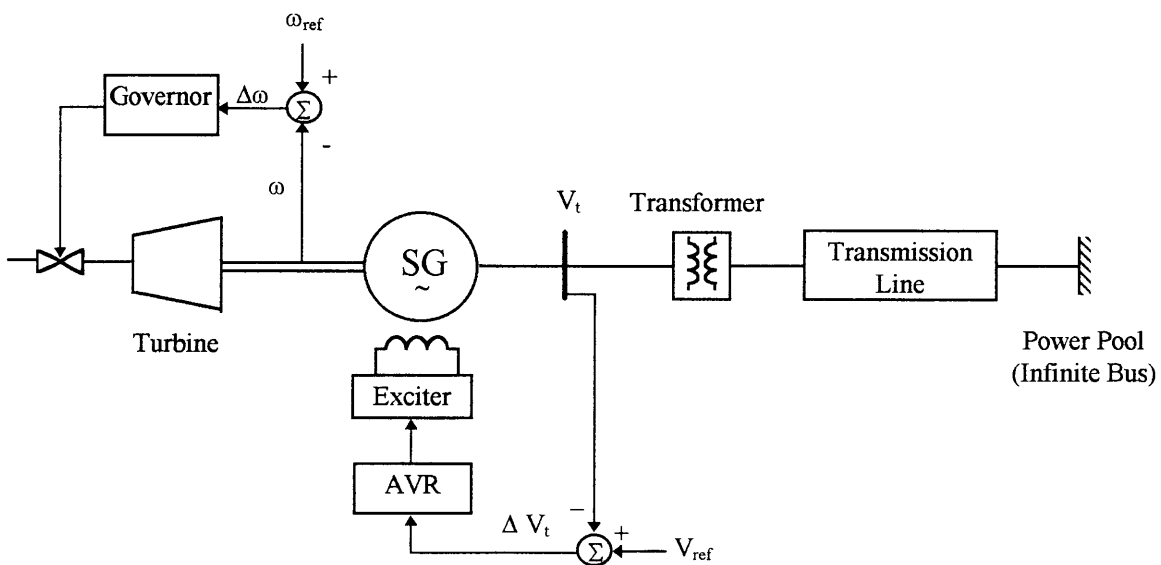


Fig. 1.1 Schematic diagram of an electric power plant.

1.3 RECENT CONTROL METHODS

For many power systems operation and control problems, there exist analytical solution methods. However, the mathematical formulations of real-world problems are derived under certain restrictive assumptions and even with these assumptions, the solution of large scale power systems problems is not trivial. On the other hand, there are many uncertainties in various power system problems because power systems are large, complex, non-linear, geographically widely distributed systems, and influenced by unexpected events. These facts make it difficult to effectively deal with many power system problems through strict mathematical formulation alone [1].

In recent years, artificial neural network and fuzzy systems have been successfully applied to various control fields and areas including consumer electronics, automotive applications, industrial process control, medical diagnosis, and many others [1-6]. In addition, the artificial neural network and fuzzy systems have, recently, gained a ground in power systems operation, planning and control application with rather promising results [1,7-8]. The salient feature of these techniques that distinguish them from the traditional control approaches is that they provide a model-free description of the control systems i.e. they do not require a mathematical model of the system under control which is otherwise an essential requirement in the conventional control methods based on classical and modern control theory.

The application of fuzzy control methodology on two power system control problems, namely the low frequency oscillation control (discussed in chapter 3) and the load frequency control of the two area system (discussed in chapter 4), will be the focus of this thesis.

knowledge of expert people and skilled operators in terms of linguistic rules as IF -
-- THEN ---.

- *Fuzzy logic can be combined with conventional control techniques.* Fuzzy logic does not necessarily replace conventional control methods (e.g. PID, ... etc.). In many cases, a fuzzy system may be used for augmenting a number of conventional controllers or used in other cases to assist an existing conventional controller (e.g. for PID gain scheduling).
- *Fuzzy logic is based on natural language.* Natural language which is used by people everyday (large, about, negative small, very big, ... etc.) form the basis of building fuzzy logic.
- *Fuzzy logic design paradigm is model-independent.* The design of fuzzy controllers don't require mathematical description (by differential or difference equations) of the input-output interdependence. Thus, when a mathematical model of the process does not exists, or exist but is too difficult to encode, or too complicated to be evaluated fast enough for real time operation, then it is appropriate to use fuzzy logic approach.

But When Not to Use Fuzzy Logic:

Of course fuzzy logic is not the best for every control problem. As the designers look into its power, they must decide where to apply it. That is when an expert is not available who can specify the rules underlying the system behaviour and the fuzzy sets that represent the characteristic of each variable; or if a simpler solution already exists.

1.5 SCOPE OF THE THESIS

The application of fuzzy logic based control scheme to two power system control problems, namely the low frequency oscillation control problem and the load frequency control problem, is the focus of this thesis. To show the effectiveness of the fuzzy based controllers, a comparison is made with other controllers based on classical and modern control theories. For the low frequency oscillations control problem, various power system stabilisers (PSS) are designed for a single machine infinite bus system to damp the oscillations and to improve the system dynamic performance. These PSSs includes the conventional PSS (CPSS) using lead compensator, linear optimal state regulator (OPTPSS), linear suboptimal output regulator (SUBPSS), rule-based PSS (RBPSS) and various types of fuzzy logic based PSS (FLPSS). In this part, only small disturbance of terminal voltage and mechanical torque have been considered. The effect of variation of various system parameters such as machine inertia and transmission line strength on the stabilisers performance have been also studied. In addition, the effect of loading conditions is also considered..

In the load frequency control problem part, various types of load frequency controllers (LFC) have been studied on two area power system. These are the conventional integral LFC (CLFC), linear optimal state regulator (OPTLFC), and various types of fuzzy logic based LFC (FLFC). Two fuzzy LFC have been proposed and another two LFC with fuzzy gain scheduling have been also proposed. The effectiveness and performance of the various LFC have been tested following a step load change disturbance in area demand both at nominal and off-nominal system operating condition characterised by the power system time constant (T_p), synchronising coefficient (T_{12}) and frequency bias (b).

1.6 THESIS OUTLINE

The thesis is divided into five chapters. Chapter 1 gives an overview on the problem of power system stabilisation and the scope of the thesis. Then, some theoretical basis on fuzzy set theory and fuzzy logic control is given in chapter 2. In chapter 3, the problem of low-frequency oscillation is presented and the design and computer simulation of different power system stabilisers as supplementary excitation controllers for a single machine infinite-bus power system are highlighted. Then, the load frequency controller (LFC) design using different control schemes for the two area power system are presented in chapter 4. In addition, chapter 4 also includes the simulation results. Finally, conclusions and recommendations are presented in chapter 5.

CHAPTER 2

BASIC CONCEPTS OF FUZZY LOGIC CONTROL

In order to understand the fuzzy application part of this thesis, one has to be aware of some basic concepts behind fuzzy logic control. So, in this chapter, a brief introduction is given about some basic concepts of the fuzzy set theory and fuzzy control. For more details on what will be briefly given and more, one can refer to some books and articles on fuzzy theory and applications given in [6,10-13]. A general introduction to the development of fuzzy logic control will be given first, and then the basic concepts will be covered.

2.1 INTRODUCTION

In 1965, *L. A. Zadeh* [14], the father of fuzzy logic, wrote the first paper on *fuzzy set*, sets with *unsharp* boundaries. These would be in better agreement with human mind, that works with shades of grey, rather than with just black and white. Fuzzy sets can represent linguistic terms like, warm, hot, high, low, big, small, close to, and more. After Zadeh seminal paper, a lot of research was conducted on this subject in an academic basis and almost ten years later, Mamdani [15] succeeded to develop the first fuzzy logic based control system implemented on a laboratory-scale steam engine. Since then, it has become one of the most active and fruitful areas in the application of fuzzy set theory [5-6] and many successful applications in a broad range of areas, ranging from consumer products to industrial process control to aerospace and bioengineering have been developed [2].

Unlike, the classical logic approach which requires a deep understanding of a system represented by exact mathematical equations, and precise numerical values, fuzzy logic incorporates an alternative way of thinking which allows modeling of complex systems using a higher level of abstraction originated from the accumulation of knowledge and experience. This means that fuzzy logic control approach is model independent which means the design of fuzzy logic controller does not require mathematical formulation and modeling of the process under control. In particular, the methodology of fuzzy logic control appears very useful when the process is complex for analysis by conventional quantitative techniques or when the available information about the system is interpreted, qualitatively, inexactly or uncertainly [6]. Thus, fuzzy logic control provides an algorithm which converts the linguistic control strategy of human expert knowledge into an automatic control strategy which can be applied for control of complex, ill-defined processes without knowing quantitative data regarding the input-output relations, which are otherwise required by conventional control methods.

What makes fuzzy logic controllers attractive and widely accepted and applied is that it is easy to understand so that the time required to learn the approach is short, simple to implement as the hardware cost is low, yields superior results to those obtained by controllers designed with conventional algorithms, and less intensive mathematical requirements [10]. Fuzzy logic controllers can be implemented using either a computer, programmable memory chips or a special fuzzy processor [6].

The application of fuzzy set theory is normally referred to as *fuzzy technology*. Japan, Europe and United States are nowadays leading the world in the area of fuzzy technology. A history of industrial applications of fuzzy logic in different areas ranging from consumer products to industrial process control, in Japan, United States, Europe, is given in [2]. The application of fuzzy sets theory in power systems operation planning and control is given in [1]. These applications includes (i) planning areas such as planning, scheduling and reliability, (ii) operation areas such as load management, load forecasting, unit commitment, state estimation, (iii) control related

areas such as power system stabilizers, load frequency control, FACTs, converter/drive, (iv) diagnosis areas such as transformer diagnosis, machine diagnosis and network diagnosis.

2.2 FUZZY SETS VERSUS CLASSICAL SETS

It is better to start with the classical or crisp set before introducing the definition of fuzzy sets.

Classical Sets:

Define a universe of discourse, X , as a collection of objects or elements all having the same characteristics. The individual elements in the universe X will be denoted as x which can be discrete or continuous valued. Thus, $X=\{x\}$. An example of a universe of discourse can be all positive integer numbers so that $X=\{0, 1, 2, \dots\}$. Furthermore, a universe of discourse can be discrete and finite or one that is continuous and infinite.

In classical set theory, if a set A is defined in a universe of discourse X , then any element in X either belongs to the set A or does not belong to it. Thus, a classical set A can be described by its characteristic function $\mu_A(x)$ as follows:

$$\mu_A(x) = \begin{cases} 1; & \text{if } x \in A \\ 0; & \text{if } x \notin A \end{cases} \quad (2.1)$$

Example: Consider the term “hot” as a set of all temperatures higher than 30 degrees. Then the characteristic function of this set denoted by μ_{hot} may be described as shown in Figure 2.1. Thus, the universe of discourse will be all real numbers, and a measured temperature of 29.999 is considered to be not hot! as it does not belong to the set of hot temperatures and thus $\mu_{\text{hot}}(29.999)=0$. As can be seen from Figure 2.1, that a

classical set has a sharp and well-defined boundary and hence classical sets sometimes are referred to as *crisp sets*.

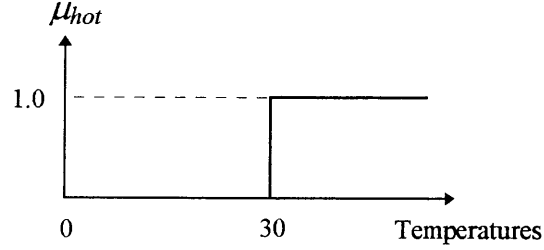


Fig. 2.1 Characteristic function of a crisp set 'hot' temperature.

Fuzzy Sets:

In *fuzzy sets*, elements defined in the universe of discourse X can belong to a fuzzy set with any value between 0 and 1. This value is called the *degree of membership* or *truth value* or simply *membership value*. Thus, a characteristic function of a fuzzy set A can be written as:

$$\mu_A(x) \in [0, 1] \quad \forall x \in X \quad (2.2)$$

The closer the value to unity, the higher the degree of membership, or truth value. Thus, the characteristic function of fuzzy set is called the *membership function*. A membership function associated with a given fuzzy set, maps an input value x to its appropriate membership value. Furthermore, the crisp set characteristic function is a special case of fuzzy membership functions.

Example: Lets consider the same example above, such that the characteristic function of the term *hot* denoted as μ_{hot} is defined based on human opinion. One can consider that 29 degrees is still fairly hot and, and that 31 degrees is still hot but not as hot as 35 degrees and higher. This results in a gradual transition from membership (completely true) to non-membership (not true at all) whereas for a crisp set, the transition is sharp.

Such a fuzzy set may be represented with a membership function μ_{hot} as shown in Figure 2.2.

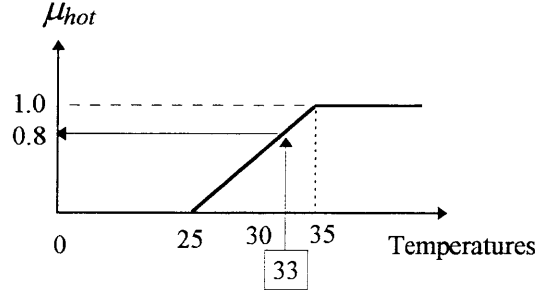


Fig. 2.2 Membership function of a fuzzy set ‘hot’ temperature.

Suppose that the measured temperature is 33 degrees, then the corresponding degree of membership will be 0.8. This means that a temperature of 33 degrees belongs to the ‘hot’ set with 80% degree of belief. However, if the temperature is 40 degrees, then this temperature is considered to be a full member in the *hot* set of temperatures.

From the above example, one can summarize the following points:

- Fuzzy sets describe vague concepts (hot weather, low speed, etc.).
- A fuzzy set admits the possibility of partial membership in it (measured temperature is fierily high, the weather is rather hot, etc.).
- The degree to which an object belongs to a fuzzy set is denoted by a membership value between 0 and 1, e.g. according to the a bove example, 33 degrees temperature is a hot temperature to the degree 0.8).

Typical Shapes of Membership Functions[11]:

Membership function is used to characterise a physical meaning of a fuzzy linguistic term such as large, medium, big, etc. These membership functions are intuitively assigned by a person intending to use the fuzzy linguistic terms. A universe of discourse of a variable (say temperature), can be partitioned into a number of fuzzy membership functions called fuzzy linguistic terms, or labels or states. A temperature,

for example, can be represented by three fuzzy linguistic terms as *low*, *medium* and *high* temperatures. Membership function can be a continuous or discrete, linear such as triangular or trapezoidal shaped functions, or non-linear function such as a bell shape function.

Typical shapes of these membership functions for the terms low, medium and high terms are shown in Figure 2.3 as non-linear continuous functions. A membership function of *low* temperature is called a *Z-shaped* function as it looks like the letter Z shape. Similarly, the *medium* temperature exhibits a membership function similar to the shape of a bell and is thus called *II-shaped* function and the *high* temperature is called a *S-shaped* function. These membership functions shown in Figure 2.3 can be modified to piece-wise continuous functions shown in Figure 2.4 without significant change of the meaning.

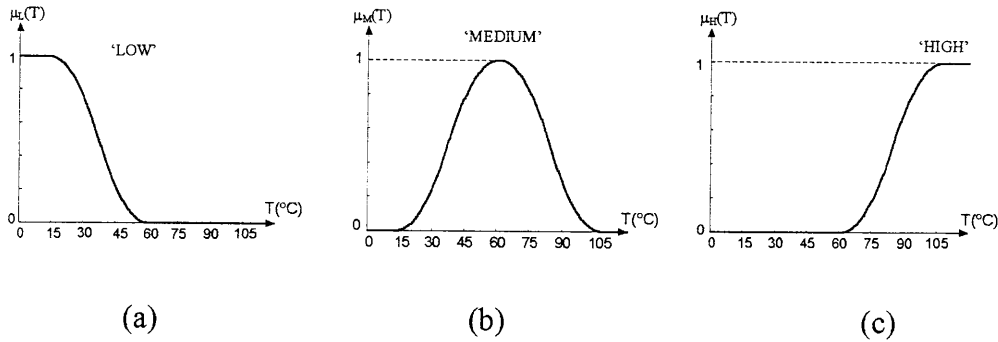


Fig. 2.3 Typical membership functions of fuzzy linguistic terms employing non-linear continuous functions [11].

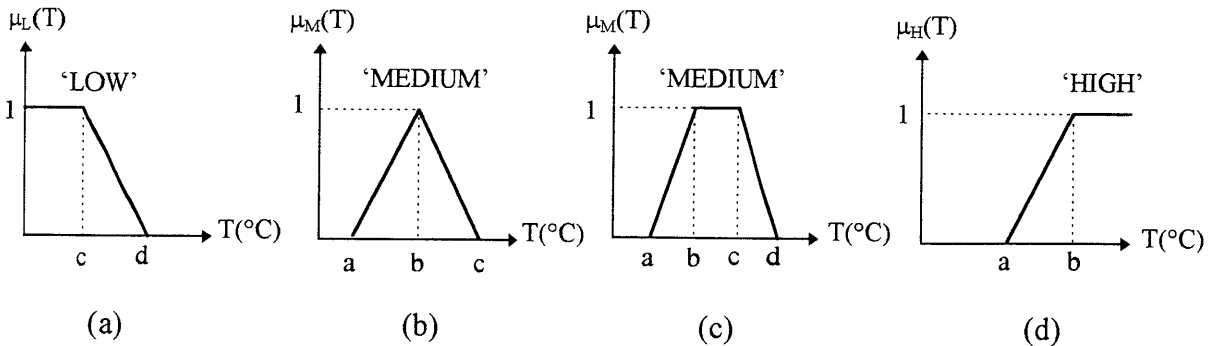


Fig. 2.4 Membership functions of fuzzy linguistic terms employing piece-wise linear continuous functions.

(a) LOW, (b) MEDIUM (triangular), (c) MEDIUM (trapezoidal), (d) HIGH.

2.3 BASIC FUZZY SET OPERATIONS

As in classical sets theory, traditional logic operations such as union, intersection, and complement can be also applied to fuzzy sets [14]. In fuzzy set theory, the membership functions which play an important role in fuzzy control, are related with each other with a logical operator like AND, OR, NOR which respectively corresponds to the intersection, union, and complement logical operations. The most common of these logical operations will be reviewed in this section.

Complement: [14]

The *complement* of a fuzzy set A is denoted by A' and is defined by (see Figure 2.5)

$$\mu_{A'}(x) = 1 - \mu_A(x), \quad \forall x \in X \quad (2.3)$$

This corresponds to the negation NOT. Figure 2.5 illustrate this operation with solid line representing the membership function of the complement fuzzy set A' .

Union: [14]

The *union* of two fuzzy sets A and B with respective membership functions $\mu_A(x)$ and $\mu_B(x)$ is a fuzzy set C , written as $C=A \cup B$, whose membership function is related to those of A and B by

$$\mu_C(x) = \text{Max}\{\mu_A(x), \mu_B(x)\}, \quad \forall x \in X \quad (2.4)$$

or in abbreviated form

$$\mu_C = \mu_A \vee \mu_B \quad (2.5)$$

This corresponds to the connective OR.

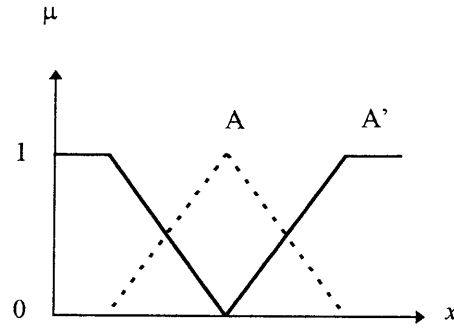


Fig. 2.5 Complement of fuzzy set A.

Intersection: [14]

The *intersection* of two fuzzy sets A and B with respective membership functions $\mu_A(x)$ and $\mu_B(x)$ is a fuzzy set C , written as $C=A \cap B$, whose membership function is related to those of A and B by

$$\mu_C(x) = \text{Min}\{\mu_A(x), \mu_B(x)\}, \quad \forall x \in X \quad (2.6)$$

or in abbreviated form $\mu_C = \mu_A \wedge \mu_B$ (2.7)

This corresponds to the connective AND.

Graphical representation of the Union and Intersection operations are illustrated by solid lines in Figure 2.6.

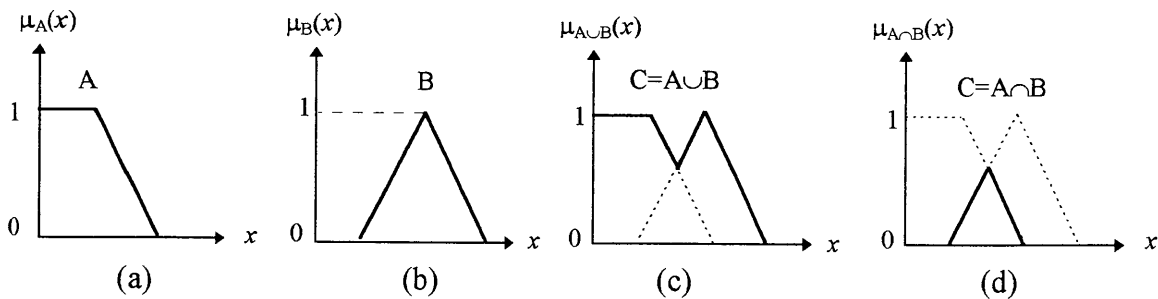


Fig. 2.6 The fuzzy set operations union & intersection of two fuzzy sets. (a) Fuzzy set A, (b) Fuzzy set B, (c) Union of A and B, (d) Intersection of A and B.

Most of the properties that hold for classical sets (e.g. associativity, distributivity, idempotency), hold also for fuzzy sets, except for the two properties of the *excluded middle laws*. These two laws do not hold for fuzzy sets, since fuzzy sets can overlap.

$$1. \text{ Law of contradiction: } A \cap A' \neq \emptyset \quad (2.8)$$

$$2. \text{ Law of excluded middle: } A \cup A' \neq X \quad (2.9)$$

Fuzzy Relation:

Let A and B be two fuzzy sets with membership functions $\mu_A(x)$ and $\mu_B(x)$, respectively. A fuzzy relation R from A to B can be visualised as a fuzzy graph and can be characterised by a membership function $\mu_R(x,y)$, which satisfies the compositional rule of inference as follows:

$$\mu_B(y) = \max_{x \in X} \{ \min[\mu_R(x,y), \mu_A(x)] \} \quad (2.10)$$

2.4 FUZZY LOGIC CONTROL

Fuzzy control systems are rule-based systems in which a set of so-called fuzzy rules represent a linguistic control strategy. The aim of fuzzy control systems is to replace a skilled operator with a fuzzy rule-based system. The basic elements of a fuzzy logic controller (FLC) is shown in Figure 2.7.

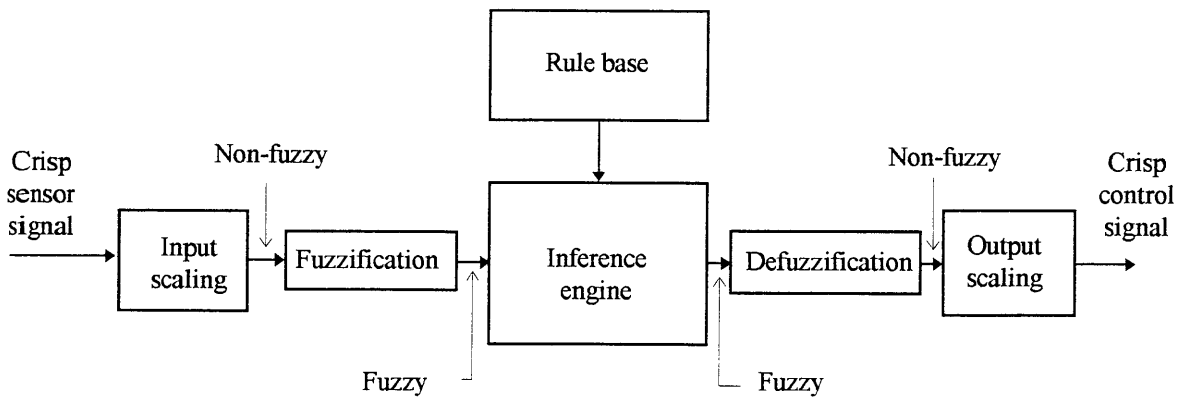


Fig. 2.7 General block diagram of a fuzzy logic controller.

Input and Output Scaling:

Normalisation or scaling of the input values and denormalisation of the output values are not strictly necessary. One can define the membership functions for the input variables on their physical domain. In that case scaling is not necessary. However, mostly both inputs and outputs of the controller are defined on a common domain, meaning the same universe of discourse (for example $X=[-1,1]$). So the physical input values (actual measured input) are being mapped to the predetermined domain by multiplying the physical input value with a scaling or normalising factor as follows:

$$x_{norm} = N_x \cdot x \quad (2.11)$$

where x is the actual measured input value, x_{norm} is the normalised value and N_x is the normalising factor. The advantage of this approach is that the fuzzification, inference engine, and defuzzification modules can be designed independently of the physical domain.

Scaling of the measured input crisp value is done to transfer the physical domains. Similarly, in case the domain of the output variable is normalised, then denormalisation is applied as:

$$y_{crisp} = N_y \cdot y \quad (2.12)$$

where y is the normalised output, y_{crisp} is the physical value and N_y is the denormalisation factor.

There are some situations where the physical domains of the input and output variables are not known a priori, which is the case in many practical systems. In such cases, the input and output are necessary and are considered to be tuning parameters.

Fuzzification:

Fuzzification is simply the process of making a crisp input fuzzy. Thus, a crisp input is mapped to a linguistic fuzzy set defined in a certain universe of discourse. In this stage, the crisp inputs are used to determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.

Control Rules:

The heart of a fuzzy logic controller is its control rules where the knowledge base and decision-making logic reside. These rules define the relation between the input and output of a fuzzy controller. The rules are defined using linguistic variables and have the form

$$\begin{aligned} &\text{'IF (a set of conditions are satisfied)} \\ &\quad \text{THEN (a set of consequences can be inferred)'} \end{aligned} \quad (2.13)$$

where the elements in the *IF*-part are called the *antecedents* and the elements of the *THEN*-part are called *consequents*. Further more, several linguistic variables might be involved in the antecedents and the conclusions of the rules. When this is the case, the system will be referred to as a multi-input multi-output (MIMO) fuzzy system. For example, for the case of two-inputs and single-output (MISO) fuzzy systems, fuzzy control rules have the form:

$$\begin{aligned} R_1: & \text{ if } x_1 \text{ is } A_{11} \text{ and } x_2 \text{ is } A_{12} \text{ then } y \text{ is } B_1 \\ R_2: & \text{ if } x_1 \text{ is } A_{21} \text{ and } x_2 \text{ is } A_{22} \text{ then } y \text{ is } B_2 \\ & \dots \dots \dots \dots \dots \dots \\ R_n: & \text{ if } x_1 \text{ is } A_{n1} \text{ and } x_2 \text{ is } A_{n2} \text{ then } y \text{ is } B_n \end{aligned} \quad (2.14)$$

where x_1 , x_2 , and y are linguistic variables representing two process state variables and one control (output) variable; A_{ij} , B_{ij} , are linguistic labels of the linguistic variables x_1 , x_2 , y in the universe of discourse U, V , and W , respectively with $i=1,2,\dots,n$, and $j=1,2$. These set of rules are often called *Fuzzy Associative Memory* (FAM) or simply

rule base. Generally, the number of rules a system requires depends on the number of input and the number of membership functions given to each variable. Consider a FLC with 2 inputs variables (error and change of error) and each is described by 7 membership functions (NB, NM, NS, Z, PS, PM, and PB). This will lead to a number of rules $7^2 = 49$. Notice that the number of rules grow exponentially with the number of inputs. A number of rule reduction methods have been reported, such as sensory fusion and hierarchical approaches [16]. Fuzzy rules are to be formed based on expert's experience, engineering knowledge, a skilled human operator control action, a fuzzy model of the process, or learning.

Inference Engine

In this block of Figure 2.7, the fuzzy logic controller performs the necessary inference operation on all fuzzy rules. More specifically, it compares the fuzzified values of the controller inputs as specified by the fuzzy rules described in the FAM. It calculates a degree of fulfilment (DOF) or a rule truth value of each rule using the logical operations defined earlier. The most well known fuzzy inference or reasoning methods are the *max-min* and *max-dot*. The mathematical equation behind them can be given as follows:

Consider a number of r rules of a FLC of which the j th rule has the form

$$R_j: IF x_1 \text{ is } A_{j1} \text{ and } x_2 \text{ is } A_{j2} \text{ and } \dots \text{ and } x_n \text{ is } A_{jn} \text{ THEN } y_j \text{ is } B_j \quad (2.15)$$

where $x_1 \dots x_n$ are the crisp inputs, y is the output variable, $A_{j1} \dots A_{jn}$ and B_j are fuzzy sets of an any shape. If U is the universe of discourse of the output, then the following equation determines the output's membership function $\mu_{Output}(y)$ according to the *max-min approach*:

$$\forall y \in U: \mu_{Output}(y) = \bigcup_{j=1}^r \left\{ \min \left[\mu_{A_{j1}}(x_1), \mu_{A_{j2}}(x_2), \dots, \mu_{A_{jn}}(x_n); \mu_{B_j}(y) \right] \right\} \quad (2.16)$$

For the *max-dot approach* the following equation can be obtained:

$$\forall y \in U: \mu_{Output}(y) = \bigcup_{j=1}^r \left\{ \min[\mu_{A_{j1}}(x_1), \mu_{A_{j2}}(x_2), \dots, \mu_{A_{jn}}(x_n)] \cdot [\mu_{B_j}(y)] \right\} \quad (2.17)$$

Notice that for the union operation in both equations above, the max operator has to be used.

In order to visualise the operation of these two methods of inference, consider the following two fuzzy rules:

$$\begin{aligned} R_1: & \text{ if } x_1 \text{ is } A_{11} \text{ and } x_2 \text{ is } A_{12} \text{ then } y \text{ is } B_1 \\ R_2: & \text{ if } x_1 \text{ is } A_{21} \text{ and } x_2 \text{ is } A_{22} \text{ then } y \text{ is } B_2 \end{aligned} \quad (2.18)$$

Then, for a given crisp inputs (say $x_1 = \text{input}(i)$ and $x_2 = \text{input}(j)$), a graphical illustrations of the operation of fuzzification and inference process is shown in Figure 2.8 and 2.9 for max-min and max-dot inference methods, respectively.

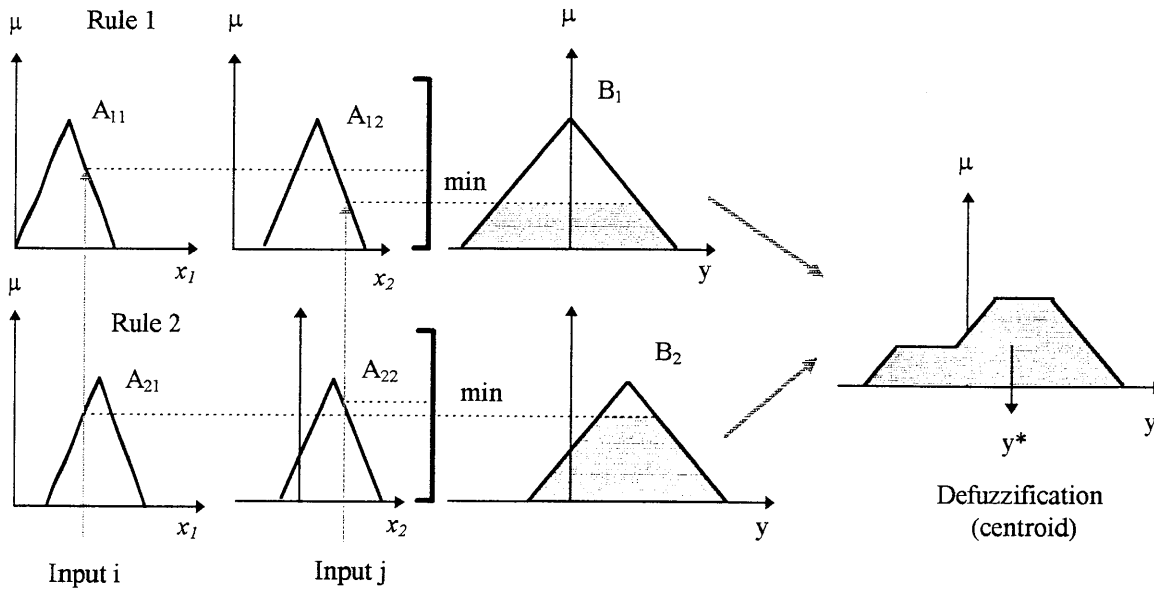


Fig. 2.8 Graphical illustration of fuzzification and inference phase according to (max-min) inference method with crisp input [12].

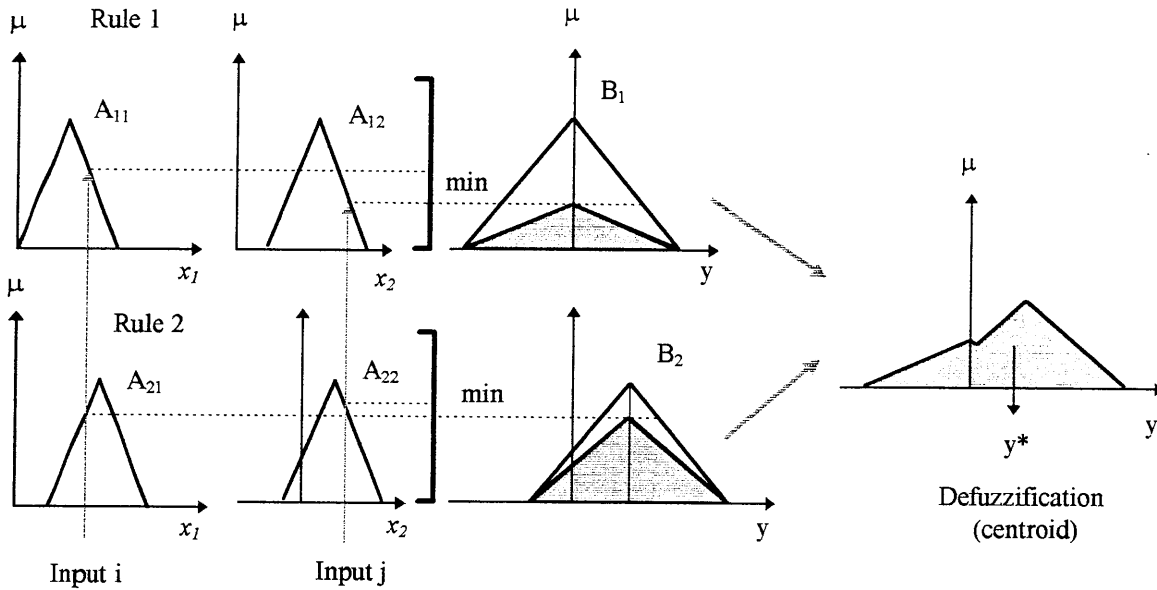


Fig. 2.9 Graphical illustration of fuzzification and inference phase according to (max-dot) inference method with crisp input [12].

Defuzzification:

Basically, *defuzzification* is a mapping from a space of fuzzy control actions defined over an output universe of discourse into a space of nonfuzzy (crisp) control action [6]. Simply, it is a process of converting a fuzzy quantity to a precise (crisp) quantity. It is employed because in all practical applications a crisp control is required.

Various defuzzification methods have been proposed in literature [6,12]. However, at present, the common defuzzification strategies may be described as the max criterion, the mean of maximum and the centre of area (centroid).

1. *The Max Criterion Method*: The max criterion produces the point at which possibility distribution of the control action (union of the fuzzy output of all the fired rules) reaches maximum value.
2. *The Mean of Maximum Method (MOM)*: The MOM strategy generates a control action which are represent the mean value of a all local control actions whose

membership functions maximum. More specifically, in the case of discrete universe, the control action may be expressed as

$$y^* = \sum_{j=1}^l \frac{w_j}{l} \quad (2.19)$$

where w_j is the support values at which the membership function reaches the maximum value $\mu_y(w_j)$ and l is the number of such support values.

3. *The Centre of Area Method (COA)*: The widely used COA strategy generate the centre gravity of the possibility distribution of a control action. In the case of discrete universe, this method yields

$$y^* = \frac{\sum_{j=1}^n \mu_y(w_j) \cdot w_j}{\sum_{j=1}^n \mu_y(w_j)} \quad (2.20)$$

where n is the number of quantization levels of the output.

As pointed out by Lee [6], the COA strategy yields superior results. However, MOM strategy yields a better transient performance while the COA strategy yields a better steady-state performance.

Takagi-Sugeno type FLC [16]:

The distinguishing mark of a Takagi-Sugeno FLC (TSFLC) is that fuzzy sets are used in the antecedents, but that output consequence is, in general, a crisp linear or non-linear function and often just a constant value. The j th fuzzy rule in TSFLC is of the form:

$$R_j: \text{IF } x_1 \text{ is } A_{j1} \text{ and } x_2 \text{ is } A_{j2} \text{ and } \dots \text{ and } x_n \text{ is } A_{jn} \text{ THEN } y_j = f_j(x_1, x_2, \dots, x_n) \quad (2.21)$$

where $x_1 \dots x_n$ are the crisp inputs, y_j is the output according to the j th fuzzy rule, $A_{j1} \dots A_{jn}$ and f_j are arbitrary functions.

With this type of FLC's, one can assign a control function for each region in the input space by separate rules. This can also be done by conventional switching of controllers, but fuzzy method offers a smooth transition between the individual controllers. That is why a sugeno inference system is extremely well suited to the task of gain scheduling. A sugeno system is also useful in modelling of non-linear systems by interpolating across a multi-linear systems linearized at different operating condition.

The final output y is the weighted combination of all the fired rules, described by

$$y_o = \frac{\sum_{j=1}^r \alpha_j \cdot y_j}{\sum_{j=1}^r \alpha_j} \quad (2.22)$$

where is the 'truth' value or 'degree of fulfilment' α_j of the j^{th} fired rule, is determined by

$$\alpha_j = \min[\mu_{A_{j1}}(x_1), \mu_{A_{j2}}(x_2), \dots, \mu_{A_{jn}}(x_n)] \quad (2.23)$$

CHAPTER 3

LOW-FREQUENCY OSCILLATIONS AND SUPPLEMENTARY CONTROLS

3.1 INTRODUCTION:

In the development of interconnection of large electric power systems, there has been spontaneous system oscillations of small magnitude and at a very low frequencies in the range of approximately 0.2 to 2.5 Hz [17]. Once started, they would continue for a while and disappear, or continue to grow causing system separation. Even in stable situations, insufficient damping of these oscillation may limit the power transfer capability of the system. With more investigations and experience accumulated from interconnected electric power system operation, power system engineers are now convinced that the low-frequency oscillations are due to the oscillation of machine rotors, behaving as rigid bodies, with respect to one another using the transmission line between them to exchange energy. In other words, they are due to the lack of damping of the mechanical mode of the interconnected system. This problem is aggravated (worsen) if the system has generating units of significantly different inertia constants interconnected by weak tie-lines. So, to damp these oscillation, additional positive damping is required which can be provided by supplementary excitation control [18].

In literature, considerable efforts have been placed on the application of supplementary excitation control, commonly known as power system stabilizer (PSS), to enhance system damping to low-frequency oscillations and to improve the dynamic stability of the power system. DeMello and Concordia [19] were the first to use the

theory of phase compensation in the frequency domain to make a thorough analysis of a lead-lag compensator which is nowadays the most widely employed power system stabilizer for enhancing the damping characteristic of a synchronous machine. Since then, numerous papers have been published on the tuning of the parameters of the lead-lag controller. A number of PSS input signals, such as rotor speed, electric power, accelerating power, terminal voltage etc., and linear combinations of these signals have been extensively investigated, and recommendations regarding their use have been reported in the literature [17,20-21,67]. The design of such conventional power system stabilizers (CPSS) requires setting of stabilizer parameters at certain fixed values determined under particular operating conditions. Although such stabilizers give satisfactory results regarding the damping of oscillations, their outcome may not be considered as the best possible. This led researches to be directed towards using the non-conventional design techniques based on modern control theory, linear optimal control [18,22-23] and linear suboptimal control [22-25].

Since the operating point of a power system drifts nonlinearly as a result of continuous loads/generating units changes (connected/disconnected) or unpredictable major disturbances such as three-phase faults, it is desirable to adapt the stabilizer parameters in real-time based on on-line measurements in order to maintain good dynamic performance over a wide range of operating conditions. This motivates the development of a self-tuning and adaptive power system stabilizer [26-28]. Although the adaptive and self-tuning PSS is capable of offering better dynamic performance than a fixed-gain PSS mentioned above, it suffers from a major drawback of requiring model identification in real-time which is very time consuming, especially for a microcomputers with limited computational capability [29-30]. Recently, alternative control schemes that does not require model identification, and requires less computational efforts than the self-tuning controllers and is easier to be implemented on a microcomputer have been reported [29]. Rule-Base Power System Stabilizers [31-32] and Fuzzy Logic Based Power System Stabilizers [29-46,57] are examples of such schemes. Also reported, the application of Artificial Neural Networks (ANN) based PSS for tuning PSS parameters [47-48] and to function as a PSS [49-51].

Recently, combination of fuzzy logic and neural network which shows promising results [52-54].

Simplicity, less intensive mathematical requirements, and performance are the most important features of FLC's. The actual installation of fuzzy logic stabilizer on a number of hydro-power stations on 1992 and 1994 in Japan was also reported [55]. More recently, Hiyama and his co-authors [56] have proposed a complete fuzzy excitation system which achieves the automatic voltage regulator (AVR) function in one control loop and gives the PSS function in another loop.

In this part of the thesis, the design and effectiveness of the following power system stabilizers have been carried out for a single machine connected to infinite-bus power system.

- (1) Conventional Lead Power System Stabilizer.
- (2) Optimal Linear Quadratic Regulator.
- (3) Suboptimal Linear Quadratic Regulator.
- (4) Rule-Based Stabilizer.
- (5) Different Fuzzy Logic Based Stabilizers.

3.2 A POWER SYSTEM MODEL FOR LOW-FREQUENCY OSCILLATION STUDIES [18]

Consider a single machine infinite-bus system shown in Figure 3.1. The simplified linearized incremental model of this synchronous machine with a voltage regulator exciter and stabilizer is shown in Figure 3.2 [17-18]. The system parameters have been taken from [18] and all of which are shown in appendix A.

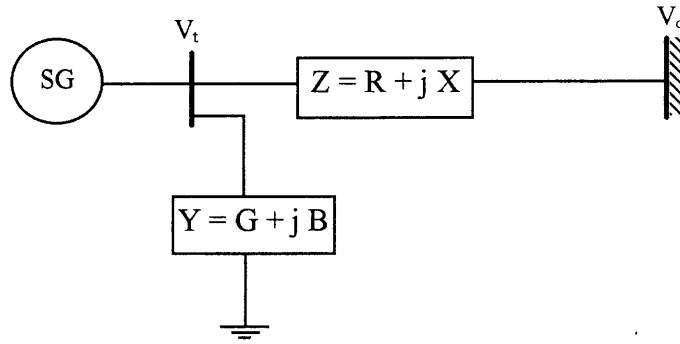


Fig. 3.1 System configuration for a single machine connected to a large power system through an external impedance.

From Figure 3.2, one can write the state equations of this system as follows:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}u(t) + \mathbf{F}d(t) ; \quad \mathbf{x}(0) = \mathbf{x}^0 \quad (3.1)$$

where

$\mathbf{x}(t) = [\Delta\omega, \Delta\delta, \Delta e'_q, \Delta E_{fd}]^T$ is the state vector.

$\mathbf{d}(t) = [\Delta V_{ref}, \Delta T_m]^T$ is the disturbance vector.

$u(t) = \Delta V_s$ is the control command (PSS output signal)

$\mathbf{A}, \mathbf{B}, \mathbf{F}$ are constant matrices defined below.

The *system matrix* **A**, the *input matrix* **B**, and the *disturbance matrix* **F** are defined as follows:

$$A = \begin{bmatrix} -D/M & -K_1/M & -K_2/M & 0 \\ \omega_b & 0 & 0 & 0 \\ 0 & -K_4/T'_{do} & -1/(T'_{do}K_3) & 1/T'_{do} \\ 0 & -K_A K_5/T_A & -K_A K_6/T_A & -1/T_A \end{bmatrix} \quad (3.2)$$

$$B = \begin{bmatrix} 0 & 0 & 0 & K_A/T_A \end{bmatrix}^T ; \quad F = \begin{bmatrix} 0 & 0 & 0 & K_A/T_A \\ 1/M & 0 & 0 & 0 \end{bmatrix}^T \quad (3.3)$$

where T denotes the transpose.

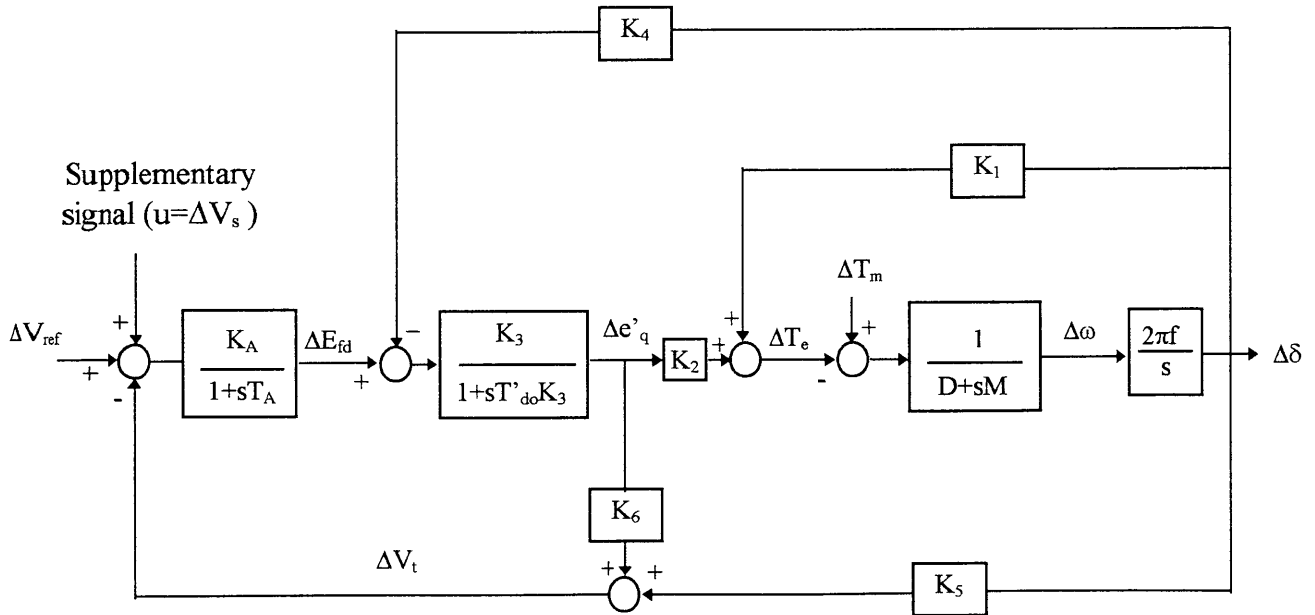


Fig. 3.2 Simplified incremental model of a single machine infinite-bus system.

3.3 SUPPLEMENTARY EXCITATION CONTROL DESIGN

In this section, the design of different supplementary excitation controller, commonly known as Power System Stabilizer (PSS), will be discussed. The basic function of the PSS is to provide a supplementary stabilising signal, u , to the excitation system of a synchronous generator in order to enhance the system damping at low-frequency oscillations. To provide damping, the PSS must produce a component of electrical torque on the rotor which is in phase with speed variations.

Thus, it is natural to use rotor speed as feedback signal to PSS. Accelerating power and frequency deviation are directly related to the rotor speed and, therefore, these three signals are widely used for the design of the PSS. Conceptually, other signals can also be used as input to the PSS, such as armature current, field current, and reactive power were also investigated and it was found that the signals derived from rotor speed are more effective than these signals. It was also reported in literature [17,56] that speed input stabilizers can contribute to negative damping of shaft torsional oscillation mode. To avoid this property, special filters have to be installed to suppress the torsional frequencies (in the range of 10 to 15 Hz). The use of accelerating power as control signal has received considerable attention due to its inherent low level of torsional interaction. Larsen and Swann in their three part paper [17], have presented an investigation into the effectiveness of three control signals, namely, rotor speed, electrical power, and frequency. They recommended that stabilizers using frequency signals should be tuned for weak systems and those using speed and power signals should be tuned for strong systems.

The only stabilizers that will be highlighted in this thesis are the conventional lead-lag stabilizer, linear optimal PI stabilizer, suboptimal PI stabilizer, Rule-based stabilizer and different types of fuzzy logic stabilizers.

3.3.1 CONVENTIONAL PSS DESIGN

The most widely employed power system stabilizer for enhancing the damping characteristic of a synchronous machine is the lead-lag controller. As first pointed out by deMello and Concordia [19] and later explained by Larsen and Swann [17], the fundamental concepts for the design of a conventional lead-lag power system stabilizer is to compensate for the gain and phase lag of the excitation system, the generator, and the power system, which collectively determine the transfer function, $G_E(s)$, from the stabilizer output to the component of electrical torque which is modulated via excitation control.

As a result, a practical speed input stabilizer [17] shown in Figure 3.3, must include (i) a phase lead compensation block which will compensate for the phase lag between the exciter input and the electrical torque for a desired range of frequencies. (ii) a stabilising gain K_C , which is set to a value which results in satisfactory damping of the critical system mode(s) and which does not cause excessive amplification of stabilizer input signal noise. This can be done by attenuating the gain at high frequencies to limit the impact of noise and minimise torsional interaction, and consequently low-pass and possibly band-reject filters are required, (iii) A stabilising signal washout stage function as high pass filter which removes dc signals, and without it, steady changes in speed would modify the terminal voltage. This will make sure that the stabilizer will not over ride the function of the voltage regulator at steady state, and (iv) stabilizer output limiters are imposed at the PSS output in order to restrict the level of generator terminal voltage fluctuations during transient conditions.

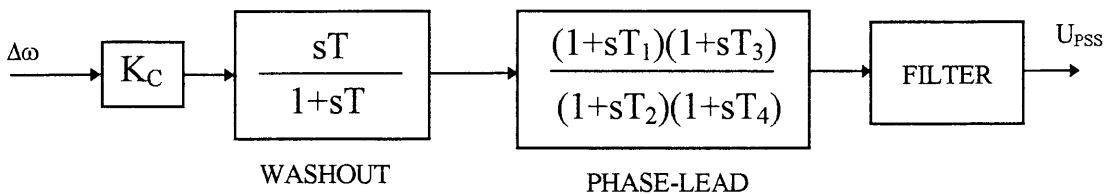


Fig. 3.3 Practical speed input PSS.

To design such PSSs requires the determination (or tuning) of six parameters for each stabilizer. These are the overall DC gain K_c , the washout time constant T , and various time constants (T_1 - T_4) for the two phase-lead network. A common approach has been to simplify the problem of tuning the six parameters to that of tuning only two by making a series of intuitive assumptions based on experience. For example, it is common to assume that: (i) the lead and lag networks are identical with known time constants i.e $T_1=T_3$ and $T_2=T_4$; (ii) based on experience, a particular value is given to the washout time constant which lies between the range of 1 to 20 seconds.

A general design procedure for selecting PSS parameters may be summarised as follows with the help of Figure 3.2: [18]:

- (1) *Calculate the undamped natural frequency of the mechanical mode ω_n using:*

$$\omega_n = \sqrt{\omega_b K_1 / M} \quad (3.4)$$

where $\omega_b = 2\pi f$ (in rad/sec), f is system frequency, K_1 is a constant for given system parameters and operating conditions, and M is the inertia constant in seconds.

- (2) *Calculate the phase lag of $G_E(s)$ between u and e_q' :*

$$G_E(s) = \frac{K_A K_3}{(1 + sT_A)(1 + sT_{do} K_3) + K_A K_3 K_6} \quad (3.5)$$

then the phase lag of $G_E(s)$ is calculated from

$$\text{phase lag of } G_E(s) = \angle G_E(s) \Big|_{s=j\omega_n} \triangleq \gamma \quad \gamma < 0 \quad (3.6)$$

- (3) *Design the Phase Lead Compensation $\angle G_C$* : For speed input PSS, the phase lead is chosen such that

$$\angle G_C + \angle G_E = 0, \quad (3.7)$$

This can be realised by operational amplifiers, with transfer function chosen in the form of

$$G_C(s) = \left(\frac{1 + sT_1}{1 + sT_2} \right)^k, \quad k=1 \text{ or } 2, T_1 > T_2 \quad (3.8)$$

where k represent the number of phase compensation blocks.

It can be shown easily that for a given T_2 and k , T_1 is determined by

$$T_1 = \frac{\tan(\beta - \frac{\gamma}{k})}{\omega_n} \quad (3.9)$$

where

$$\beta = \tan^{-1}(\omega_n T_2) \quad (3.10)$$

- (4) *Design a Gain K_C for the supplementary Excitation:*

For a given a damping coefficient ξ_n , then the gain K_C is calculated using

$$K_C = \frac{2\xi_n\omega_n M}{K_2 |G_C(j\omega_n)| |G_E(j\omega_n)|} \quad (3.11)$$

- (5) *Design a Reset Block* : The supplementary excitation control should be activated only when the low-frequency oscillation begins to develop, and it should be

automatically terminated when the system oscillation ceases. It should not interfere with the regular function of excitation during steady-state operation at the system frequency. A reset block is therefore necessary as shown in Figure 3.3. The washout time constant, T , should be selected large so that it will have no effect on the phase shift or gain at the oscillating frequency, and hence sT is larger than unity and

$$\left(\frac{sT}{1+sT} \right) \approx 1 \quad \text{at } s = j\omega_n \quad (3.12)$$

and at steady state i.e. $s \rightarrow 0$, $s\Delta\omega = 0$. Hence, the PSS will have no effect on steady state of the system.

Following the above procedure, will lead to the final configuration of the supplementary excitation controller (PSS). If only one compensation block was found to be sufficient as will be shown in the following chapter, the block diagram of a supplementary excitation control with one compensation block and one reset filter is shown in Figure 3.4.

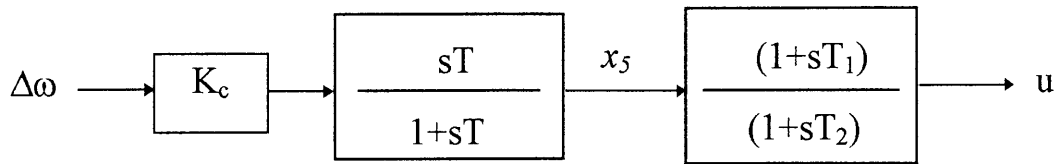


Fig. 3.4 Conventional PSS [18].

With this stabilizer configuration shown in Fig. 3.4, two new states are added and the closed loop system will be

$$\dot{\mathbf{x}}_c(t) = \mathbf{A}_c \mathbf{x}(t) + \mathbf{F}_c \mathbf{d}(t) \quad (3.13)$$

where the new state vector is

$$\mathbf{x}_c(t) = [\Delta \omega, \Delta \delta, \Delta e'_q, \Delta E_{fd}, x_5, u]^T \quad (3.14)$$

and the closed loop state and disturbance matrices are

$$\mathbf{A}_c = \left[\begin{array}{cccc|cc} & & & & 0 & 0 \\ & & & & 0 & 0 \\ & & & & 0 & 0 \\ & & & & 0 & \frac{K_A}{T_A} \\ & & & & \hline -D/M & -K_1/M & -K_2/M & 0 & -1/T & 0 \\ -\frac{DK_c T_l}{MT_2} & -\frac{K_1 K_c T_l}{MT_2} & -\frac{K_2 K_c T_l}{MT_2} & 0 & \frac{K_c}{T_2} \left(1 - \frac{T_l}{T} \right) & -\frac{1}{T_2} \end{array} \right] \quad (3.15)$$

$$\mathbf{F}_c = \left[\begin{array}{cccc|cc} 0 & 0 & 0 & \frac{K_A}{T_A} & 0 & 0 \\ \frac{1}{M} & 0 & 0 & 0 & \frac{1}{M} & \frac{K_c T_l}{MT_2} \end{array} \right]^T \quad (3.16)$$

3.3.2 OPTIMAL LINEAR REGULATOR CONTROL DESIGN

The Linear Quadratic Regulator (LQR) design problem has been extensively investigated for the past four decades [18,58-59]. Consequently, the theory of linear optimal control has been very well developed. As pointed out in [22], the shift towards optimal control, and in particular towards optimal linear regulator (LQR) control theory, was motivated by the following reasons:

- (i) Optimal control provides a systematic way of designing a state feedback LQR.
- (ii) The resulting stabilizer is guaranteed to stabilise the system and to provide a guaranteed level of performance, and therefore the problem of where to place the close loop poles does not arise.
- (iii) The LQR provides sufficient stability margins, and therefore is robust to small parameter changes.
- (iv) Well developed design algorithm.

As a result, a number of papers have been published concerning the application of optimal LQR theory to the design of power system stabilizers [18,22-25]. Here, LQR control design will be first introduced and then the application of LQR to PSS will be given.

Linear State Regulator Control Design [18]:

Given a linear, time-invariant system represented by the following state equation,

$$\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t); \mathbf{x}(t_0) = \mathbf{x}^0 \quad (3.17)$$

where $\mathbf{x}$ is the state vector, $\mathbf{u}$ is the control vector, and $\mathbf{A}, \mathbf{B}$ are constant matrices obtained at a particular operating condition.

Then, the control problem is to find an admissible control $\mathbf{u}$ such that the following quadratic performance index J is minimised,

$$J = \frac{1}{2} \int_0^{\infty} (\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{u}^T \mathbf{R} \mathbf{u}) dt \quad (3.18)$$

where $\mathbf{Q}$ and $\mathbf{R}$ are positive semidefinite and positive definite constant matrices respectively. Then, for a controllable system (3.17), such control law can be given by

$$\mathbf{u} = -\mathbf{K}\mathbf{x}(t) \quad (3.19)$$

where $\mathbf{K}$ is obtained from solution of the algebraic matrix Riccati equation as:

$$\mathbf{A}^T \mathbf{S} + \mathbf{S} \mathbf{A} - \mathbf{S} \mathbf{B} \mathbf{R}^{-1} \mathbf{B}^T \mathbf{S} + \mathbf{Q} = \mathbf{0} \quad (3.20)$$

$$\mathbf{K} = \mathbf{R}^{-1} \mathbf{B}^T \mathbf{S} \quad (3.21)$$

With $\mathbf{u}$ given by (3.19), the closed loop system becomes

$$\dot{\mathbf{x}}(t) = (\mathbf{A} - \mathbf{B}\mathbf{K})\mathbf{x}(t) \quad (3.22)$$

Design of PSS [22]:

The state equation representing the linearized equivalent model of the power system given in section (3.2) for low-frequency oscillation study obtained at a particular operating condition, is given as

$$\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) + \mathbf{F} \mathbf{d}(t) ; \mathbf{x}(0) = \mathbf{x}^0 \quad (3.23)$$

$$\mathbf{y}(t) = \mathbf{C} \mathbf{x}(t) \quad (3.24)$$

where $\mathbf{x} = [\Delta\omega \ \Delta\delta \ \Delta e'_q \ \Delta E_{fd}]^T$ is the state vector, $\mathbf{u} = \Delta V_s$ is the supplementary control signal, $\mathbf{d} = [\Delta V_t \ \Delta T_m]^T$ is the disturbance vector, $\mathbf{y}$ is the output vector and $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{F}$ are constant matrices.

Applying the optimal state regulator control directly without any modification, will result in a non-zero steady state values $\mathbf{x}_{ss}$ as a result of the external disturbance d . At steady state, $\dot{\mathbf{x}}(t)=0$ and hence

$$\mathbf{0} = \mathbf{A} \mathbf{x}(t) + \mathbf{B} u(t) + \mathbf{F} d(t) \quad (3.25)$$

This gives,

$$\mathbf{x}_{ss} = -(\mathbf{A} - \mathbf{BK})^{-1} \mathbf{F} d \quad (3.26)$$

Thus, the disturbance will result in an off-set in the system's steady-state, the magnitude of which depends on the magnitude of the disturbance. One simple way of suppressing this off-set is to introduce integral control together with state feedback constant gains $\mathbf{K}$.

When the terminal voltage set point is changed by ΔV_{ref} , then it is desirable to track this set point. To achieve this, we need to introduce an integral state 'q' defined as:

$$\dot{q}(t) = \Delta V_{ref} - \Delta V_t \quad (3.27)$$

where ΔV_t is the actual measured voltage deviation and ΔV_{ref} is the input change in reference set point. So, at steady state, $\dot{q}(t) = 0$ leading to $\Delta V_t = \Delta V_{ref}$.

From the incremental model shown in Figure 3.2, ΔV_t can be written in terms of the states variables $\mathbf{x}$ as:

$$\Delta V_t = K_j \Delta \delta + K_e \Delta e'_q = \mathbf{H} \mathbf{x}(t) \quad (3.28)$$

where $\mathbf{H}$ is given by

$$\mathbf{H} = [0 \ K_5 \ K_6 \ 0] \quad (3.29)$$

Substituting (3.27) in (2.26), we get

$$\dot{q}(t) = \Delta V_{ref} - \mathbf{H}\mathbf{x}(t) \quad (3.30)$$

Combining equation (3.30) with (3.24), yields to the following augmented system equation,

$$\dot{\mathbf{x}}_a(t) = \mathbf{A}_a \mathbf{x}_a(t) + \mathbf{B}_a u(t) + \mathbf{F}_a \mathbf{d}(t) \quad (3.31)$$

$$\mathbf{y}_a(t) = \mathbf{C}_a \mathbf{x}_a(t) \quad (3.32)$$

where

$$\mathbf{x}_a = [\mathbf{x} \ q]^T ; \ \mathbf{y}_a = [\mathbf{y} \ q]^T \quad (3.33)$$

$$\mathbf{A}_a = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ -\mathbf{H} & 0 \end{bmatrix} ; \quad \mathbf{B}_a = \begin{bmatrix} \mathbf{B} \\ 0 \end{bmatrix} ; \quad \mathbf{C}_a = \begin{bmatrix} \mathbf{C} & 0 \\ 0 & 1 \end{bmatrix} \quad (3.34)$$

$$\mathbf{F}_a = \begin{bmatrix} \mathbf{F} \\ \mathbf{z} \end{bmatrix} ; \quad \mathbf{z} = [1 \ 0] \quad (3.35)$$

Then, we can obtain a control stabilising signal u , given by

$$\mathbf{u} = -\mathbf{K}_a \mathbf{x}_a(t) \quad (3.36)$$

which minimises the performance index J_a of the augmented system defined as,

$$J_a = \frac{1}{2} \int_0^{\infty} (\mathbf{x}_a^T \mathbf{Q}_a \mathbf{x}_a + \mathbf{u}^T \mathbf{R} \mathbf{u}) dt \quad (3.37)$$

The control law (3.36) may be split as

$$\mathbf{u}(t) = -\begin{bmatrix} \mathbf{K}_P & \mathbf{K}_I \end{bmatrix} \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{q}(t) \end{bmatrix} \quad (3.38)$$

where $\mathbf{K}_P$ and $\mathbf{K}_I$ are the proportional and integral gains of the PSS, respectively. The block diagram in Figure 3.5 illustrates the elements of the overall feedback control system.

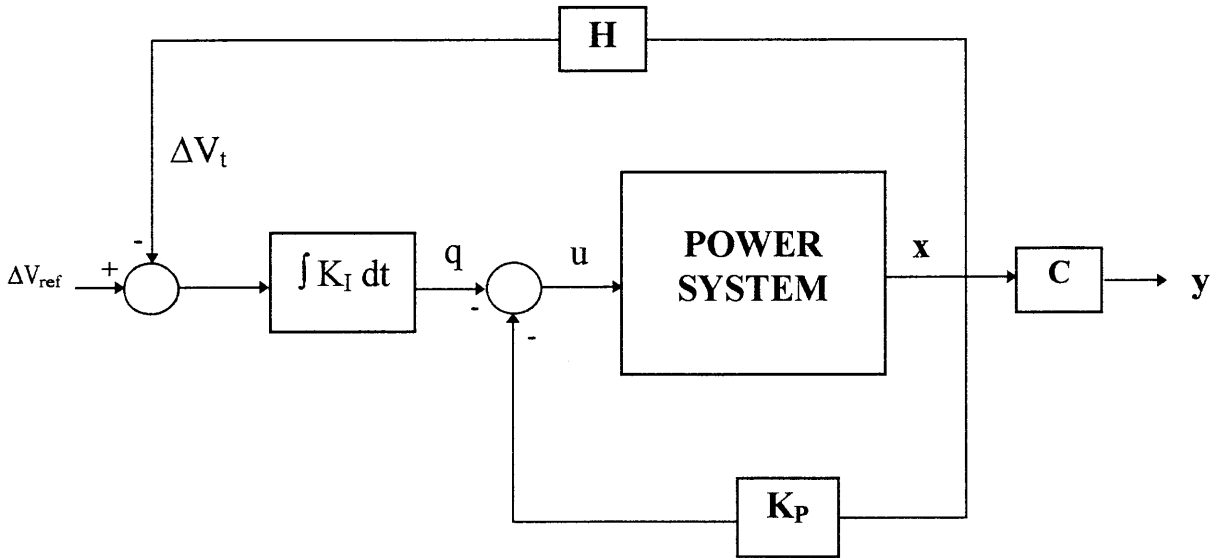


Fig. 3.5 State-feedback optimal PI stabilizer [22].

3.3.3 SUBOPTIMAL LINEAR REGULATOR CONTROL DESIGN

In the optimal state regulator, the control law $\mathbf{u}$ is realised by feeding back all the states $\mathbf{x}(t)$. If some of the states are not accessible (not measurable) for feedback, one has to go for a state observer whose complexity is comparable to that of the system itself. Thus, it is natural to seek a procedure that relies on the use of feedback from only the accessible state variables.

So, let the output variables of a system described by a vector $\mathbf{y}$ whose elements are all or some of the measurable states, i.e.

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) \quad (3.39)$$

We will seek a control law which is a linear combination of the output variables only, i.e.

$$\mathbf{u}(t) = -\mathbf{K}^0\mathbf{y}(t) \quad (3.40)$$

where $\mathbf{K}^0$ is the suboptimal constant feedback matrix.

The problem of finding a control law $\mathbf{u}$ given by (3.40) which minimises the performance index,

$$J = \frac{1}{2} \int_0^{\infty} (\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{u}^T \mathbf{R} \mathbf{u}) dt \quad (3.41)$$

and subjected to constraint (3.17) is referred to as the *output regulator control problem*.

The suboptimal control law of (3.40) is determined by solving the following equations [59-62],

$$\mathbf{A}_c = \mathbf{A} - \mathbf{B}\mathbf{K}^0 \mathbf{C} \quad (3.42)$$

$$\mathbf{V}\mathbf{A}_c + \mathbf{A}_c^T \mathbf{V} + \mathbf{C}^T \mathbf{K}^0 \mathbf{B}\mathbf{K}^0 \mathbf{C} + \mathbf{Q} = \mathbf{0} \quad (3.43)$$

$$\mathbf{P} \mathbf{A}_c^T + \mathbf{A}_c \mathbf{P} + \mathbf{I} = \mathbf{0} \quad (3.44)$$

$$\mathbf{K}^0 = \mathbf{R}^{-1} \mathbf{B}^T \mathbf{V} \mathbf{P} \mathbf{C}^T [\mathbf{C} \mathbf{P} \mathbf{C}^T]^{-1} \quad (3.45)$$

With $\mathbf{u}$ given in (3.40), the closed loop system becomes,

$$\dot{\mathbf{x}}(t) = (\mathbf{A} - \mathbf{B}\mathbf{K}^0 \mathbf{C})\mathbf{x}(t) \quad (3.46)$$

The iterative solution of the above equations requires an initial choice of $\mathbf{K}^0$ such that the closed loop system (3.46) is stable. This iterative method is a bit complex, and hence it is worthwhile to seek an easier approach to the solution of the suboptimal problem. As a result, two alternative non-iterative methods have been reported [59,63-64] namely, the minimum error excitation method and the minimum norm excitation method. However, the drawback of these methods is that their suboptimal solution does not guarantee the stability of the closed loop system. Here, the final results will be presented, and for more details, refer to [59,63-64].

Minimum Error Excitation:

The constant output feedback matrix $\mathbf{K}^0$ is obtained using [63]

$$\mathbf{K}^0 = \mathbf{K}^* \mathbf{P} \mathbf{C}^T [\mathbf{C} \mathbf{P} \mathbf{C}^T]^{-1} \quad (3.47)$$

where $\mathbf{K}^*$ is the optimal state feedback matrix obtained using (3.21) and $\mathbf{P}$ is obtained from the Liapunov equation,

$$\mathbf{P} [\mathbf{A}-\mathbf{BK}^*]^T + [\mathbf{A}-\mathbf{BK}^*] \mathbf{P} + \mathbf{I} = \mathbf{0} \quad (3.48)$$

Minimum Norm Excitation:

The constant output feedback matrix $\mathbf{K}^0$ is obtained using [64]

$$\mathbf{K}^0 = \mathbf{K}^* \mathbf{C}^T [\mathbf{C} \mathbf{C}^T]^{-1} \quad (3.49)$$

where $\mathbf{K}^*$ is the optimal state feedback matrix obtained using (3.21).

Suboptimal PSS Design:

The design of Suboptimal PSS will follow the same modification adopted in the design of optimal PSS, except that the optimal state feedback gain matrix $\mathbf{K}$ is replaced by the output feedback gain matrix $\mathbf{K}^0$ which can be partitioned into $\mathbf{K}_P^0$ and $\mathbf{K}_I^0$ as shown in Figure 3.6. In this controller, three feedback signals have been considered as the measured output signals, namely the speed deviation $\Delta\omega$, the load angle deviation $\Delta\delta$ and the terminal voltage deviation ΔV_t . So, the output vector $\mathbf{y}$ can be written as:

$$\mathbf{y} = \mathbf{C}\mathbf{x} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\omega \\ \Delta\delta \\ \Delta e_q' \\ \Delta E_{fd} \end{bmatrix} \quad (3.50)$$

Then, the augmented system output will be,

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{q} \end{bmatrix} = \begin{bmatrix} \mathbf{C} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{q} \end{bmatrix} \quad (3.51)$$

That is,

$$\mathbf{y}_a = \mathbf{C}_a \mathbf{x}_a \quad (3.52)$$

Thus, the suboptimal control law will be

$$\mathbf{u} = -\mathbf{K}^0 \mathbf{y}_a = -\begin{bmatrix} \mathbf{K}_P^0 & \mathbf{K}_I^0 \end{bmatrix} \begin{bmatrix} \mathbf{y} \\ \mathbf{q} \end{bmatrix} \quad (3.53)$$

where

$$q(t) = \int (\Delta V_{ref} - \Delta V_t) dt \quad (3.54)$$

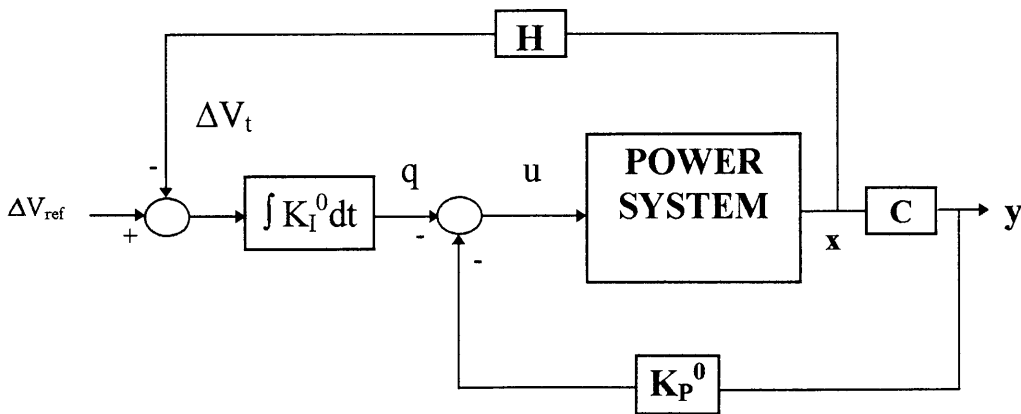


Fig. 3.6 Suboptimal PI stabilizer [22].

3.3.4 RULE BASED POWER SYSTEM STABILIZER (RBPSS)

This type of stabilizer was proposed by T. Hiyama [31-32]. The proposed rule-based stabilizer has been constructed using a micro-computer, an A/D and D/A conversion boards. The speed deviation used as the input signal to the stabilizer. The supplementary stabilizing signal, u , generated from the stabilizer is fed to the excitation control loop as shown in Figure 3.7. The damping of the oscillations can be achieved by applying a proper control signal that has an effect of controlling the acceleration and deceleration of the generator. The accelerating control of the generator is achieved by applying a negative stabilizing signal to the excitation loop, because the electrical output of the generating unit can be decreased by the negative stabilizing signal. On the contrary, the decelerating control is achieved by applying a positive stabilizing signal to the excitation loop, because the electrical output can be increased by the positive stabilizing signal.

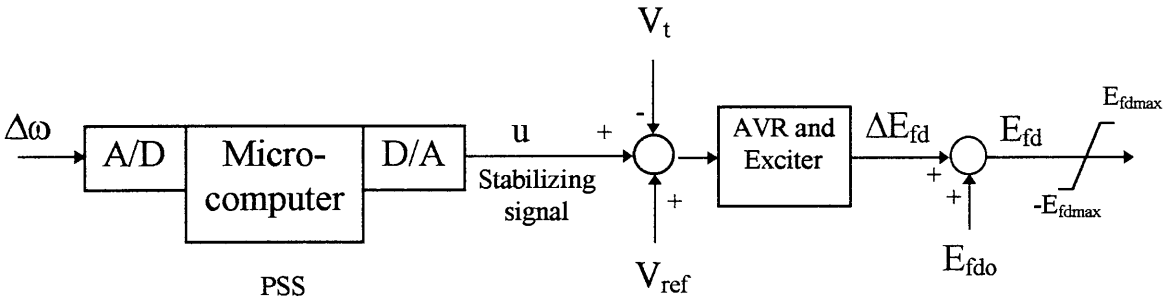


Fig. 3.7 Configuration of the Hiyama rule-based PSS within the excitation control loop.

To achieve this control strategy, the generator operating state is first identified in terms of the quantities of the speed deviation and the acceleration in the phase plane. The phase plane is divided into six sectors as shown in Figure 3.8. Each sector represents a particular operating condition which should be treated by a particular control rule. From these control rules, together with the generator condition characterised by the speed deviation and acceleration, the supplementary stabilizing signal is determined and applied to the excitation control loop at each sampling time.

The supplementary stabilizing signal, $u(t)$, is given by

$$u(t) = U(k), \quad \text{for} \quad kT_s \leq t < (k+1)T_s \quad (3.55)$$

in a discrete form, where T_s represents the sampling time and k is an integer.

The control rules can be extracted from the common sense and knowledge of the relationship between the current state of the power system and the suitable control action required to restore the system to the equilibrium state. Suppose that the generator operating state at time $t=kT_s$ is given by a point $p(k)$ in the phase plane as shown in Figure 3.8. In the phase plane, the points in the upper-half plane represent positive acceleration while the points in the lower-half represent the deceleration. In addition, the points in the right-half indicates the speed is faster than the desired synchronous speed, and the points in the left-half plane indicates that the speed is lower than the desired one. The origin 0 is the desired equilibrium point, and all the control efforts should be directed to shift the generator state $p(k)$ towards the origin 0 as soon as possible.

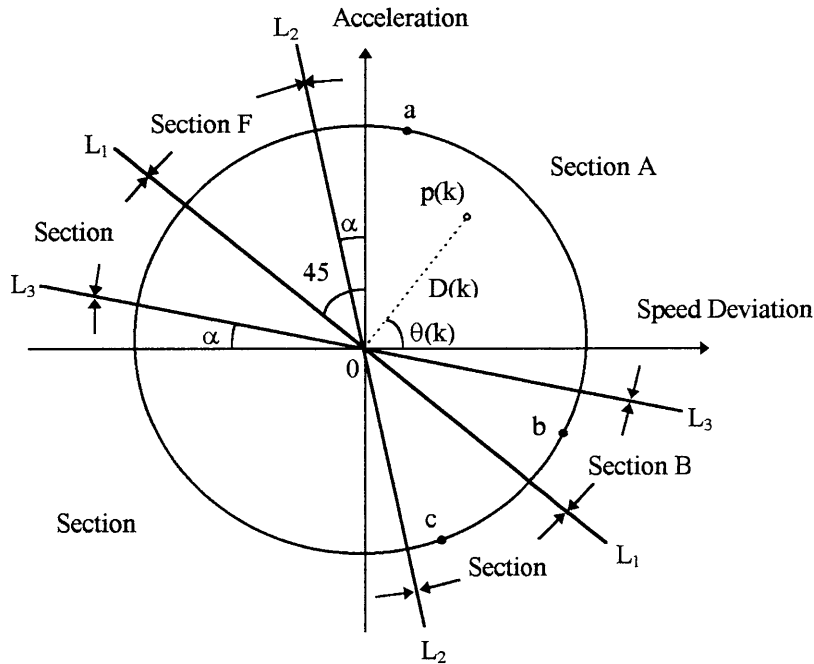


Fig. 3.8 Six sector phase plane.

The required control strategies to achieve the above objective can be summarised for the sample points a, b, and c which lies in sectors A, B and C, respectively.

- (a) At the sampling point (a) in the sector 'A', strong decelerating control is required because the generator speed is almost equal to the desired speed, but the acceleration is quite large at the positive side which means that the speed deviation is in the direction of growing sharply. Therefore, a stabilising signal should be positive large.
- (b) At the sampling point (b) in the sector 'B', the speed deviation is large positive but the acceleration is quite large negative (i.e. speed decelerating). This means that the positive speed deviation is decreasing and the state is in the direction of equilibrium state. Therefore, slightly decelerating control is required to shift the generator speed to the desired speed and hence a stabilising signal should be positive small.
- (c) At the sample point c in sector 'C', slightly accelerating control is required to prevent the excessive shift in the speed deviation to the negative side because the generator speed is fairly close to the desired speed from the positive side with the relatively higher deceleration. Therefore, the stabilising signal should be negative small.
- (d) In sectors D, E, and F, the situation is completely opposite to those in sectors A, B, and C, respectively. Therefore, the control rules should be inverted.

So, to control the excitation levels depending on the speed/acceleration state of the generator, the control rule for each sector is expressed mathematically as follows considering the above strategies

$$\text{Rule 1: If } p(k) \in \text{sector A, then } U(k) = G(k) U_{\max} \quad (3.56)$$

$$\text{Rule 2: If } p(k) \in \text{sector B, then } U(k) = G(k) U_{\min} \quad (3.57)$$

$$\text{Rule 3: If } p(k) \in \text{sector C, then } U(k) = -G(k) U_{\min} \quad (3.58)$$

$$\text{Rule 4: If } p(k) \in \text{sector D, then } U(k) = -G(k) U_{\max} \quad (3.59)$$

$$\text{Rule 5: If } p(k) \in \text{sector E, then } u(k) = -G(k) U_{\min} \quad (3.60)$$

$$\text{Rule 6: If } p(k) \in \text{sector F, then } u(k) = G(k) U_{\min} \quad (3.61)$$

where

$$G(k) = D(k)/D_r \quad \text{for } D(k) < D_r \quad (3.62a)$$

$$G(k) = 1.0 \quad \text{for } D(k) \geq D_r \quad (3.62b)$$

$$D(k) = |p(k)| \quad (3.63)$$

The term $G(k)$ indicates the gain factor at the time $t = kT_s$, and $G(k)$ given by a non-linear function shown in Figure 3.9. It is quite reasonable that the $G(k)$ is proportional to the distance $D(k)$ from the desired equilibrium point, i.e. the origin in the phase plane, because more effort is required to bring the generator condition $p(k)$ towards the desired equilibrium point in the case where the $p(k)$ is farther from the origin.

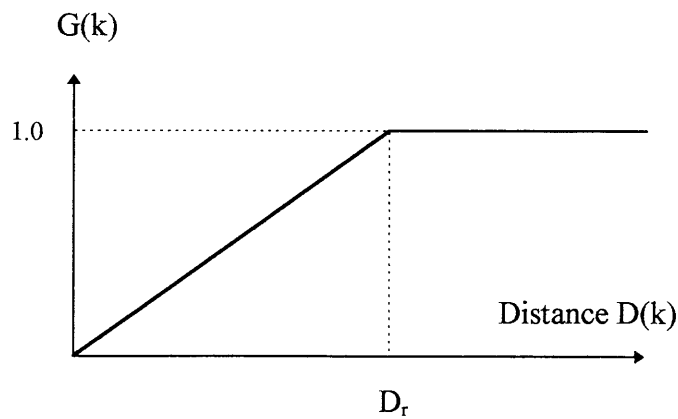


Fig. 3.9 Gain factor $G(k)$ related to distance D_r .

In addition, there exist some restriction on the magnitude of the stabilising signal. Therefore, the gain factor $G(k)$ is restricted to 1.0 beyond the pre-specified distance D_r , and therefore the maximum and minimum stabilising signals become $U_{\max}$ and 0 in sector A, $U_{\min}$ and 0 in in sector B, 0 and $-U_{\min}$ in sector C, 0 and $-U_{\max}$ in sector D, 0 and $-U_{\min}$ in sector E, and $U_{\min}$ and 0 in sector F, respectively. As a result, this rule-based stabilizer will act as a bang-bang control.

Parameter setting

In the above rule-based stabilizer, there exist several parameters to be adjusted to their optimal values. In this study, the switching line L_1 between the positive and negative stabilising signals is fixed 45° apart from the vertical axis for simplicity. The shifting of this switching line, L_1 , may be necessary to further improve the generator behaviour. The location of the other switching lines L_2 and L_3 , are to be selected by adjusting the angle α as shown in Figure 3.8. The maximum value of the stabilising signal $U_{\max}$ depends on the generating unit. Therefore, the value of $U_{\max}$ should be specified to the highest value which is applicable to the generating unit at which the rule-based stabilizer is installed. However, in this study, $U_{\max}$ is considered as an adjustable parameter as it was not given for the generating unit taken in this study. The value of $U_{\min}$ should be selected not to exceed the setting of $U_{\max}$. Finally, the value of D_r should be selected not too small causing hunting around the equilibrium point because of excessive control action nor too big causing sluggish control. Therefore, there exist four adjustable parameters α , D_r , $U_{\min}$, and $U_{\max}$.

For optimal parameter settings, the following discrete-type, time weighted, quadratic performance index is considered:

$$J = \sum_{k=1}^M [t_k \Delta\omega(k)]^2 \quad (3.64)$$

- where k : integer number.
 M : integer number denotes the total number of samples.
 t_k : time at the k^{th} sample = kT_s .
 $\Delta\omega(k)$: speed deviation at $t = kT_s$.

The adjustable parameters are set to the values which minimize the above performance index.

In summary, the stabilising signal $U(k)$ is determined through the following steps at every sampling time:

- (1) Sample the alternator speed deviation $\Delta\omega$ and compute the acceleration signal using one past set of previous sampled speed deviation $\Delta\omega(k-1)$ as:

$$A(k) = [\Delta\omega(k) - \Delta\omega(k-1)] / T_s \quad (3.65)$$

where A is the acceleration.

- (2) Compute $\theta(k)$ and $D(k)$, from the phase plane as shown in Figure 3.8.
 Based on the value of $\theta(k)$, one can locate the sector in which the state $p(k)$ is located.

$$\theta(k) = \tan^{-1} [A(k) / \Delta\omega(k)] \quad (3.66)$$

$$D(k) = \sqrt{\Delta\omega(k)^2 + A(k)^2} \quad (3.67)$$

- (3) Compute the gain factor $G(k)$ using equation (3.62).
- (4) Compute the stabilizing signal $U(k)$ using the rule concerning the sector in which the state $p(k)$ lie.
- (5) Increase k by 1 and repeat steps 1 through 4

3.3.5 FUZZY LOGIC POWER SYSTEM STABILIZERS (FLPSS)

The control objective as it has been mentioned is to enhance the damping characteristics of the power system through the application of a supplementary stabilising signal to its excitation control loop. Here, the required stabilising signal is to be generated based on fuzzy logic control. The application of fuzzy logic control for power system stabilisers was motivated by the work of Hiyama and Nakano [65]. Their proposed fuzzy controller has been demonstrated to be suitable for enhancing the damping characteristics of a power system. Then, several researches were conducted in this field to investigate different aspects in the design and application of fuzzy control schemes for PSS to enhance the overall damping characteristic and stability of a power system. In this section, some of those fuzzy logic based power system stabilizers will be discussed with emphases on the proposed stabilizer where the speed is utilised as the input signal to the fuzzy PSS.

The three fuzzy logic based power system stabilizers that will be highlighted in this section are those proposed by Hiyama & Lim [44], Hassan, Malik & Hope [42], and Hsu & Cheng [29].

Hiyama & Lim FLPSS [44]:

Hiyama and Lim proposed a fuzzy logic stabilizer which is an improved version to that proposed earlier by Hiyama and Nakano [65]. Thus, a review of the fuzzy control scheme of Hiyama and Nakano [65] will be given first and then the modification that has been done by Hiyama and Lim will be mentioned.

Review of fuzzy control scheme of Hiyama and Nakano, [65]

The state of the generating unit, can be given by a point $p(k)$ in the speed/acceleration phase plane at the k th sampling as shown in Figure 3.10. The point $p(k)$ is given at the k th sampling by

$$p(k) = \{ Z_s(k), Z_a(k) \} \quad (3.68)$$

where Z_s = speed deviation ; Z_a = acceleration.

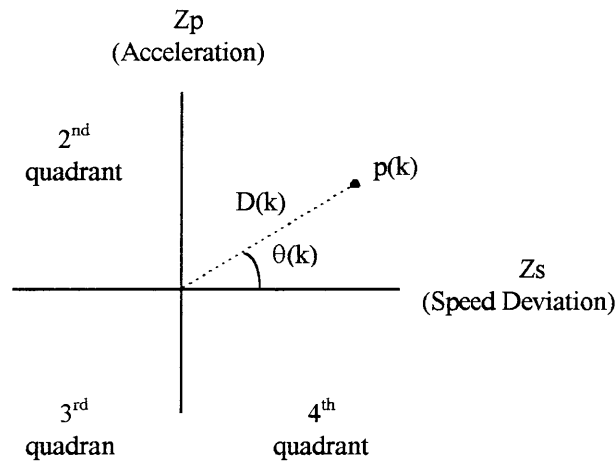


Fig. 3.10 Speed/acceleration phase plane.

The objective now is to bring this system state, $p(k)$, to the equilibrium point, i.e. the origin of the phase plane, through a supplementary control signal $u(t)$. The required supplementary stabilising signal, $u(t)$, is given by

$$u(t) = U(k), \quad ; kT_s \leq t < (k+1)T_s \quad (3.69)$$

where T_s : is the sampling period
 k : is an integer.

The required control strategies are the same as in the rule-based stabilizer. Deceleration control is only needed when the generator state is in the first quadrant,

deceleration and acceleration control in the second and fourth quadrants, and acceleration control only in the third quadrant. Hence, two fuzzy membership functions, $N(\theta(k))$ and $P(\theta(k))$, are defined as shown in Figure 3.11 to represent respectively the degree of deceleration and acceleration control. The switching between the acceleration and deceleration control is taking place in the second and in the fourth quadrant in the fuzzy manner described by Figure 3.11. Unlike the rule-base scheme where the control signal changes in a bang-bang manner, in fuzzy control scheme the changes are smooth and hence providing a smooth transition from one state to another.

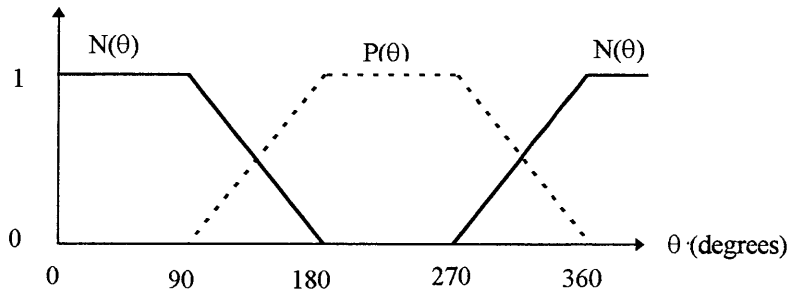


Fig. 3.11 Membership functions [65].

The following is a summary of the steps required to determine the value of stabilising signal $U(k)$ at the k th sampling interval:

- (1) Compute the acceleration signal using one past set of previous sampled speed deviation $\Delta\omega(k-1)$ using equation (3.65).
- (2) Compute $\theta(k)$ and $D(k)$, as shown in Figure 3.10.
- (3) Determine the membership values of $N(\theta(k))$ and $P(\theta(k))$.
- (4) Compute the stabilizer gain $G(k)$, shown in Figure 3.9, using eq. (3.62).
- (5) Compute the stabilizing signal $U(k)$ using:

$$U(k) = \frac{G(k)[N(\theta) - P(\theta)]U_{max}}{[N(\theta) + P(\theta)]} \quad (3.70)$$

where U_{max} is the maximum stabilising signal.

Repeat the above steps for every sampling time.

Fuzzy Controller proposed by Hiyama and Lim [44]:

The calculation of the stabilising signal $U(k)$ is done using exactly the same steps proposed by Hiyama and Nakano [65], except one modification is made in the first step. The calculated acceleration, A , in step 1 above is replaced by a scaled acceleration, A_s , computed as:

$$A_s = F_a * A \quad (3.71)$$

where

- F_a scaling factor.
- A the acceleration.
- A_s scaled acceleration.

Finally, we need to select the values of adjustable parameters (F_a , D_r , U_{max}) of the fuzzy stabilizer such that the performance index given by equation (3.64) is minimised.

A modification to this fuzzy controller has been also reported. The modification was proposed by Hiyama and Sameshima [66] where they added two more adjustable parameters to be tuned. The two parameters are (β) which represent the location of the switching line between the positive and negative stabilising signals and (α) which represents the size of cross sections between sectors A and B of the phase plane shown in Figure 3.12.

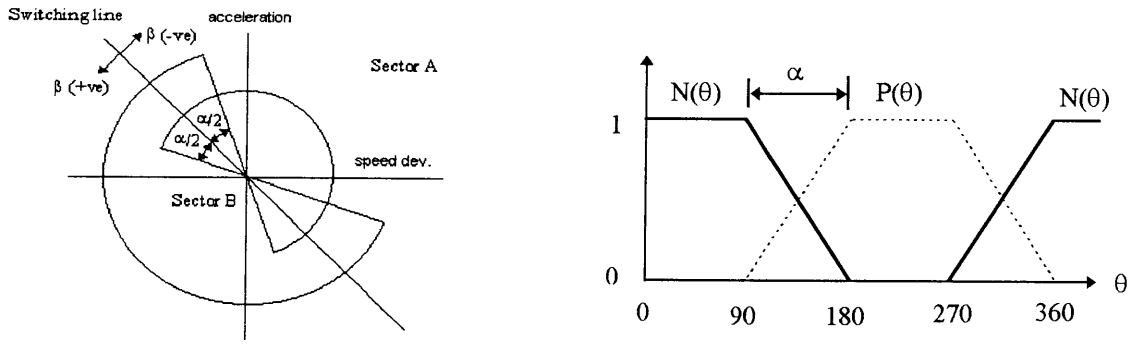


Fig. 3.12 Phase plane and membership functions.

Hassan, Malik and Hope FLPSS [42]

In this fuzzy logic stabilizer, an improvement to the performance of the fuzzy stabilizer proposed by Hiyama and Lim [44] has been achieved by introducing two modifications. The first proposed modification is that the fuzzy membership functions, $N(\theta)$ and $P(\theta)$, shown in Figure 3.11 are replaced by a standard fuzzy membership functions shown in Figure 3.13. The mathematical description of the proposed standard membership functions are given as follows:

$$S(x; a, b, c) = \begin{cases} 0 & \text{for } x \leq a \\ 2[(x - a) / (c - a)]^2 & \text{for } a < x \leq b \\ 1 - 2[(x - c) / (c - a)]^2 & \text{for } b < x < c \\ 1 & \text{for } x \geq c \end{cases} \quad (3.72)$$

$$\Pi(x; B, C) = \begin{cases} S(x; C - B, C - B/2, C) & \text{for } x \leq C \\ 1 - S(x; C, C + B/2, C + B) & \text{for } x > C \end{cases} \quad (3.73)$$

Then the introduced functions, $N(\theta)$ and $P(\theta)$, are expressed in terms of the above standard functions as follows:

$$Ps(\theta) = \Pi(\theta; 2\pi - \theta_i, \theta_m) \quad (3.74)$$

$$Ns(\theta) = \begin{cases} 1 - S(\theta; \theta_i, \theta_{m1}, \theta_m) & \text{for } \theta \leq \theta_m \\ S(\theta; \theta_m, \theta_{m2}, 2\pi) & \text{for } \theta > \theta_m \end{cases} \quad (3.75)$$

where,

$$\begin{aligned} \theta_m &= (2\pi + \theta_i) / 2 \\ \theta_{m1} &= (\theta_i + \theta_m) / 2 \\ \theta_{m2} &= (2\pi + \theta_m) / 2 \end{aligned} \quad (3.76)$$

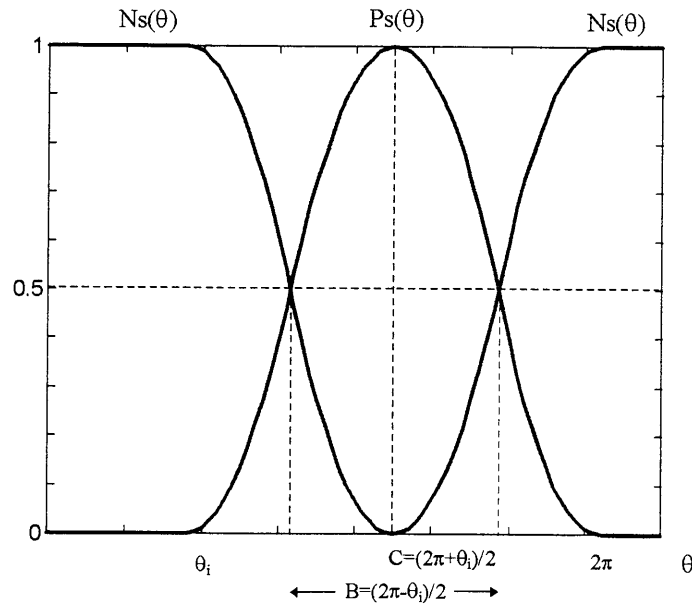


Fig. 3.13 Membership functions of Ns and Ps [42-43]

Comparing the membership Functions of Figure 3.11 and 3.13, it can be seen that the domain of $P(\theta)$ of Figure 3.11 is fixed ($90^\circ < \theta < 360^\circ$). On the other hand, the domain of the function $Ps(\theta)$ shown in Figure 3.13 is tuneable ($\theta_i < \theta < 360^\circ$). Thus, θ_i is considered as a tuning factor (parameter). This factor will affect the shapes of both functions $Ps(\theta)$ and $Ns(\theta)$, where $Ns(\theta) = 1 - Ps(\theta)$. Also, it can be seen from Figure 3.13 that both functions are symmetric around the average angle C between θ_i and 360° . It is also clear that the functions shown in Figure 3.11 are special case of the standard functions shown in Figure 3.13.

The second modification that has been also introduced is that the stabilising signal $U(k)$ given by equation (3.70) is simplified as follows:

$$U(k) = G(k) [Ns(\theta) - Ps(\theta)] U_{\max} \quad (3.77)$$

$$\text{since} \quad Ps(\theta) + Ns(\theta) = 1.0 \quad (3.78)$$

This will save some computational efforts due to the elimination of the term $[Ps(\theta) + Ns(\theta)]$.

To reduce the computation cycles of equation (3.77), more simplification can be introduced by simplifying equation (3.77) to:

$$U(k) = G(k) [1 - 2 Ps(\theta)] U_{\max} \quad (3.79)$$

The Main Tuning Parameters:

The parameters to be tuned in this fuzzy stabilizer are 'Fa', 'Dr', ' θ_i ', and $U_{\max}$. The optimal values of these parameters are selected such that the quadratic performance index defined in equation (3.64) is minimised.

Hsu and Cheng FLPSS [29]

The fuzzy excitation controller proposed by Hsu and Cheng is shown in Figure 3.14 where the measured generator speed deviation ($\Delta\omega$) and the calculated acceleration ($\dot{\Delta\omega}$) are used as input signals. These signals are first expressed in some linguistic variables using membership functions in fuzzy set notations before they are processed by the fuzzy controller. A set of decision rules expressed in linguistic variables are established based on previous experience with the study system to relate input signals with output (control) signal. These decision rules, are converted into a fuzzy relation matrix R which can be stored in computer memory. Then, using the fuzzified input variables with the relation matrix, the membership values of the controller output signal expressed in fuzzy linguistic terms can be obtained. Finally, the control signal is converted from linguistic term to numerical value before it is fed into the system. From Figure 3.14, Sf_1 , Sf_2 and Sf_3 are the normalising or scaling factors whose values are to be selected to get the optimal system performance. This proposed controller has been tested on a single machine infinite-bus system. It has been found that the fuzzy excitation controller can improve the dynamic performance of a power system over a wide of operating conditions as compared to a fixed gain PI controller.

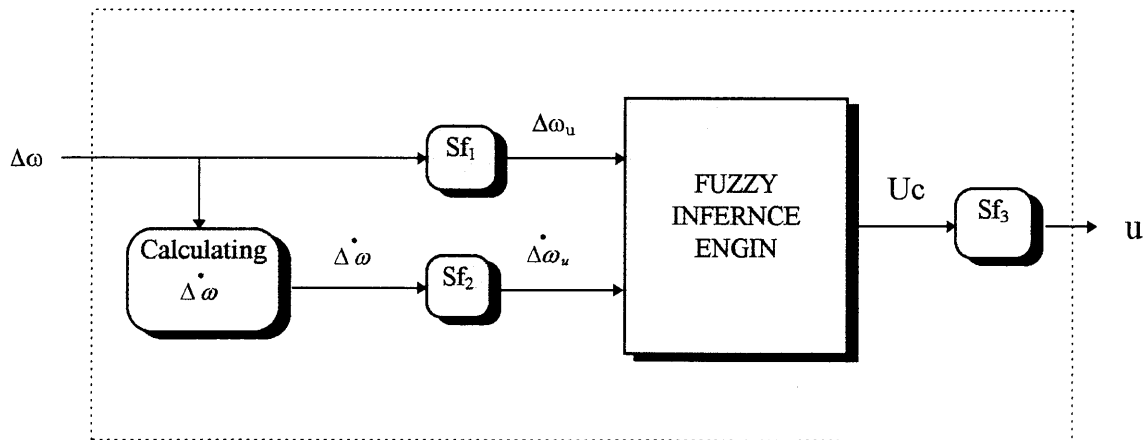


Fig. 3.14 Fuzzy excitation controller (PSS) proposed by Hsu and Cheng [29].

A detail discussion of the design of Hsu and Cheng fuzzy stabilizer may be described as follows:

1- *Calculation of the Acceleration:* From two samples of measured speed deviation

$\Delta\omega$, the acceleration $\dot{\Delta\omega}$ can be calculated as:

$$\dot{\Delta\omega}(k) \cong \frac{\Delta\omega(k) - \Delta\omega(k-1)}{T_s} \quad (5.80)$$

where $\Delta\omega(k)$ = speed deviation at $t = kT_s$

T_s = sampling period.

2- *The Decision Rules:* The decision rules expressed in linguistic variables are established to relate the controller input signals to the controller output. These decision rules are expressed using linguistic variables such as large positive (LP), medium positive (MP), small positive (SP), very small (VS), small negative (SN), medium negative (MN), and large negative (LN). Through the combination of the two input signals each of which is quantized into seven linguistic terms (LN, MN, SN, VS, SP, MP, and LP), there will be 49 decision rules which are presented in Table 3.1, where each entry represents a particular rule.

Table 3.1 Decision Rules (FAM).

		Acceleration ($\dot{\Delta\omega}$)						
		LN	MN	SN	VS	SP	MP	LP
Speed deviation $\Delta\omega$	LP	VS*	SP	MP	LP	LP	LP	LP
	MP	SN	VS	SP	MP	MP	LP	LP
	SP	MN	SN	VS	SP	SP	MP	LP
	VS	MN	MN	SN	VS	SP	MP	MP
	SN	LN	MN	SN	SN	VS	SP	MP
	MN	LN	LN	MN	MN	SN	VS	SP
	LN	LN	LN	LN	LN	MN	SN	VS

* Rule 1

For example, rule 1 can be read as follows:

$$\begin{aligned} \text{Rule 1:} \quad & \text{IF } \Delta\omega \text{ is LP, AND } \dot{\Delta\omega} \text{ is LN,} \\ & \text{THEN } U_c \text{ (controller output) should be VS.} \end{aligned} \quad (3.81)$$

- 3- *The Fuzzy Relation Matrix*: Using fuzzy set notations, the decision table in Table 3.1 can be converted into a fuzzy relation matrix given in Table 3.2 where controller output obtained by applying a particular rule, is expressed in membership functions. For example, Rule 1 in above becomes,

$$\begin{aligned} & \text{IF } \Delta\omega \text{ is LP, AND } \dot{\Delta\omega} \text{ is LN,} \\ & \text{THEN the controller output } U_c \text{ can be characterised by the fuzzy set} \\ & \{ (LN,0), (MN,0), (SN,0.5), (VS,1), (SP,0.5), (MN,0), (LP,0) \}. \end{aligned} \quad (3.82)$$

Note that in the above rule, we are still not certain whether $\Delta\omega$ is LP and $\dot{\Delta\omega}$ is LN. The degree of belief in the “condition part” of the rule can be specified through the use of membership functions as described below.

- 4- *Membership Functions of the Stabilizer Inputs*: To express the controller inputs in linguistic variables LP, MP, SP, VS, SN, MN, and LN, the two crisp inputs $\Delta\omega$ and $\dot{\Delta\omega}$ are first normalized/scaled respectively by scaling factors Sf_1 and Sf_2 . The values of the input scaling factors ‘ Sf_1 and Sf_2 ’, and the output scaling factor ‘ Sf_3 ’, are to be selected from the tuning process which is done at the end after a complete formulation of the fuzzy controller. So, when the scaling factors are adjusted, then the scaled inputs will be,

$$\begin{aligned} \Delta\omega_u &= Sf_1 \Delta\omega \\ \dot{\Delta\omega}_u &= Sf_2 \dot{\Delta\omega} \end{aligned} \quad (3.83)$$

Using these normalized quantities, controller inputs can be described by membership functions for the linguistic variables, as shown in Table 3.3. For a value of $\Delta\omega_u$ or $\dot{\Delta\omega}_u$ which is not listed in Table 3.3, linear interpolation must be employed to determine the membership functions. For example, at a particular sampling instant, let the controller inputs be, say, $\Delta\omega_u = 0.2$ and $\dot{\Delta\omega}_u = -0.1$. From Table 3.3, the two controller inputs can be described by the following fuzzy sets,

$$\Delta\omega_u : \{(\text{LN},0),(\text{MN},0),(\text{SN},0.2),(\text{VS},0.5),(\text{SP},0.7),(\text{MP},0.9),(\text{LP},1)\} \quad (3.84a)$$

$$\dot{\Delta\omega}_u : \{(\text{LN},0.8),(\text{MN},1),(\text{SN},0.9),(\text{VS},0.7),(\text{SP},0.4),(\text{MP},0.2),(\text{LP},0)\} \quad (3.84b)$$

5- *Membership Function of the Controller Output:* The membership function of the controller output can be determined by considering the contribution of all the rules. It is obvious from Table 3.2 that there are 49 rules which can be used to generate the desired controller output. Consider Rule 1, in eqn. (3.82). The membership value for the premise “if part” can be calculated as

$$\begin{aligned} \mu(x_1) &= \mu(\text{'}\Delta\omega \text{ is LP' and '}\dot{\Delta\omega} \text{ is LN'}) \\ &= \min(\mu(\text{'}\Delta\omega \text{ is LP'}), \mu(\text{'}\dot{\Delta\omega} \text{ is LN'})) \end{aligned} \quad (3.85)$$

From equation (3.84), we have $\mu(\text{'}\Delta\omega \text{ is LP'}) = 1$, and $\mu(\text{'}\dot{\Delta\omega} \text{ is LN'}) = 0.8$. Thus the membership value of the premise is,

$$\mu(x_1) = \min(1, 0.8) = 0.8 \quad (3.86)$$

Given the membership value of the ‘premise’ and the fuzzy relation matrix, the membership value for the controller output characterised by the seven linguistic variables LN, MN, SN, VS, SP, MP, LP can be obtained using the following compositional rule of inference

$$\begin{aligned}
\mu_{Uc,1}(LN) &= \min(\mu_R(x_1, LN), \mu(x_1)) \\
&= \min(0, 0.8) \\
&= 0
\end{aligned} \tag{3.87}$$

Note that this is the membership value of the controller output 'LN' if only Rule 1 exists. To take the 49 rules of Table 3.2 into account, the membership values for the 'premise' of all the other 48 rules $\mu(x_i)$, $i=2, \dots, 49$, must be determined in the same way as we have done in equation (3.86) for $\mu(x_1)$. Thus the final value for controller output 'LN' can be figured out using the composition rule

$$\mu_{Uc}(LN) = \max_{xi}(\min(\mu_R(x_i, LN), \mu(x_i))) \tag{3.88}$$

The membership values for all the other six variables $\mu_{Uc}(MN)$, $\mu_{Uc}(SN)$, $\mu_{Uc}(VS)$, $\mu_{Uc}(SP)$, $\mu_{Uc}(MP)$, and $\mu_{Uc}(LP)$ can be computed in exactly the same way. The final results of the preceding example are as follows.

$$\begin{aligned}
\mu_{Uc}(LN) &= 0.5 & ; & & \mu_{Uc}(SP) &= 1.0 \\
\mu_{Uc}(MN) &= 0.7 & ; & & \mu_{Uc}(MP) &= 0.9 \\
\mu_{Uc}(SN) &= 0.8 & ; & & \mu_{Uc}(LP) &= 0.7 \\
\mu_{Uc}(VS) &= 0.9 & & & &
\end{aligned} \tag{3.89}$$

6- *The controller output:* Once the membership values for the controller output have been reached, a suitable algorithm must be employed to determine the controller output signal from these membership values. The algorithm adopted in Hsu fuzzy controller is the 'maximum algorithm' in which the signal with largest membership value is chosen as the controller output signal. Thus, from equation (3.89), the controller output for the considered example is SP.

But since the system can take only numerical values of u , the controller output expressed in linguistic terms must be converted back to numerical values before it can be fed into the system. For this purpose, conversion Table 3.4 has been established and can be stored in the computer memory as a look-up table. It should be noted that the numerical values selected in Table 3.4 will suit a particular system and hence it should be readjusted for other systems. This can be done by tuning the output scaling factor Sf_3 . In regard to the example above, suppose that the numerical values was found at $Sf_3=1$. Thus, it is obvious from Table 4 that the numerical value of the control signal U_c for the considered example is 0.005 p.u. and hence the actual output signal $u=Sf_1*U_c=0.005$. If instead, a centroid defuzzification method is adapted then the control signal U_c should be computed using all the membership values for all the linguistic terms of the output variable. Thus, the value of U_c using centroid method is,

$$\begin{aligned}
 U_c &= [\mu_{U_c}(LN)*U_c(LN) + \mu_{U_c}(MN)*U_c(MN) + \dots + \mu_{U_c}(LP)*U_c(LP)] / \sum \mu_{U_c} \\
 &= 0.029/5.5 \\
 &= 0.00527 \text{ p.u}
 \end{aligned} \tag{3.90}$$

Selecting the scaling factors:

Finally, when the fuzzy stabilizer is formulated as per the above procedure, the input and output scaling factors (Sf_1 , Sf_2 , and Sf_3) are to be tuned to get the best system performance. The optimal values of these parameters can be selected according to the minimization of the performance index defined by equation (3.64).

Table 3.2 Fuzzy Relation Matrix.

X_i	controller inputs ($\Delta\omega, \Delta\dot{\omega}$)	controller output						
		LN	MN	SN	VS	SP	MP	LP
		membership value						
		$\mu_R(x_i, LN)$	$\mu_R(x_i, MN)$	$\mu_R(x_i, SN)$	$\mu_R(x_i, VS)$	$\mu_R(x_i, SP)$	$\mu_R(x_i, MP)$	$\mu_R(x_i, LP)$
X_1	(LP, LN)	0	0	0.5	1	0.5	0	0
X_2	(LP, MN)	0	0	0	0.5	1	0.5	0
X_3	(LP, SN)	0	0	0	0	0.5	1	0.5
X_4	(LP, VS)	0	0	0	0	0	0.5	1
X_5	(LP, SP)	0	0	0	0	0	0.5	1
X_6	(LP, MP)	0	0	0	0	0	0.5	1
X_7	(LP, LP)	0	0	0	0	0	0.5	1
X_8	(MP, LN)	0	0.5	1	0.5	0	0	0
X_9	(MP, MN)	0	0	0.5	1	0.5	0	0
X_{10}	(MP, SN)	0	0	0	0.5	1	0.5	0
X_{11}	(MP, VS)	0	0	0	0	0.5	1	0.5
X_{12}	(MP, SP)	0	0	0	0	0.5	1	0.5
X_{13}	(MP, MP)	0	0	0	0	0	0.5	1
X_{14}	(MP, LP)	0	0	0	0	0	0.5	1
X_{15}	(SP, LN)	0.5	1	0.5	0	0	0	0
X_{16}	(SP, MN)	0	0.5	1	0.5	0	0	0
X_{17}	(SP, SN)	0	0	0.5	1	0.5	0	0
X_{18}	(SP, VS)	0	0	0	0.5	1	0.5	0
X_{19}	(SP, SP)	0	0	0	0.5	1	0.5	0
X_{20}	(SP, MP)	0	0	0	0	0.5	1	0.5
X_{21}	(SP, LP)	0	0	0	0	0	0.5	1
X_{22}	(VS, LN)	0.5	1	0.5	0	0	0	0
X_{23}	(VS, MN)	0.5	1	0.5	0	0	0	0
X_{24}	(VS, SN)	0	0.5	1	0.5	0	0	0
X_{25}	(VS, VS)	0	0	0.5	1	0.5	0	0
X_{26}	(VS, SP)	0	0	0	0.5	1	0.5	0
X_{27}	(VS, MP)	0	0	0	0	0.5	1	0.5
X_{28}	(VS, LP)	0	0	0	0	0.5	1	0.5
X_{29}	(SN, LN)	1	0.5	0	0	0	0	0
X_{30}	(SN, MN)	0.5	1	0.5	0	0	0	0
X_{31}	(SN, SN)	0	0.5	1	0.5	0	0	0
X_{32}	(SN, VS)	0	0.5	1	0.5	0	0	0
X_{33}	(SN, SP)	0	0	0.5	1	0.5	0	0
X_{34}	(SN, MP)	0	0	0	0.5	1	0.5	0
X_{35}	(SN, LP)	0	0	0	0	0.5	1	0.5
X_{36}	(MN, LN)	1	0.5	0	0	0	0	0
X_{37}	(MN, MN)	1	0.5	0	0	0	0	0
X_{38}	(MN, SN)	0.5	1	0.5	0	0	0	0
X_{39}	(MN, VS)	0.5	1	0.5	0	0	0	0
X_{40}	(MN, SP)	0	0.5	1	0.5	0	0	0
X_{41}	(MN, MP)	0	0	0.5	1	0.5	0	0
X_{42}	(MN, LP)	0	0	0	0.5	1	0.5	0
X_{43}	(LN, LN)	1	0.5	0	0	0	0	0
X_{44}	(LN, MN)	1	0.5	0	0	0	0	0
X_{45}	(LN, SN)	1	0.5	0	0	0	0	0
X_{46}	(LN, VS)	1	0.5	0	0	0	0	0
X_{47}	(LN, SP)	0.5	1	0.5	0	0	0	0
X_{48}	(LN, MP)	0	0.5	1	0.5	0	0	0
X_{49}	(LN, LP)	0	0	0.5	1	0.5	0	0

Table 3.3 Membership functions for the controller inputs.

Normalized inputs	Membership functions						
$(\Delta\omega_u \text{ or } \dot{\Delta\omega}_u)$	LN	MN	SN	VS	SP	MP	LP
-1.0	1	0.7	0.5	0.3	0	0	0
-0.2	1	0.9	0.7	0.5	0.2	0	0
-0.1	0.8	1	0.9	0.7	0.4	0.2	0
-0.03	0.6	0.8	1	0.9	0.6	0.4	0.2
0	0.4	0.6	0.8	1	0.8	0.6	0.4
0.03	0.2	0.4	0.6	0.9	1	0.8	0.6
0.1	0	0.2	0.4	0.7	0.9	1	0.8
0.2	0	0	0.2	0.5	0.7	0.9	1
1.0	0	0	0	0.3	0.5	0.7	1

Table 3.4 Conversion table from linguistic variables to numerical values

	LN	MN	SN	VS	SP	MP	LP
Uc	-0.12	-0.02	-0.005	0	0.005	0.02	0.12

3.4 SIMULATION AND RESULTS

The computer simulation of a single machine infinite-bus system model and its dynamic performance following various disturbances is covered in this section. The system data for the single machine infinite bus model is shown in Appendix A1. The performance of the various stabilizers designed in the previous sections will be compared at various system operating conditions and for different generator inertia constant and transmission line reactance.

3.4.1 Setting of Stabilizers Parameters:

The parameters of the stabilizers have been tuned to provide an optimum performance at the nominal operating condition ($P_e=1$ p.u , $Q_e= 0.015$ pu.u., $V_t=1.05$ p.u.). and following 10% step change in the excitation reference voltage. The final setting of each stabilizer parameters is calculated and given as follows:

(a) Conventional Power System Stabilizer (CVPSS):

The parameters of lead compensator is calculated as per the design procedure given in section 3.3.1. At the nominal operating condition, the undamped natural frequency ω_n and the phase lag of the transfer function G_E are found to be 4.407 rad/sec and -47.57° respectively. Then, for a given values of the damping coefficient ξ_n , lead time constant T_2 and washout time constant T which are chosen as [Yu,1983],

$$\xi_n = 0.3, T_2 = 0.1 \text{ sec}, T = 3.0 \text{ sec}$$

the remaining parameters, K_c and T_1 , are then calculated and found to be

$$T_1 = 0.6851 \text{ sec}, K_c = 7.09$$

(b) Optimal and Suboptimal Power System Stabilizers:

The control weighting R is chosen as unity and the state weighting matrix Q_a is found through several trial and error procedure to give the best dynamic performance following 10% step change in reference voltage. The weighting

matrix is assumed diagonal and the final result for the optimal and suboptimal PSS is given as:

$$Q_a = \text{diag} [1, 10, 1, 0.035, 450] \quad \text{for the optimal PSS.}$$

$$Q_a = \text{diag} [1, 5, 1, 0.035, 450] \quad \text{for the suboptimal PSS.}$$

(c) Rule Based and Fuzzy Logic Power System Stabilizers:

The parameters of both the rule based stabilizers (RBPSS) and the various fuzzy logic stabilizers (FLPSS) have been tuned so as to minimise the quadratic performance index given in section 3.3.4, following 10% step change in excitation reference voltage. The final settings is summarised in Table 3.5. The conversion table used to convert from linguistic variables to numerical values for fuzzy stabilizer proposed by Hsu and Cheng [29] is shown in Table 3.6.

Table 3.5 Rule based and fuzzy logic final parameters settings.

TYPE OF STABILIZER	FINAL PARAMETER SETTINGS
Hiyama Rule Based PSS	$\alpha = -10 \text{ deg.}$, $D_r = 0.04$, $U_{\min} = 0.05$, $U_{\max} = 3$
Hiyama and Lim FLPSS	$F_a = 0.16$, $D_r = 0.05$, $U_{\max} = 3.4$
Hassan, Malik and Hope FLPSS	$F_a = 0.08$, $D_r = 0.03$, $\theta_i = 105 \text{ deg.}$, $U_{\max} = 3$
Hsu and Cheng FLPSS	$Sf_1 = 45$, $Sf_2 = 10$, $Sf_3 = 0.2$

Table 3.6 Conversion table from linguistic variables to numerical values.

	LN	MN	SN	VS	SP	MP	LP
Uc	-3.6	-2.4	-1.2	0	1.2	2.4	3.6

3.4.2 Testing Scenarios:

In order to compare the effectiveness and performance of the stabilizers, a digital computer simulation is performed and the following small disturbances are considered,

- 10% step change in excitation reference voltage V_{ref} .
- 10% step change in mechanical input torque T_m for 0.3 sec.

In addition, the performance of the stabilizers have been investigated on four operating conditions which are given in Table 3.7. Further more, the effect of variation in generator inertia 'M' from 50% to 150% of the nominal value and transmission line reactance ' X_{TL} ' from 10% to 150% are also investigated.

Table 3.7 Generator operating conditions used in the simulations.

	P1 (normal)	P2	P3	P4
Pe (in p.u.)	1	0.4	1.4	1
Qe (in p.u.)	0.015	0.015	0.015	-0.075

3.4.3 Eigenvalue Analysis:

The eigenvalue analysis is done to investigate the mode of oscillations and the damping characteristics of the system achieved by the conventional PSS (CVPSS), optimal stabilizer (OPTPSS) and suboptimal stabilizer (SUBPSS). Table 3.8 shows the eigenvalues corresponding to the four operating conditions shown in Table 3.7. It can be seen from this table that the system damping is improved and the system is stabilised when the stabilizers have been added. Similarly, Table 3.9 and Table 3.10 respectively shows the impact of variation in inertia constant and the transmission line reactance on the system modes corresponding to operating point P1. Table 3.11 shows the effect of varying the operating point and system parameters simultaneously. In Table (3.8-3.11), the mechanical mode is marked with a star.

Table 3.8 System eigenvalues at different operating conditions.

Operating points	No PSS	CVPSS	OPTPSS	SUBPSS
P1	(0.295±j4.96)* -10.39±j3.28 (unstable)	-1.13±j4.33 -4.62±j7.48 -18.7, -0.337	-1.6±j5.4 -2.77±1.67 -187.5	-1.32±j5.86 -1.3±j2.83 -14.94
P2	(0.0025±j4.87)* -10.1±j3.79 (unstable)	-0.75±j4.65 -6.14±j6.12 -0.335, -16.4	-0.92±j5.1 -2.55±j2.23 -187.55	-0.74±j5.02 -2.82±j2.22 -13.08
P3	(0.775±j4.88)* -10.87±j3.13 (unstable)	-0.83±j4.63 -4.425±j7.73 -19.69	-1.96±j5.32 -3.11±j1.26 -187.63	-0.67±j2.84 -1.288±j6.42 -16.27

Table 3.9 Effect of varying inertia M on system eigenvalues corresponding to P1.

Case	No PSS	CVPSS	OPTPSS	SUBPSS
'M' reduced by 50%	(0.43±j6.85)* -10.53±j3.67 (unstable)	-2.26±j10.57 -2.36±j4.26 -0.337, -20.97	-1.82±j7.35 -3.04±j1.53 -187.6	-1.22±j7.7 -1.26±j3.03 -15.23
'M' increased by 50%	(0.223±j4.1)* -10.32±j3.11 (unstable)	-0.56±j3.75 -5.75±j6.6 -0.337, -17.57	-1.46±j4.48 -2.6±j1.78 -187.6	-1.41±j4.88 -1.38±j2.61 -14.62

Table 3.10 Effect of X_{TL} on system eigenvalues corresponding to P1.

Case	No PSS	CVPSS	OPTPSS	SUBPSS
X_{TL} increased by 50%	(0.41±j3.8)* -10.49±j4.27 (unstable)	-0.47±j3.3 -5.39±j7.8 -0.339, -18.43	-2.01±j4.53 -2.79±j1.05 -187.6	-1.13±j2 -1.65±j5.4 -14.61
X_{TL} decreased by 90%	(-0.0003±j9.38)* -2.56, -17.91 (stable)	-0.52±j11.31 -0.338, -3.62 -21.86	-0.81±j9.52 -1.72±j1.16 -187.96	-0.54±j9.48 -0.537±j1.62 -18.32

Table 3.11 Effect of operating condition and system parameters on eigenvalues.

M reduced by 50%, X_{TL} reduced by 90% and operating condition P4			
No PSS	CVPSS	OPTPSS	SUBPSS
(-0.024±j13.22)* -2.501, -17.92 (stable)	0.191±j16.01 -3.53±j0.47 -0.338, -23.79	-0.87±j13.3 -1.74±j1.1 -187.96	-0.587±j13.3 -0.49±j1.496 -18.32

3.4.4 Computer Simulation:

In the following graphs, the following abbreviations has been considered:

- OPT : response with the optimal stabilizer.
- SUP : response with the suboptimal stabilizer.
- CV : response with the conventional stabilizer.
- RB : response with the rule-based stabilizer.
- Hym : response with the Hiyama and Lim fuzzy logic stabilizer.
- Has : response with the fuzzy logic stabilizer proposed by Hassan, Malik and Hope.
- Hsu : response with the Hsu fuzzy logic stabilizer.

The system response following 10% step change in reference voltage is shown in Fig. 3.15 corresponding to system operating at P1 without PSS. This shows that the system is unstable as it was shown in the eigenvalue analysis. For the same disturbance and system operating condition, the system is stabilised and the damping is greatly improved after adding the PSS as can be seen from Fig. 3.16. It can be clearly seen that fuzzy stabilizers provide a comparable robustness as the optimal stabilizer and much better than the other stabilizers. For the same operating point considered in Fig. 3.16, the system response following a 10% step change in input mechanical power (or reduction in load demand) persisting for a period of 0.3 sec. is shown in Fig. 3.17. In this case, both the suboptimal and conventional has got a comparable response as the optimal stabilizer while the rule base stabilizer and the fuzzy logic stabilizer provided a better system response, i.e. lower overshoot and shorter settling time, than the optimal stabilizer for the angular speed deviation and rotor angle deviation curves. In Fig. 3.18, the system operating condition is changed to a lower value (operating point P2 in Table 3.7) and system disturbed by a 10% step change in mechanical power for 0.3 sec. is shown. From this figure, one can see the effect of changing system operating condition on the fixed gain stabilizers (CVPSS, OPTPSS, and SUBPSS). The system response following the 10% step change in mechanical power for 0.3 sec. when the system loading is changed to a higher value (P3 in Table 3.7) is shown in Fig. 3.19. It

shows low damping characteristics provided by conventional and suboptimal as compared to the optimal while, on the other hand, the rule based and fuzzy logic based stabilizers provided a better damping characterises to the mechanical mode of oscillation.

The effect of variation in system parameters such as inertia constant, M , and transmission line reactance, X_{TL} , are also investigated. Fig. 3.20 shows the system response to a 10% step change in mechanical torque for 0.3 sec. when M is reduced by 50% from the nominal value with system operating at point P1. On the other hand, Fig. 3.21 shows the system response following a 10% in mechanical torque for 0.3 sec with inertia, M , increased by 50% from the nominal value and the system operating at point P1. From, Fig. 3.20 and 3.21, one can see the effect of decreasing the inertia constant on increasing system oscillations which agrees with the results of the eigenvalue analysis shown in Table 3.9. One can also see that the fuzzy logic stabilizers still can provide good damping characteristics for the mechanical mode of oscillations.

The effect of changing in transmission line reactance on system response following a 10% step change in mechanical power is shown in fig. 3.22 and 3.23. In Fig. 3.22, the transmission line reactance is decreased by 90% while the system operating at point P1. On the other hand, in Fig. 3.23, the reactance is increased by 50% from nominal value while the system operating at point P1. It can be seen from Fig. 3.22 and 3.23 that the reduction in transmission line reactance has an effect of increasing the system oscillations which agrees with eigenvalue analysis shown in Table 3.10. It can be also seen that the fuzzy stabilizer shows a superior effect in damping the mechanical oscillations.

Finally, a worse case is simulated by reducing both the machine inertia constant by 50% and transmission line reactance by 90%. The system response following a 10% step change in mechanical torque for 0.3 sec with system operating at P1 is shown in Fig. 3.24.

Though at this condition the system without PSS is stable with low damping as shown in Table 3.11, the system is destabilised when the conventional stabilizer (CPSS) is added and the system turns to be oscillatory when the rule based stabilizer is added as shown in Fig. 3.24. On the other hand, the fuzzy logic responding very effectively to damp the oscillation.

The given above scenarios and simulation results, reveal the superiority and capability of the fuzzy logic stabilizers to provide good damping characteristic over a wide range of operating conditions. It showed also that the fuzzy logic stabilizers are relatively insensitive to system parameter variations such as system inertia constant and transmission line reactance.

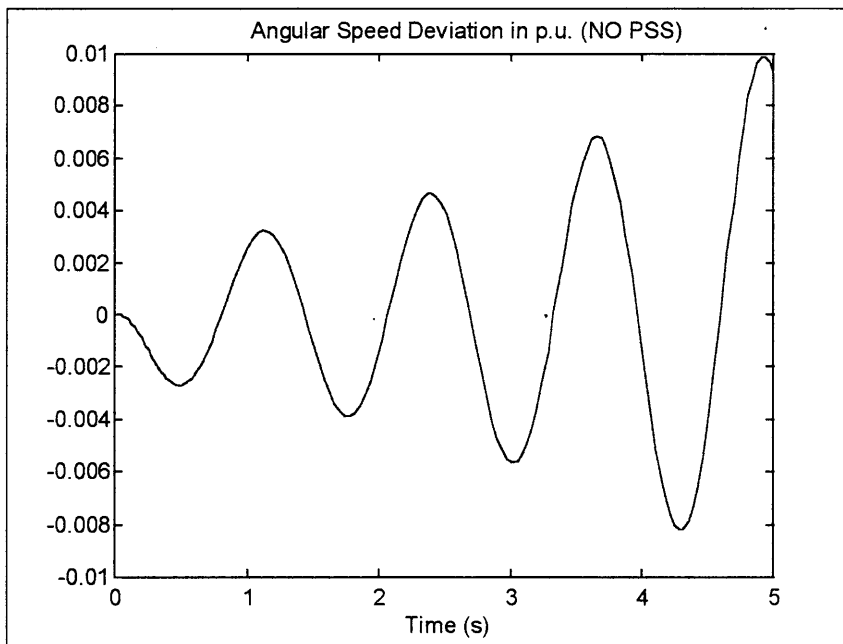


Fig. 3.15 Angular speed variations following 0.1 step change in excitation reference voltage for uncontrolled case (NO PSS).

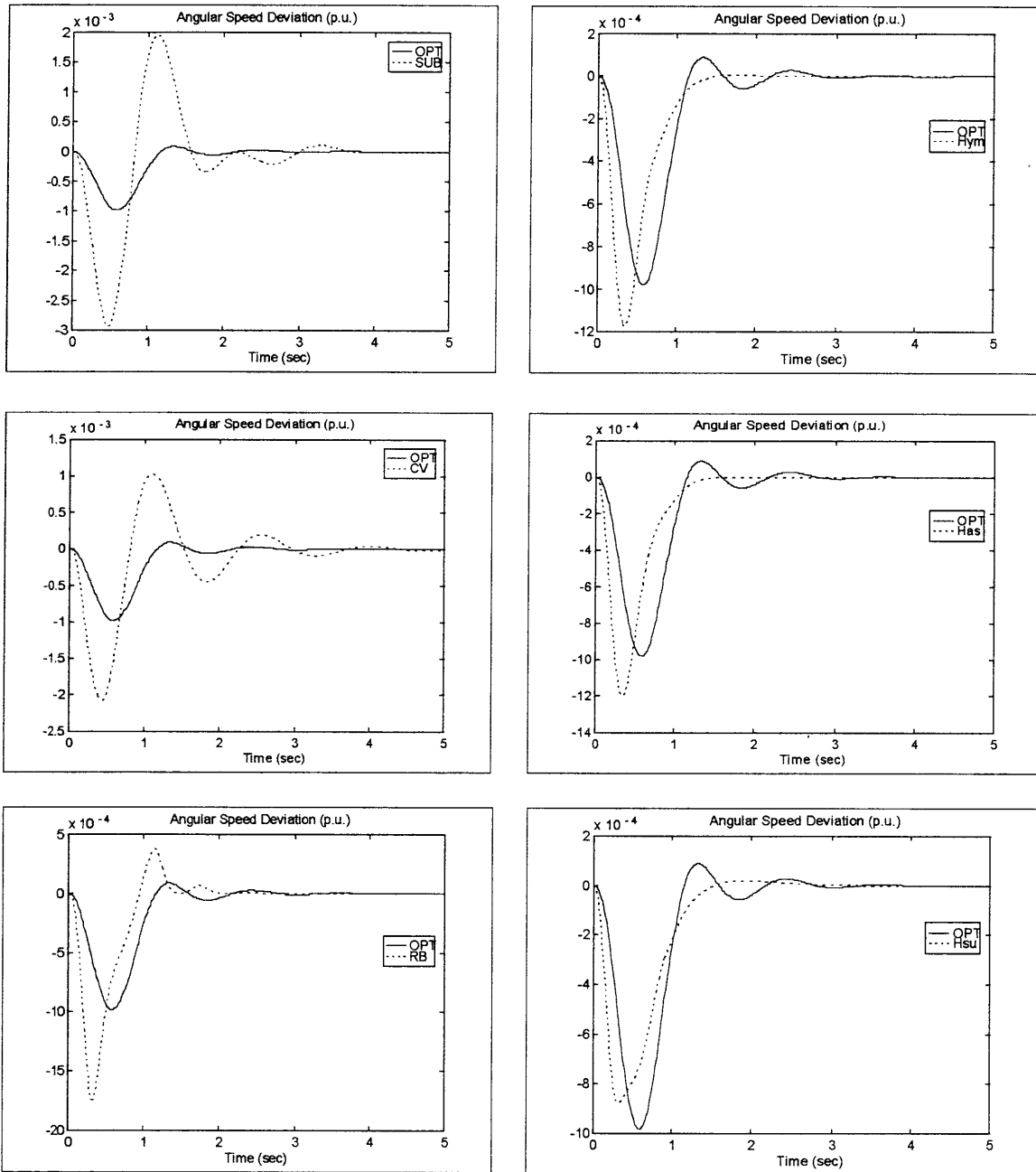


Fig. 3.16a Angular speed variations following 10% step change in excitation reference voltage with system at normal operating condition.

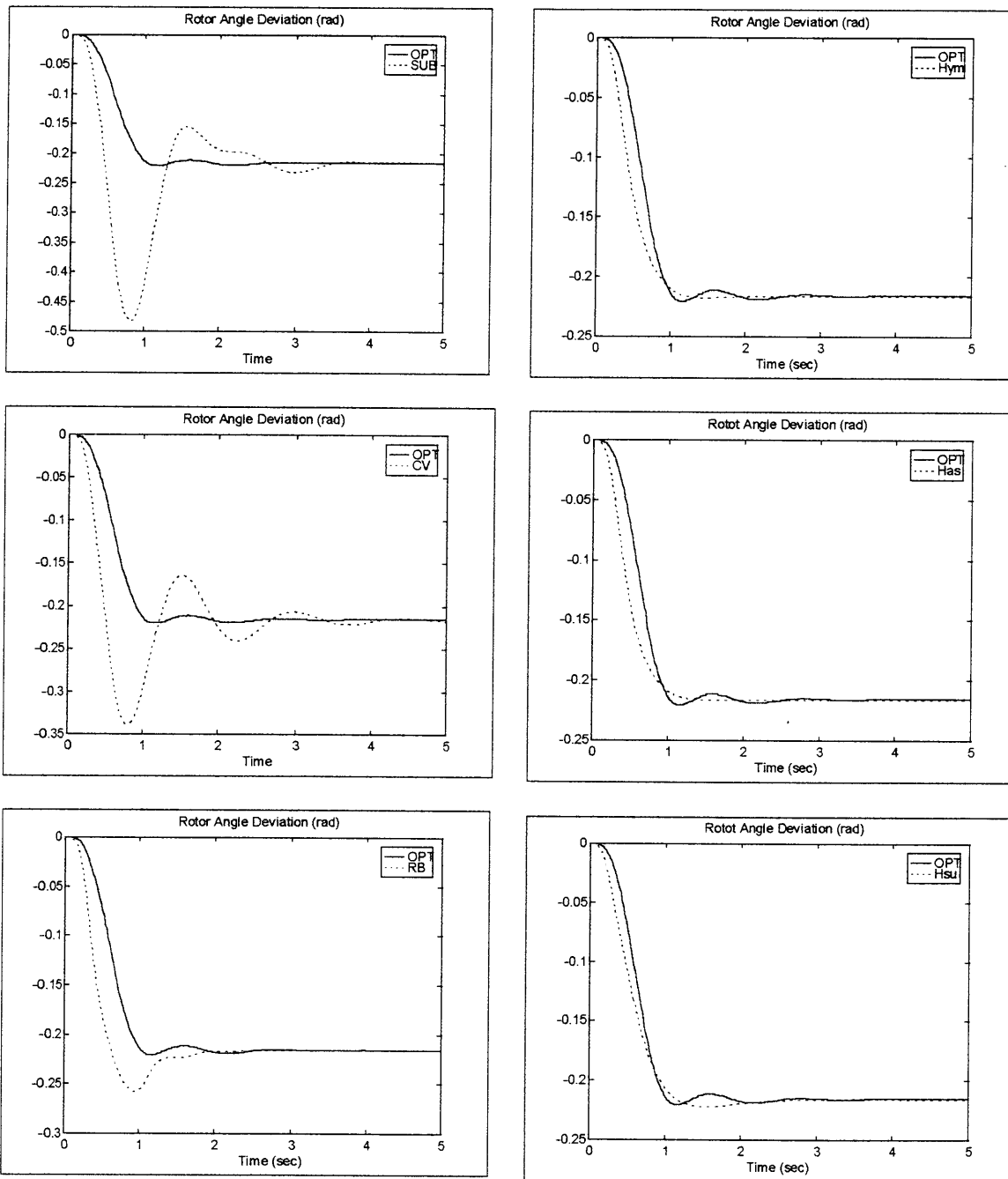


Fig. 3.16b Rotor angle variations following 10% step change in excitation reference voltage with system at normal operating condition.

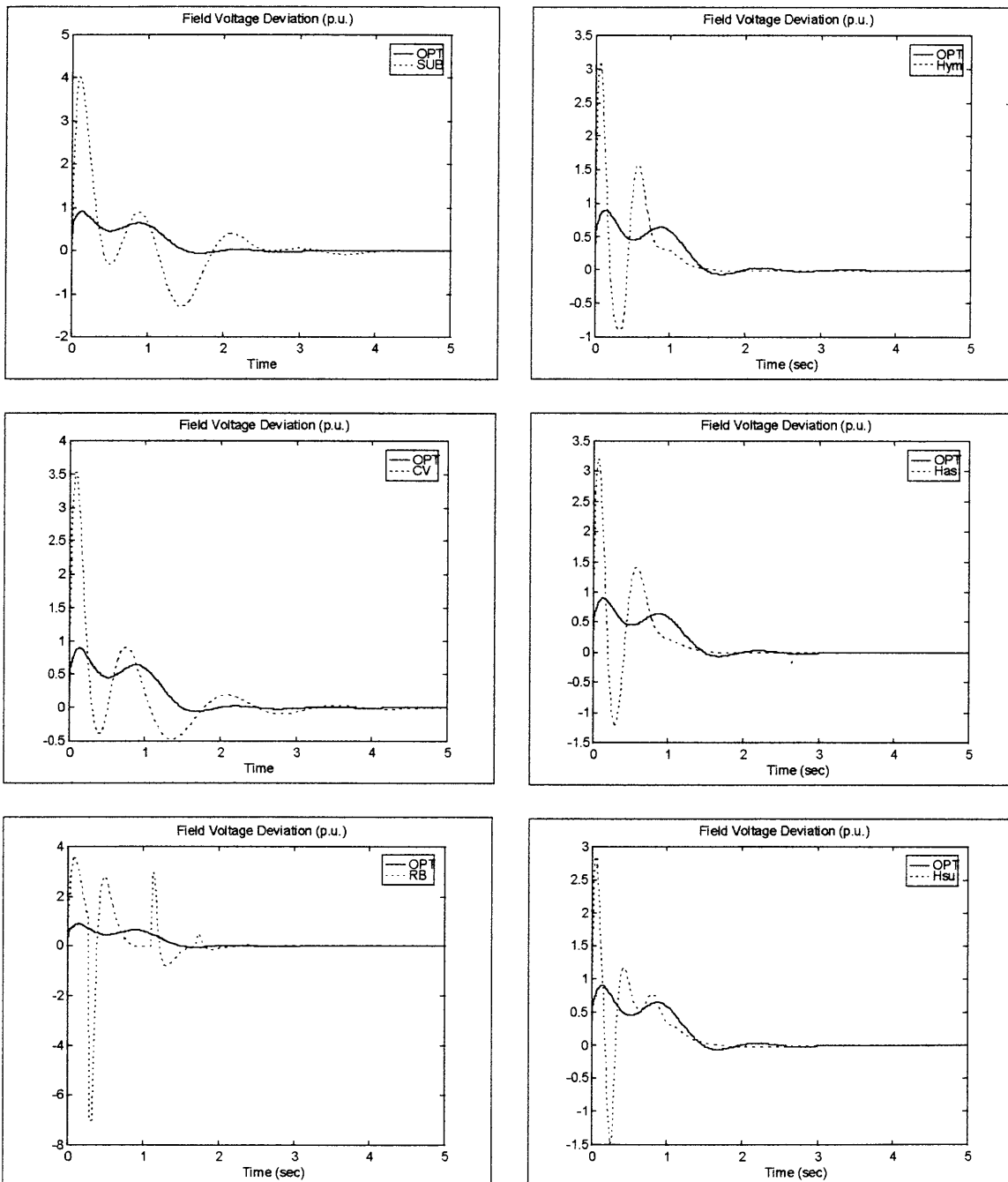


Fig. 3.16c Field voltage variations following 10% step change in excitation reference voltage with system at normal operating condition.

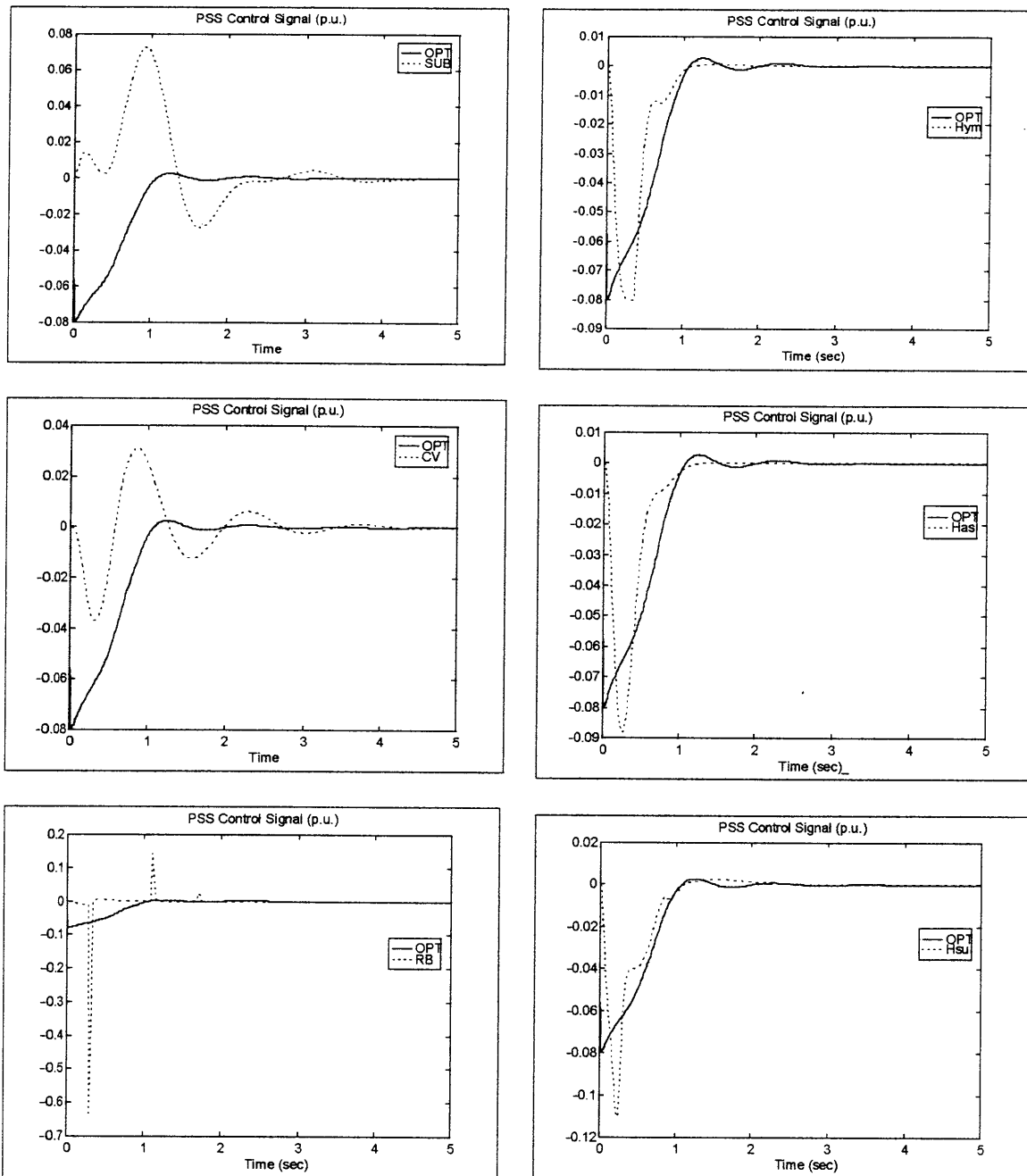


Fig. 3.16d PSS control signal following 10% step change in excitation reference voltage with system at normal operating condition.

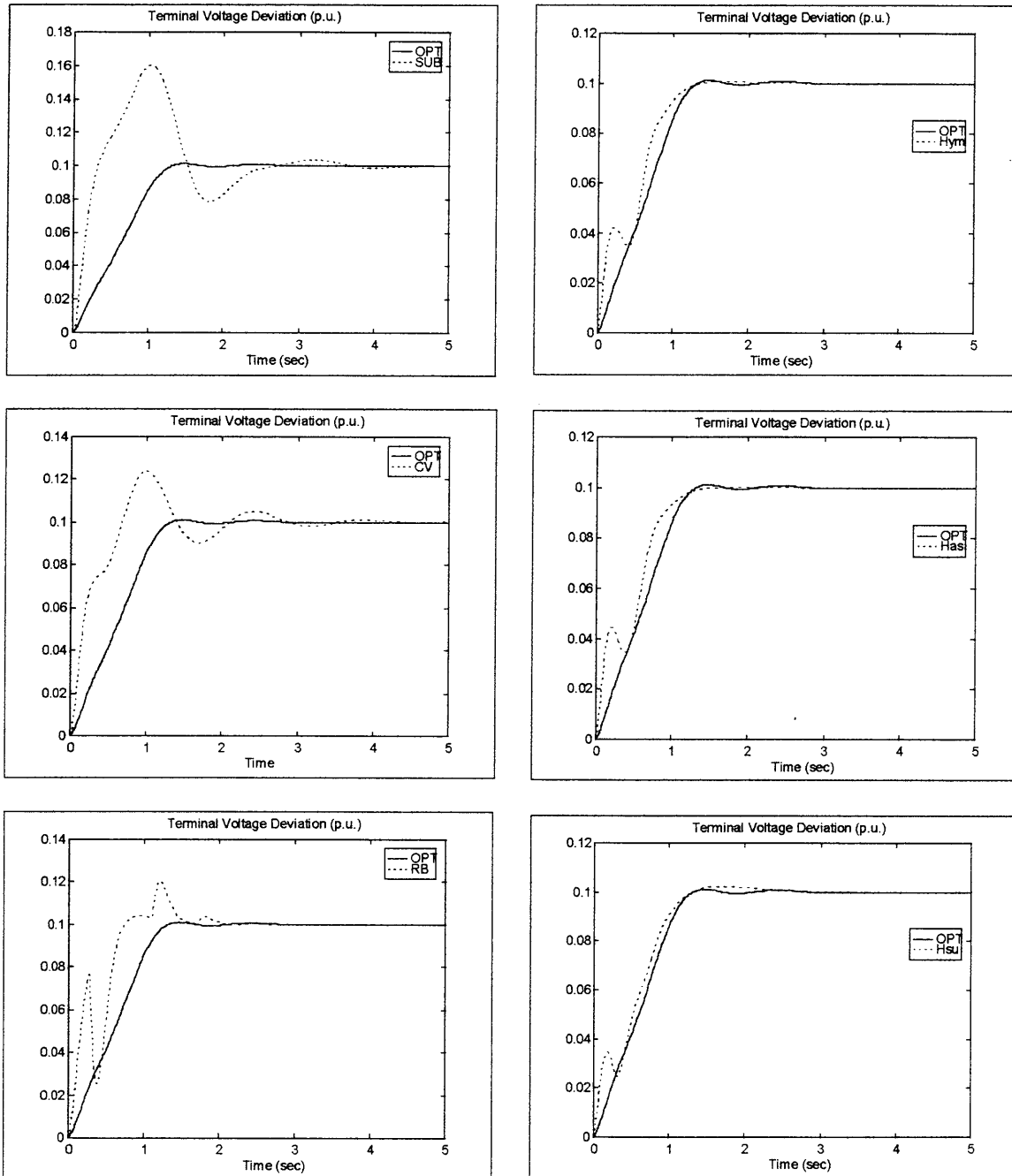


Fig. 3.16e Terminal voltage variations following 10% step change in excitation reference voltage with system at normal operating condition.

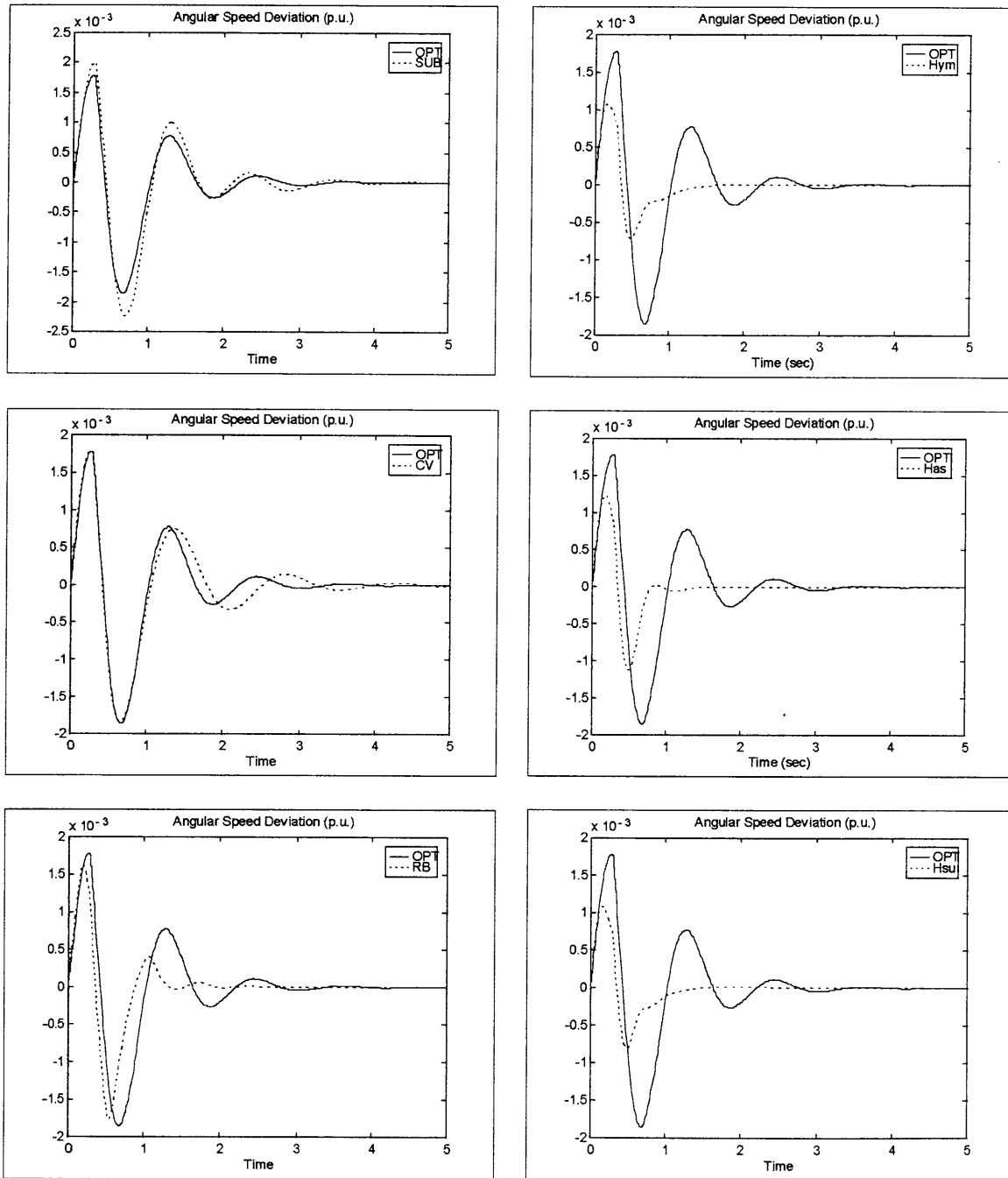


Fig. 3.17a Angular speed variations following 0.1 p.u. step change in mechanical torque for 0.3 sec with normal operating condition.

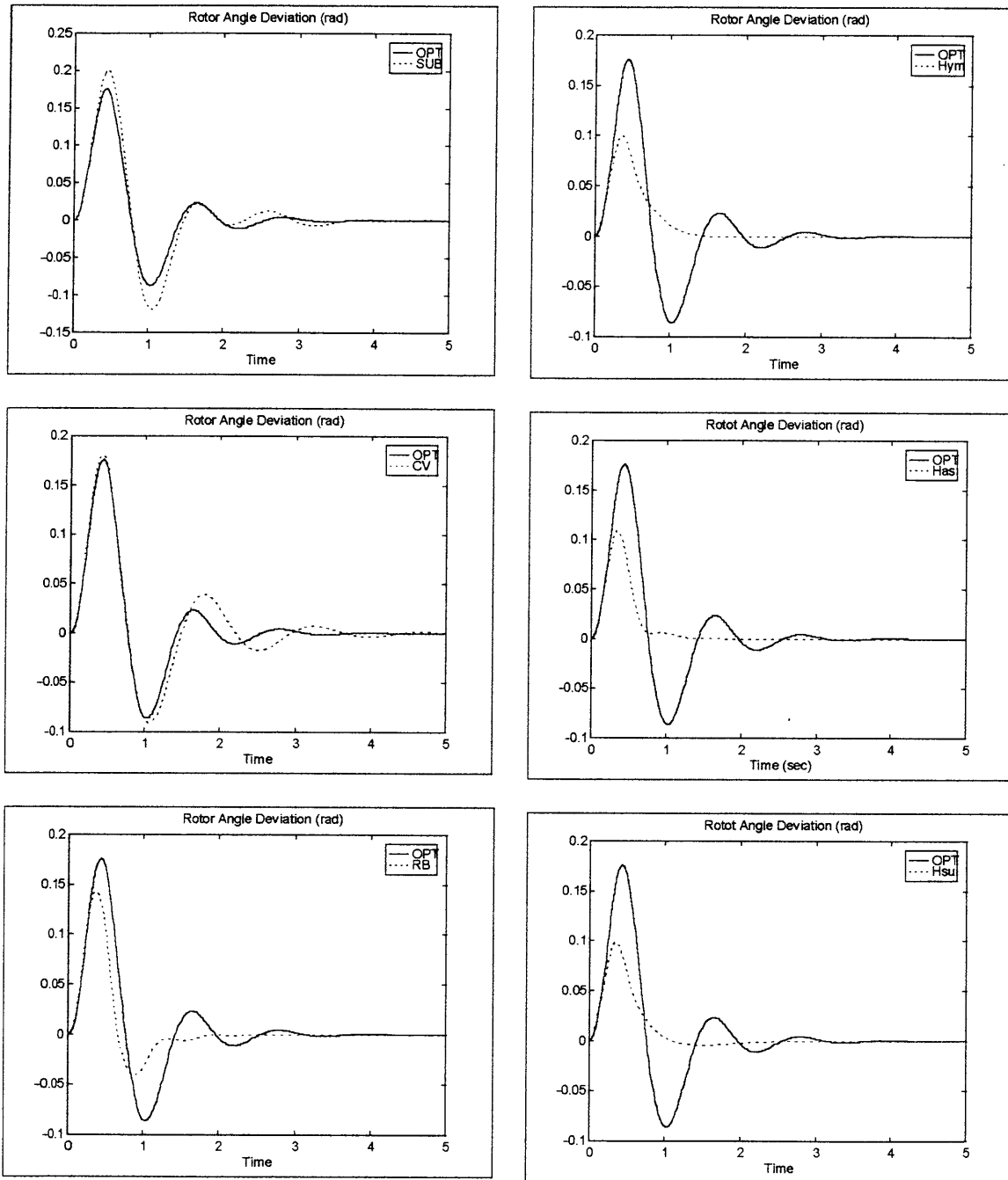


Fig. 3.17b Rotor speed variations following 0.1 p.u. step change in mechanical torque for 0.3 sec with normal operating condition.

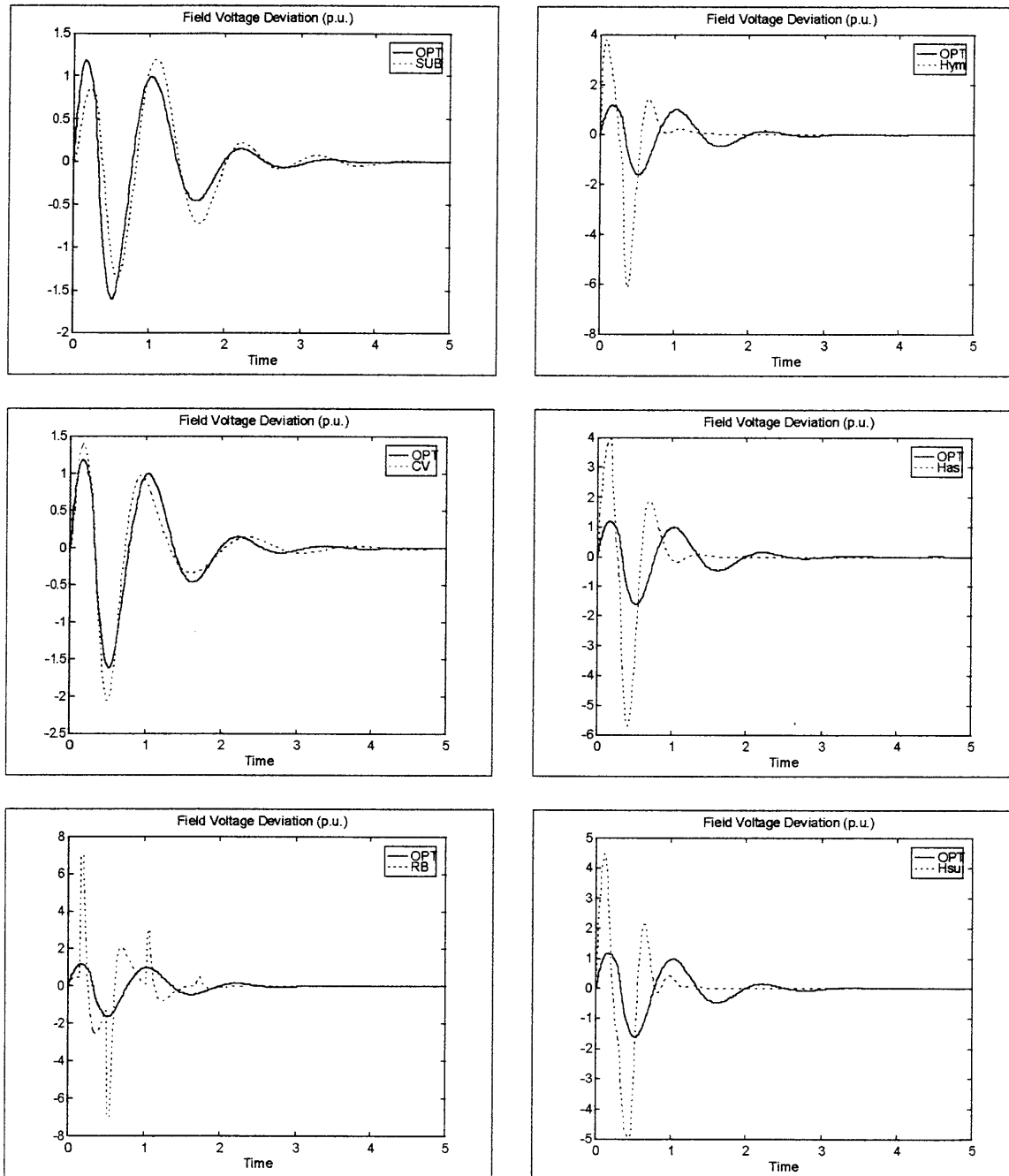


Fig. 3.17c Field voltage variations following 0.1 p.u. step change in mechanical torque for 0.3 sec with normal operating condition.

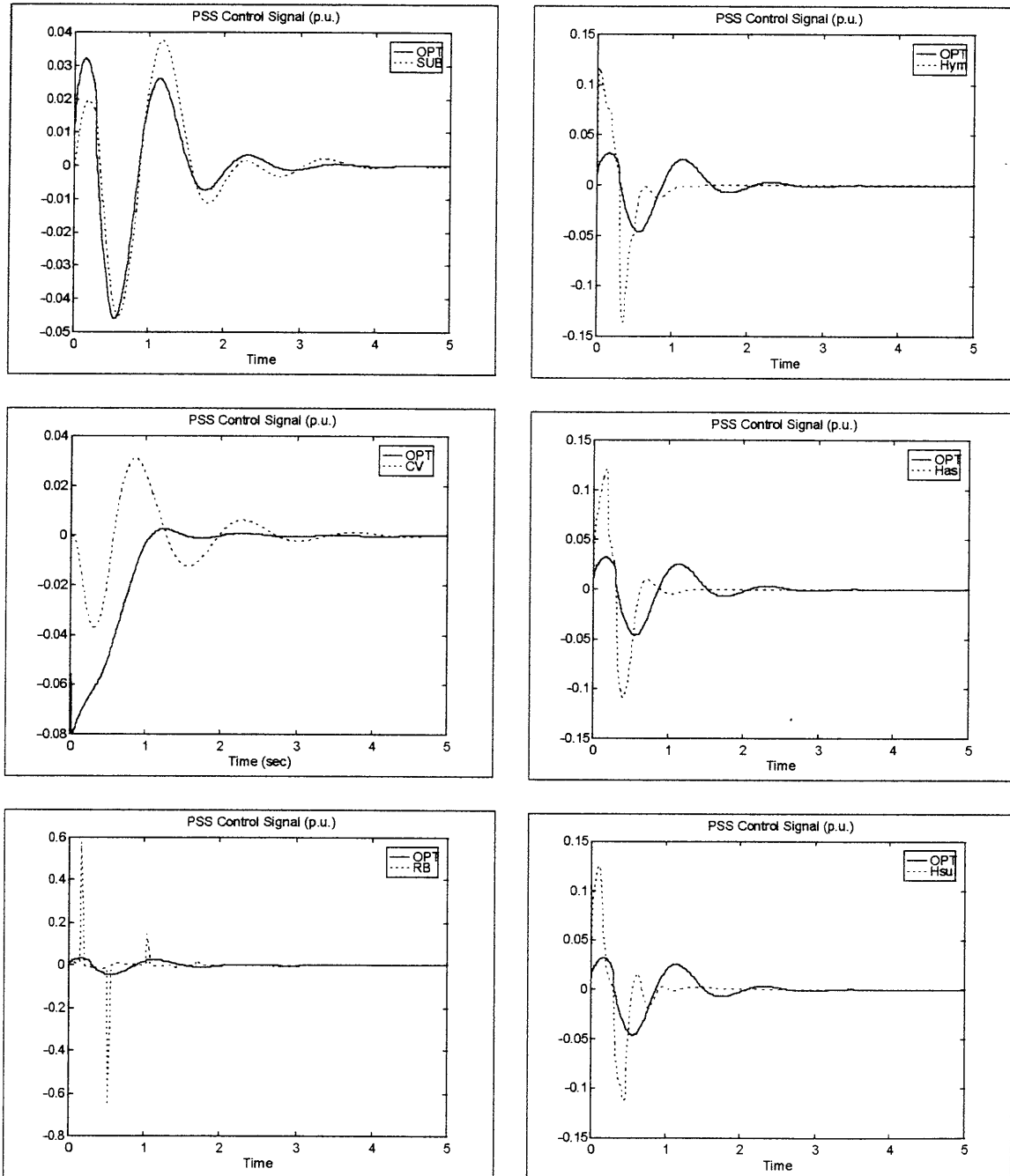


Fig. 3.17d PSS control signal variations following 0.1 p.u. step change in mechanical torque for 0.3 sec with normal operating condition.

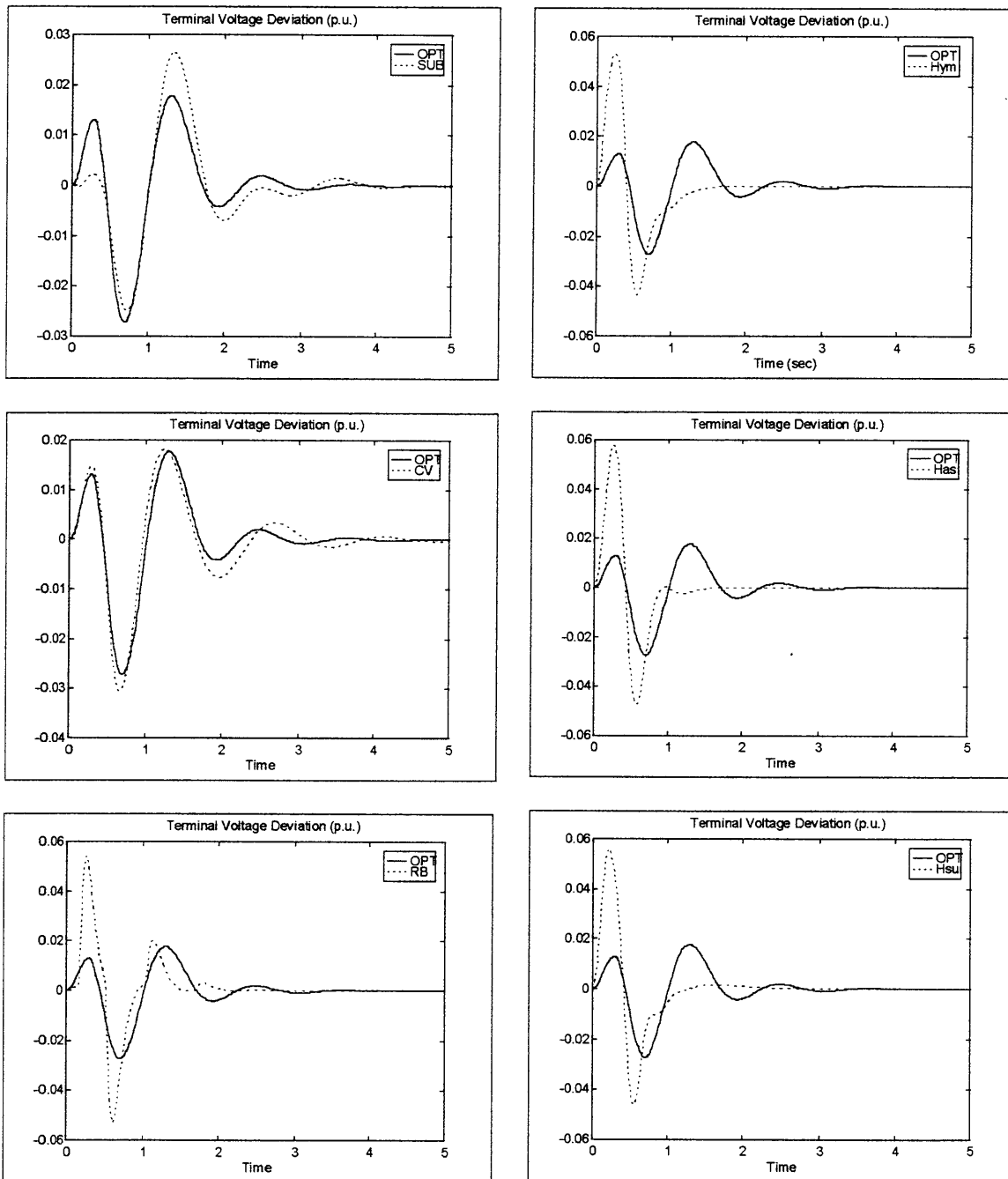


Fig. 3.17e Terminal voltage variations following 0.1 p.u. step change in mechanical torque for 0.3 sec with normal operating condition.

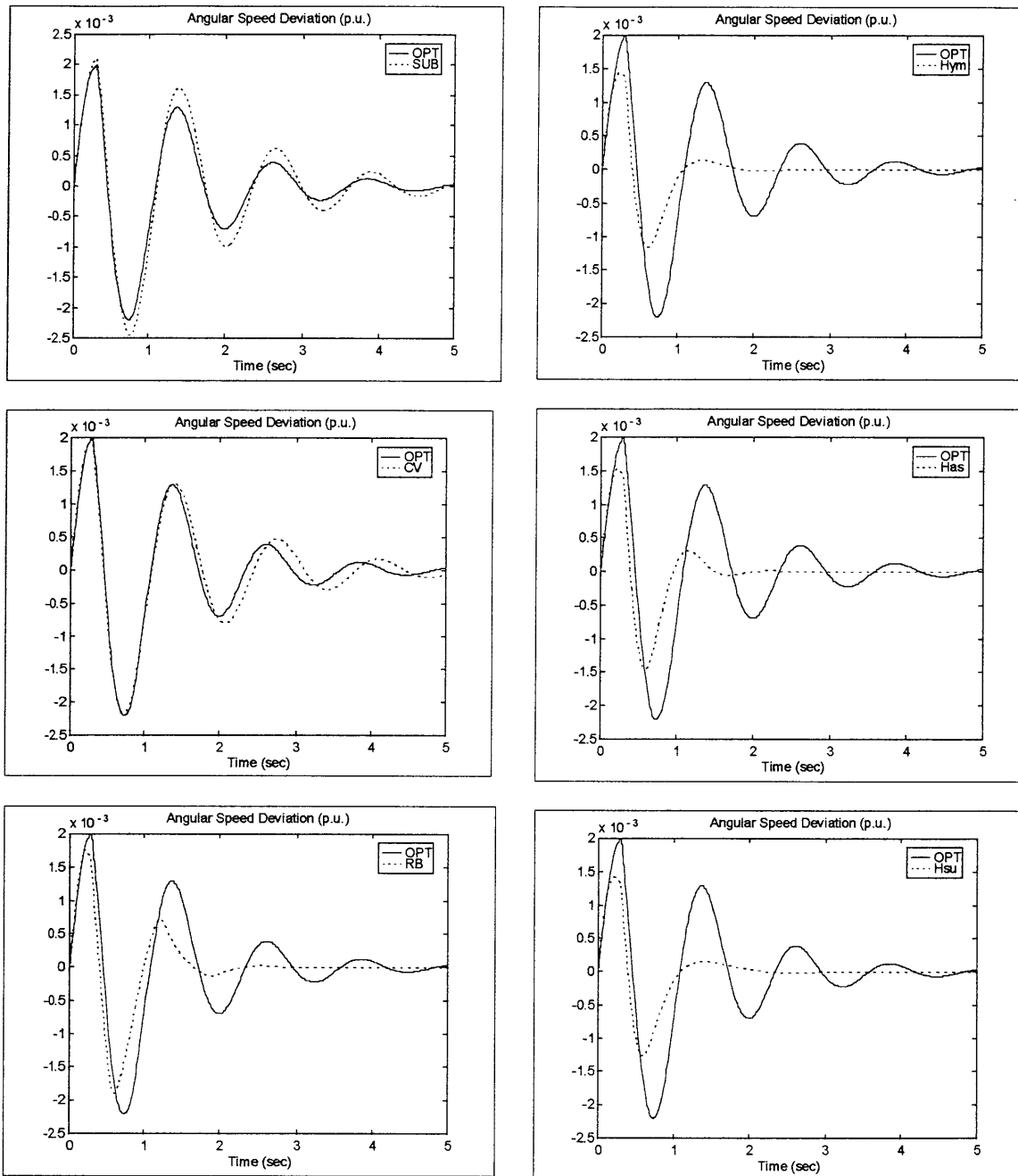


Fig. 3.18a Angular speed variations following 0.1 p.u. change in mechanical torque for 0.3 sec at off-nominal operating condition ($P_e=0.4$ p.u.).

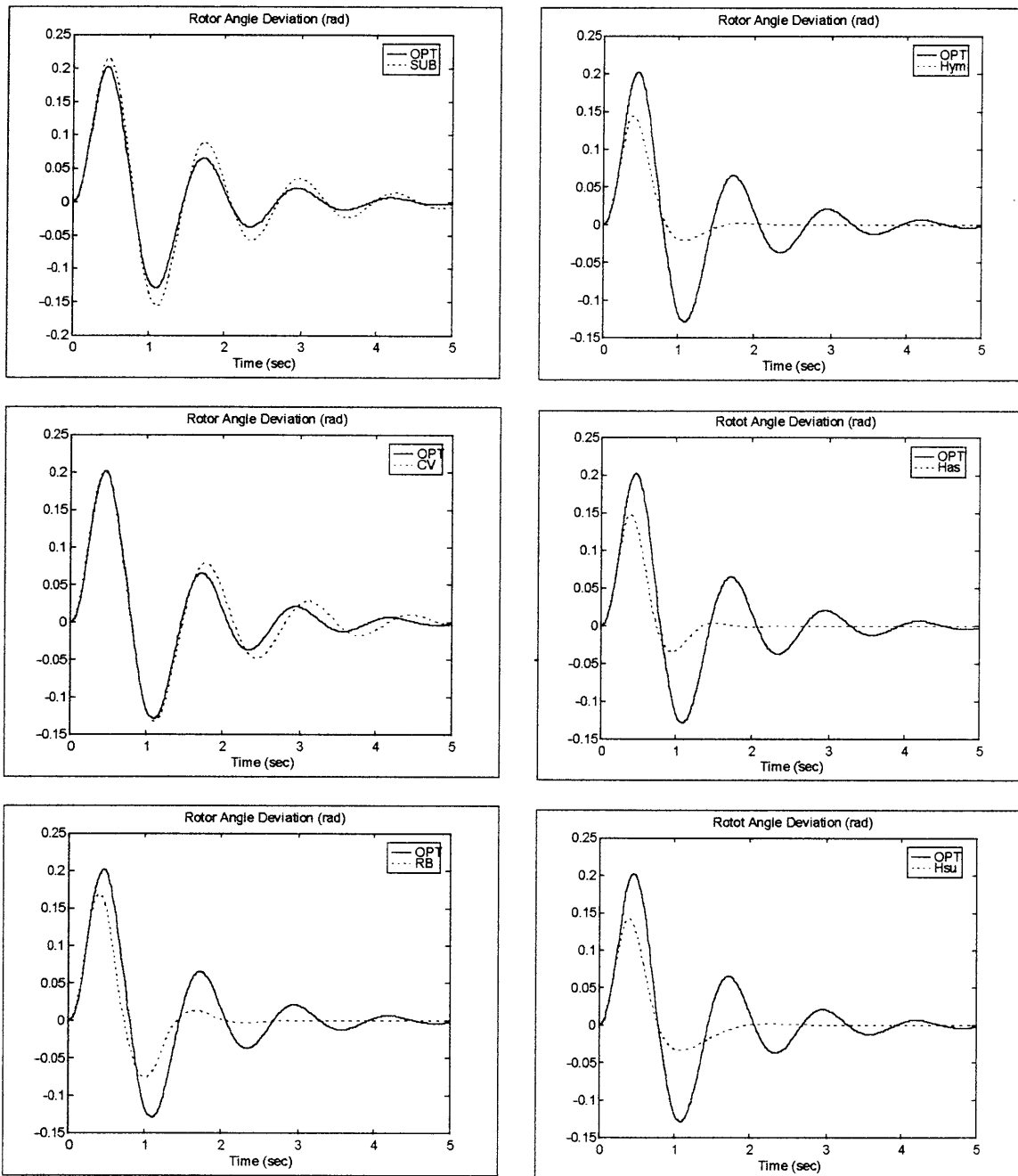


Fig. 3.18b Rotor angle variations following 0.1 p.u. change in mechanical torque for 0.3 sec at off-nominal operating condition ($P_e=0.4$ p.u.).

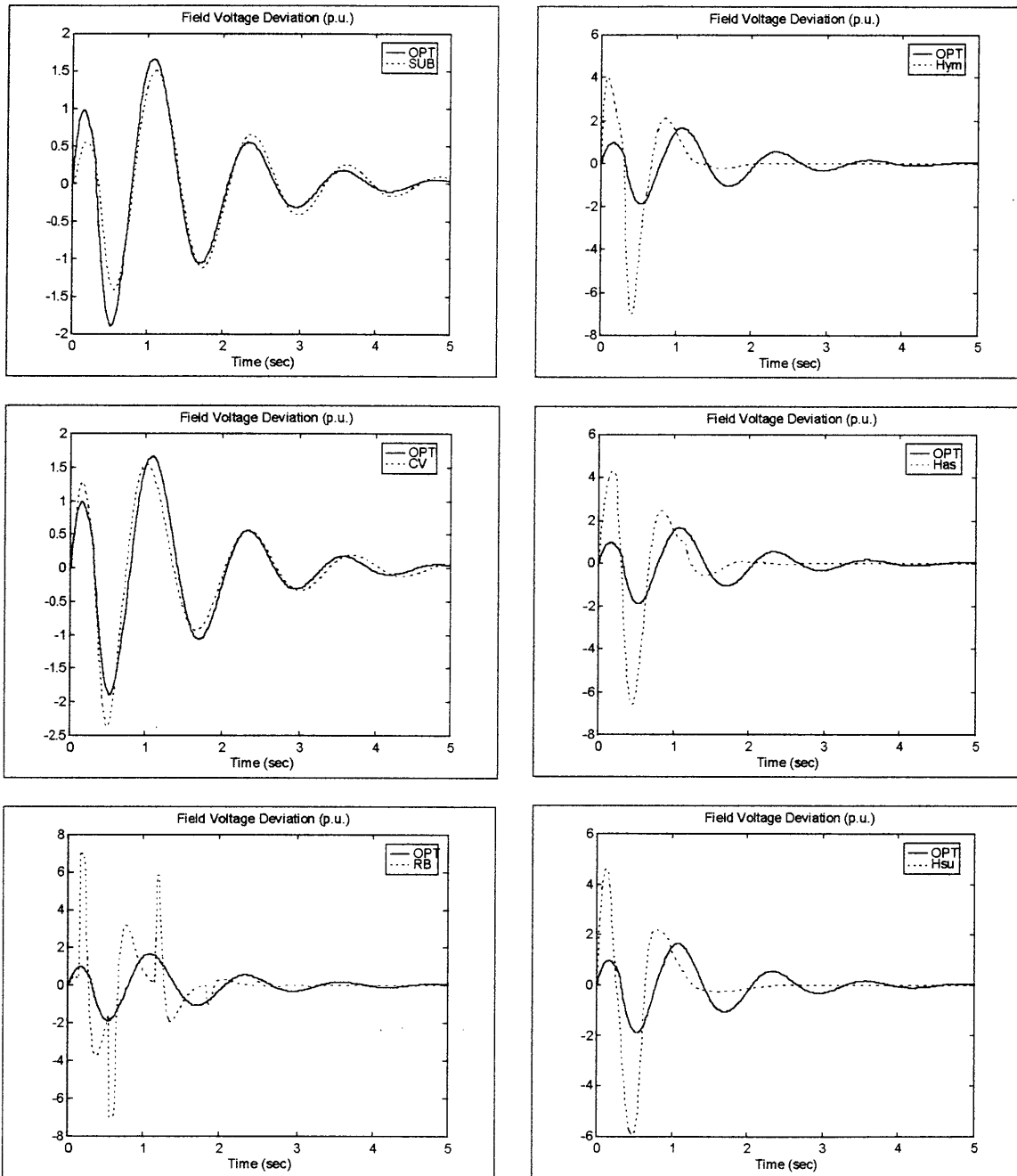


Fig. 3.18c Field voltage variations following 0.1 p.u. change in mechanical torque for 0.3 sec at off-nominal operating condition ($P_e=0.4$ p.u.).

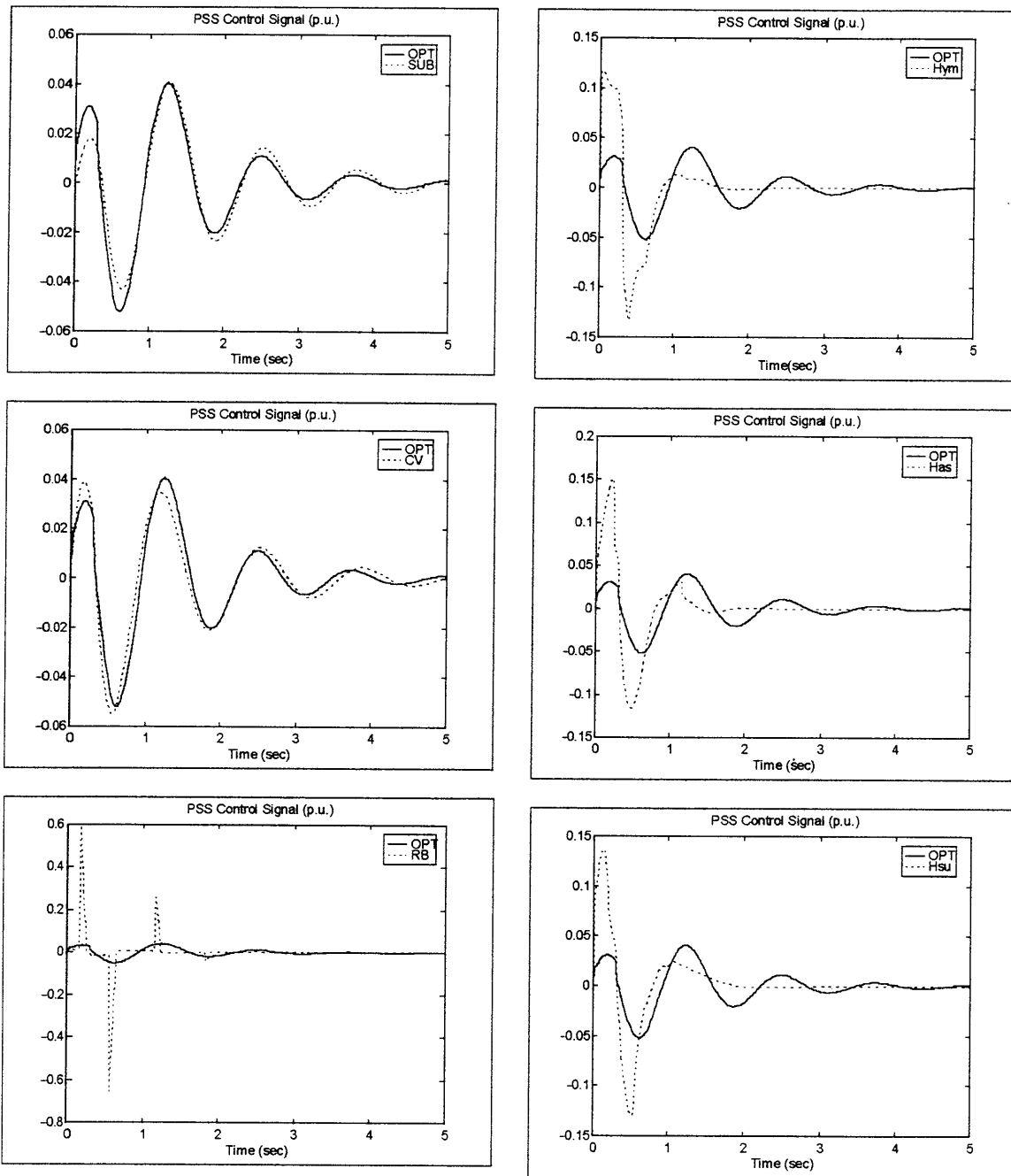


Fig. 3.18d PSS control signal variations following 0.1 p.u. change in mechanical torque for 0.3 sec at off-nominal operating condition ($P_e=0.4$ p.u.).

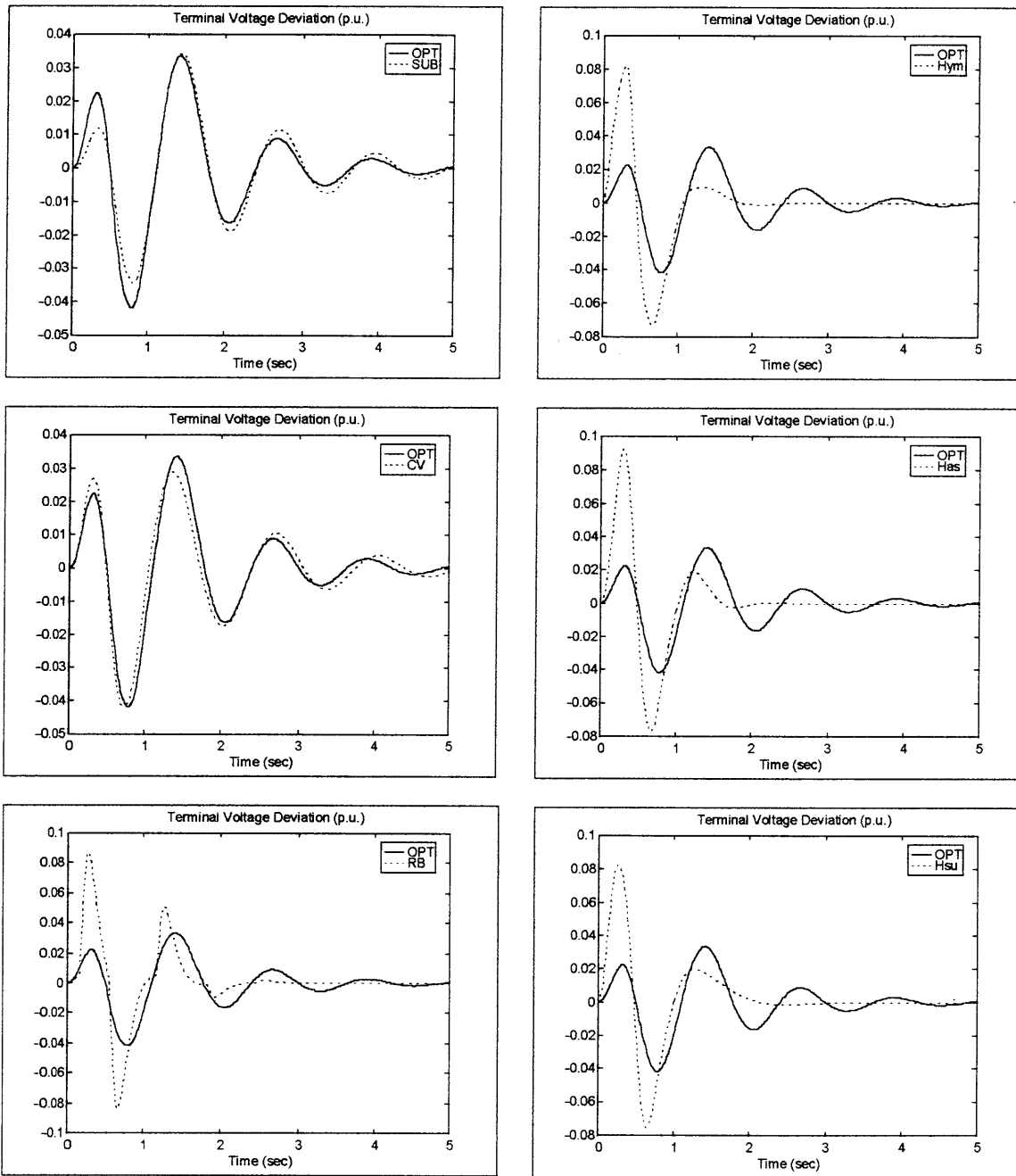


Fig. 3.18e Terminal voltage variations following 0.1 p.u. change in mechanical torque for 0.3 sec at off-nominal operating condition ($P_e=0.4$ p.u.).

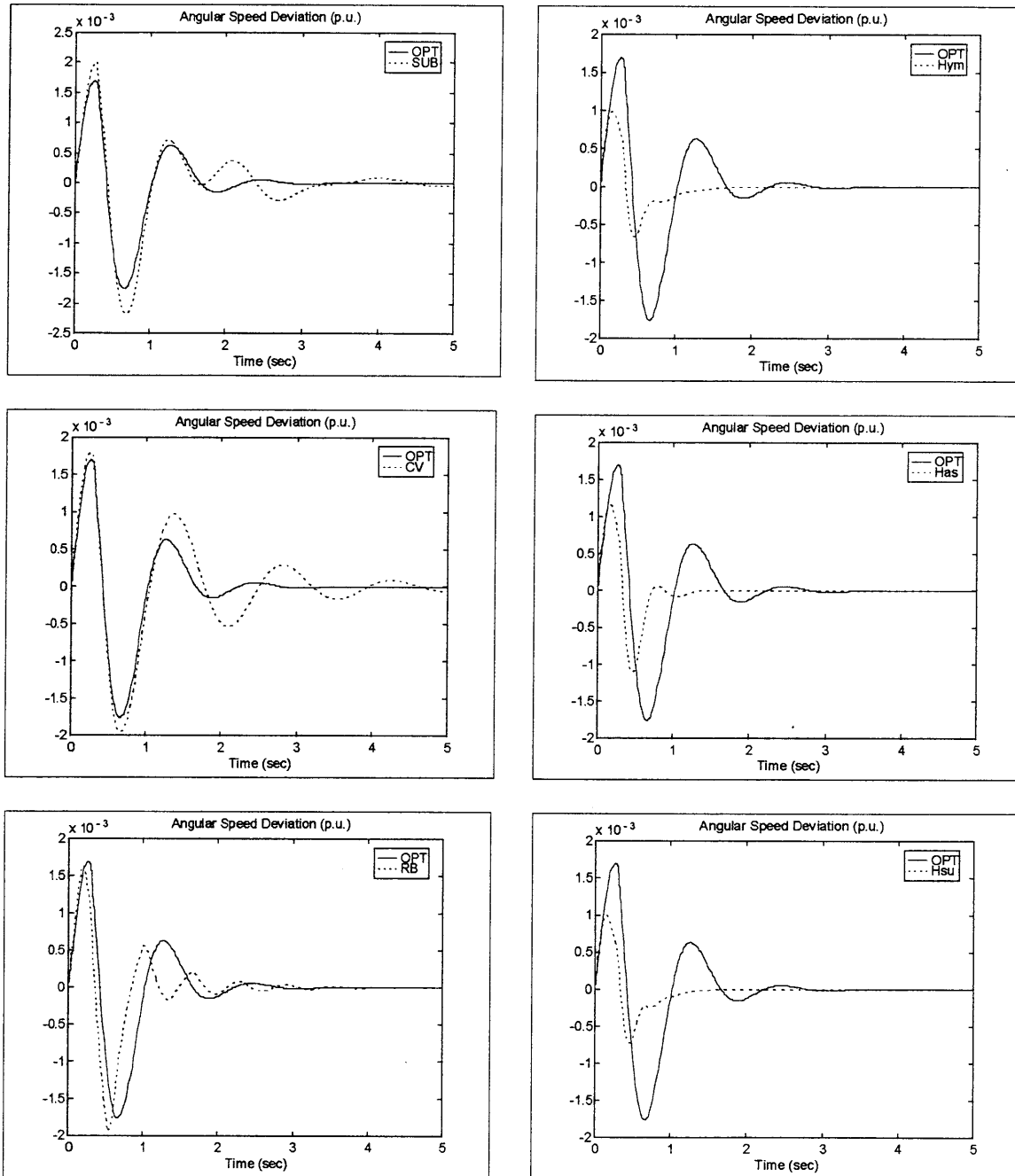


Fig. 3.19a Angular speed variations following 0.1 p.u. step change in input mechanical power at off-nominal operating condition ($P_e=1.4$ p.u.)

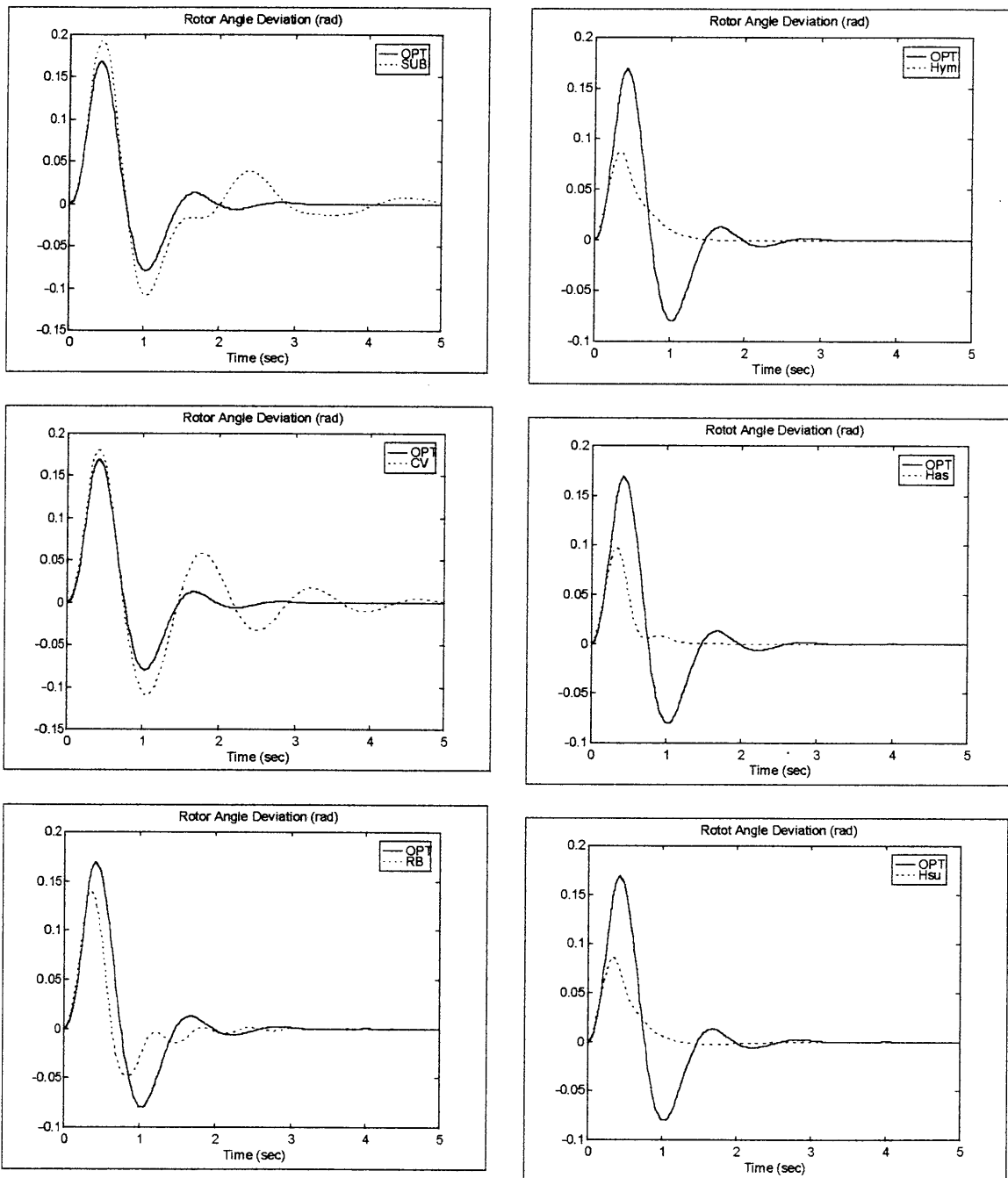


Fig. 3.19b Rotor angle variations following 0.1 p.u. step change in input mechanical power at off-nominal operating condition ($P_e=1.4$ p.u.)

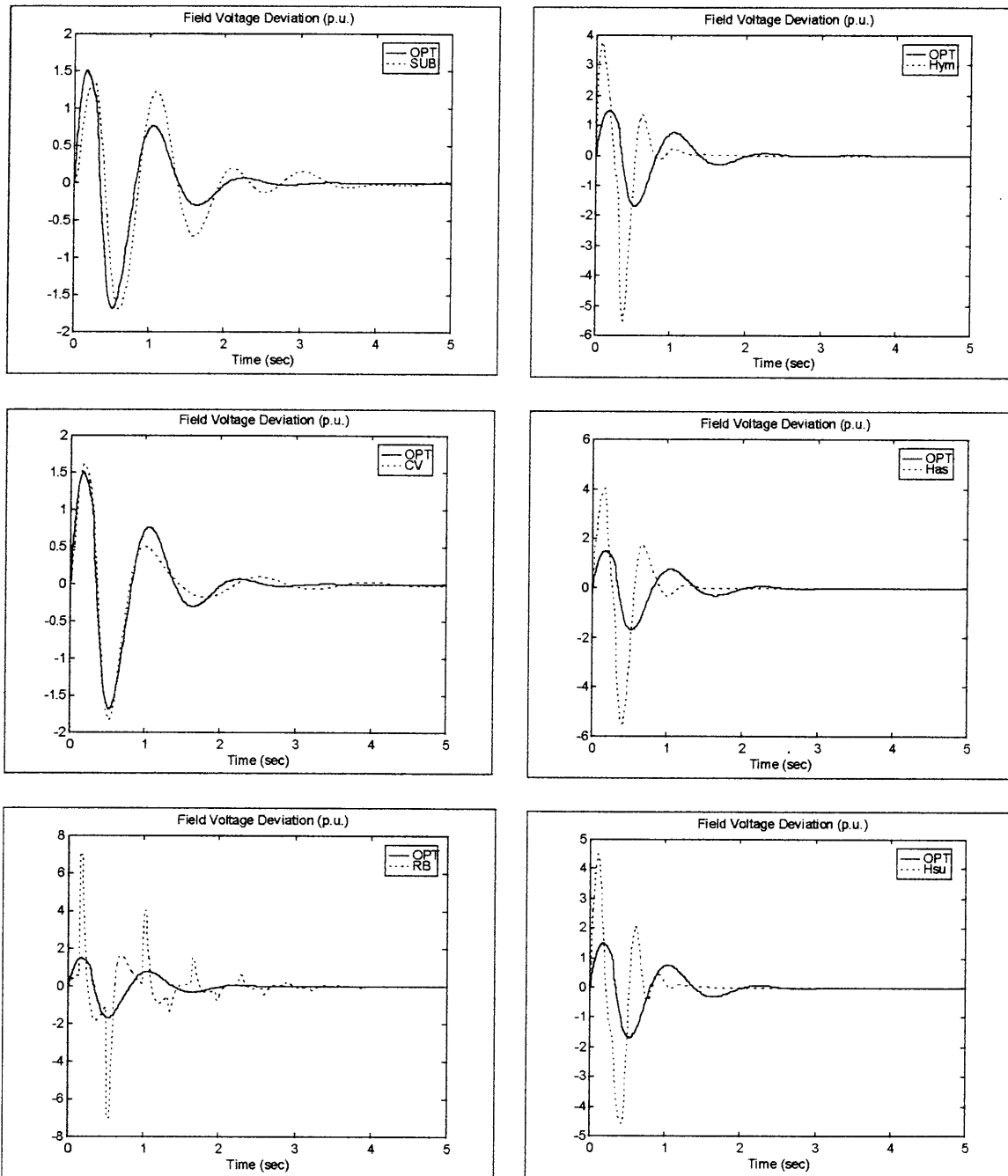


Fig. 3.19c Field voltage variations following 0.1 p.u. step change in input mechanical power at off-nominal operating condition ($P_e=1.4$ p.u.)

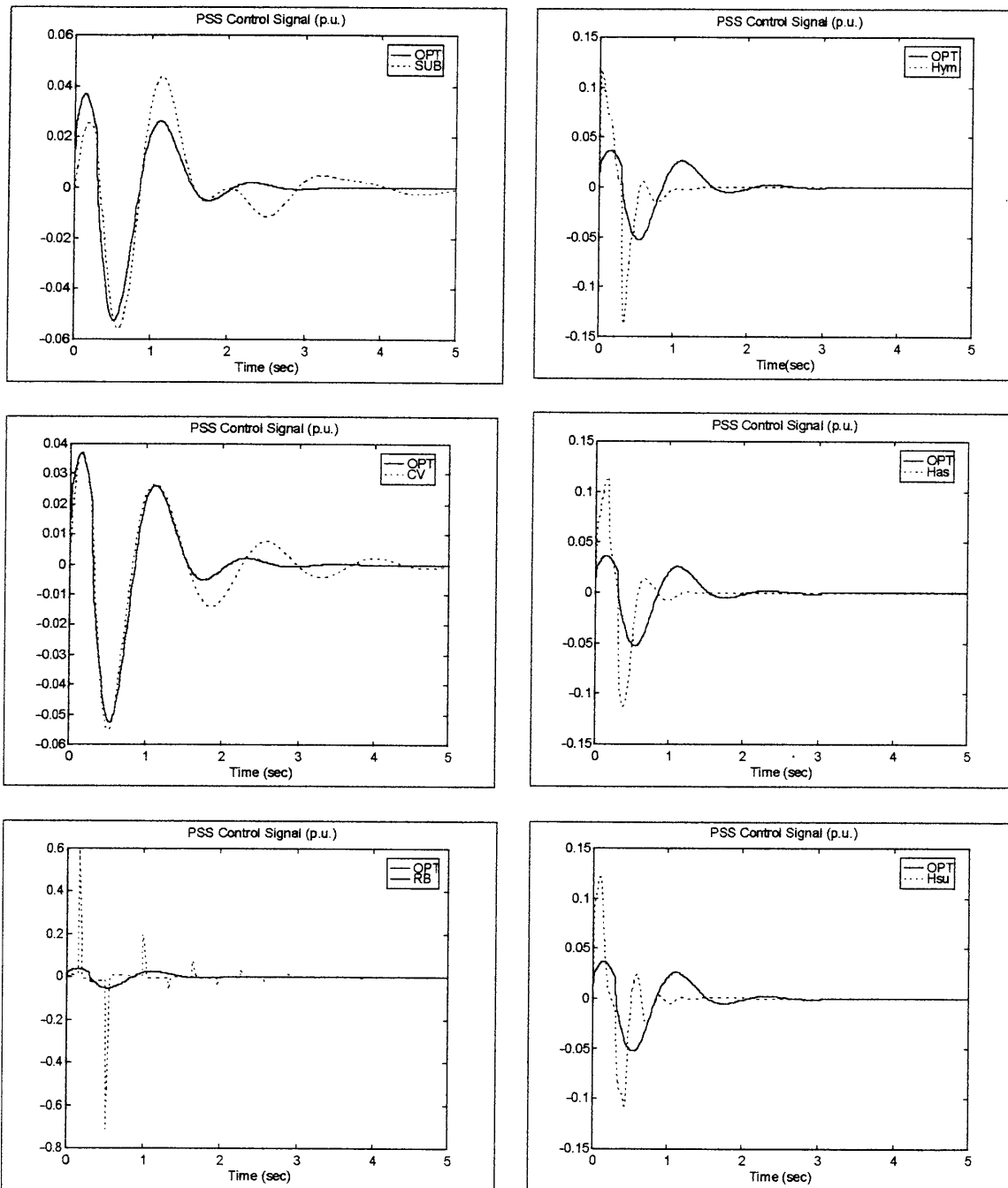


Fig. 3.19d PSS control signal variations following 0.1 p.u. step change in input mechanical power at off-nominal operating condition ($P_e=1.4$ p.u.)

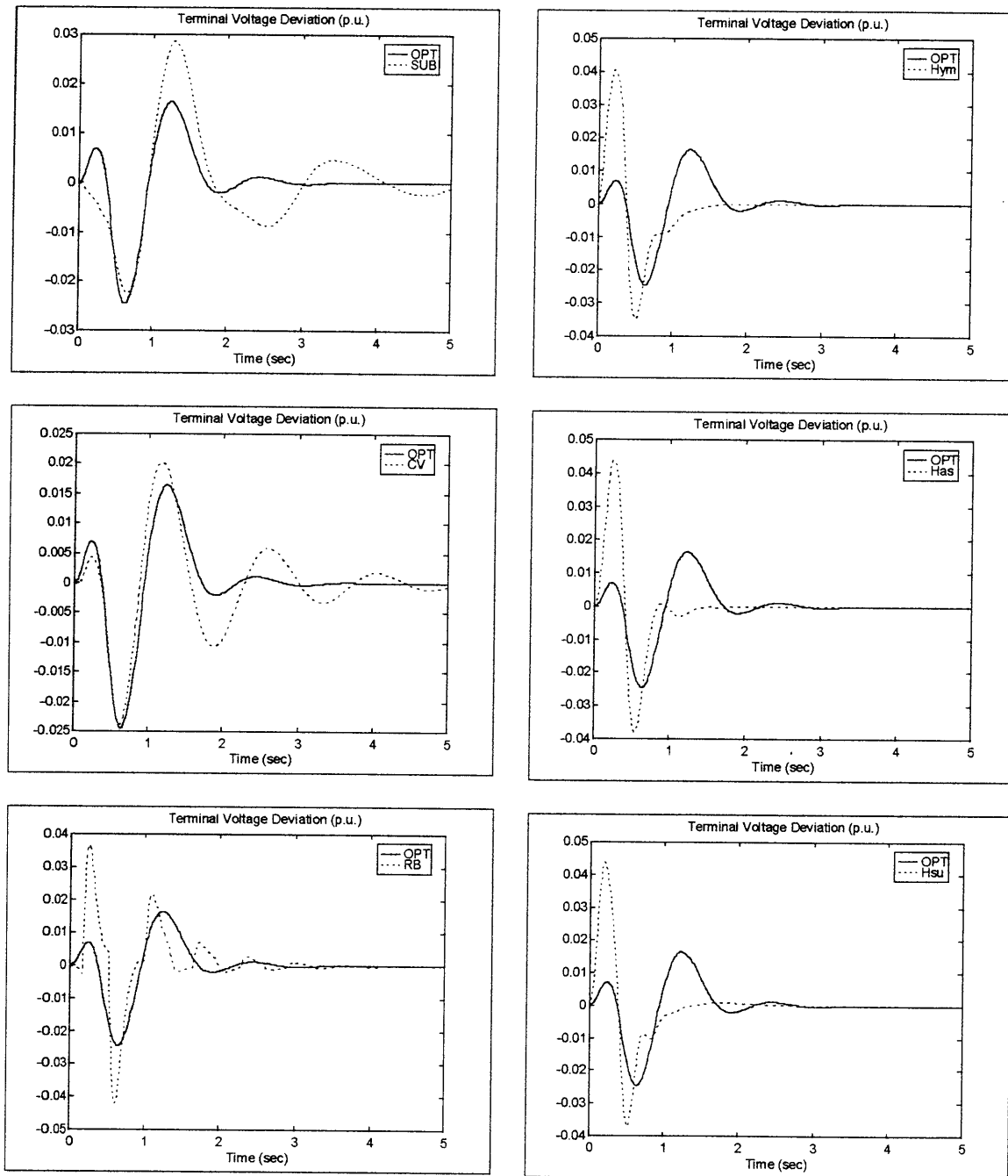


Fig. 3.19e Terminal voltage variations following 0.1 p.u. step change in input mechanical power at off-nominal operating condition ($P_e=1.4$ p.u.)

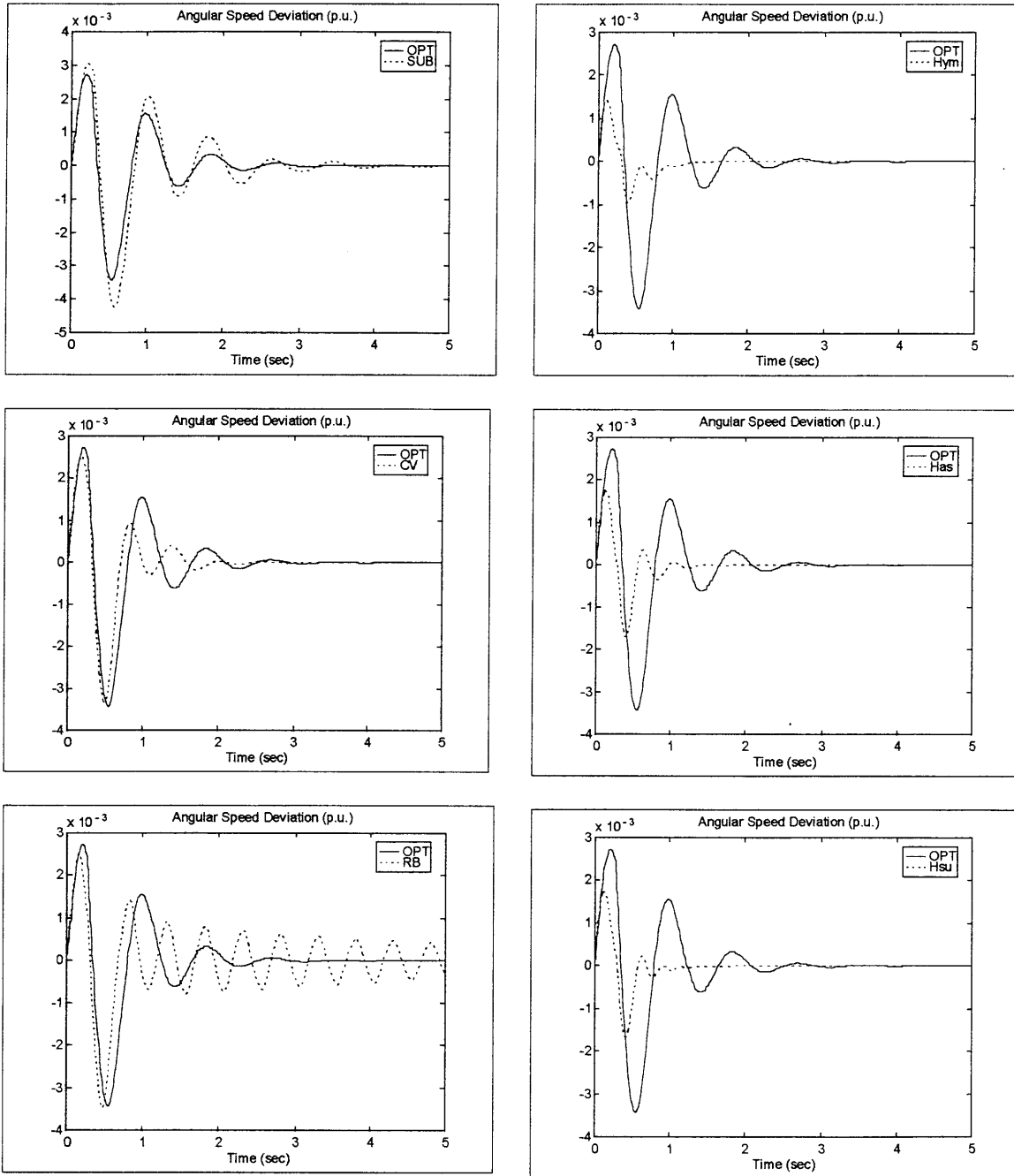


Fig. 3.20a Angular speed variations following 0.1 p.u. change in input mechanical power with inertia constant reduced by 50% from nominal.

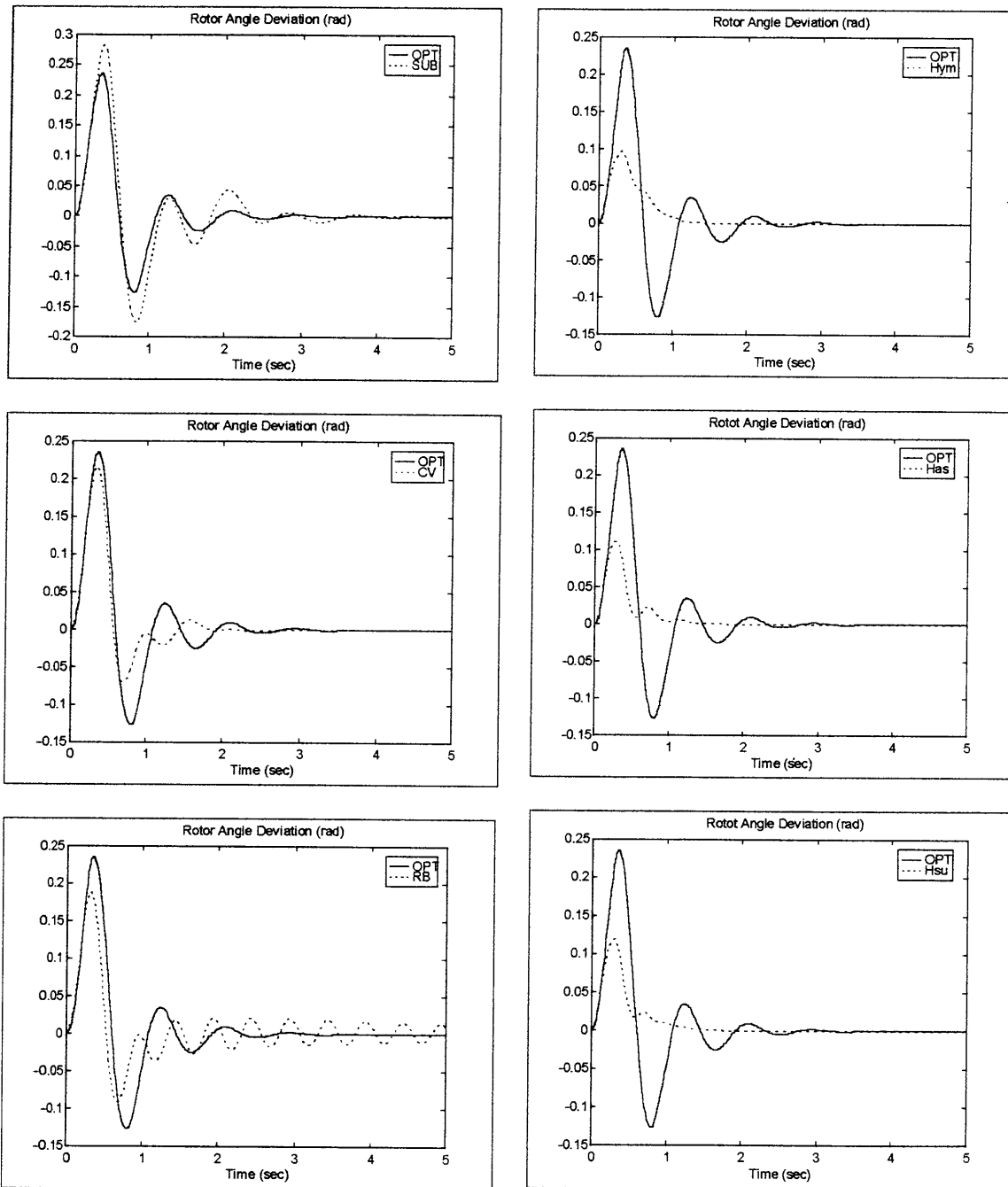


Fig. 3.20b Rotor angle variations following 0.1 p.u. change in input mechanical power with inertia constant reduced by 50% from nominal.

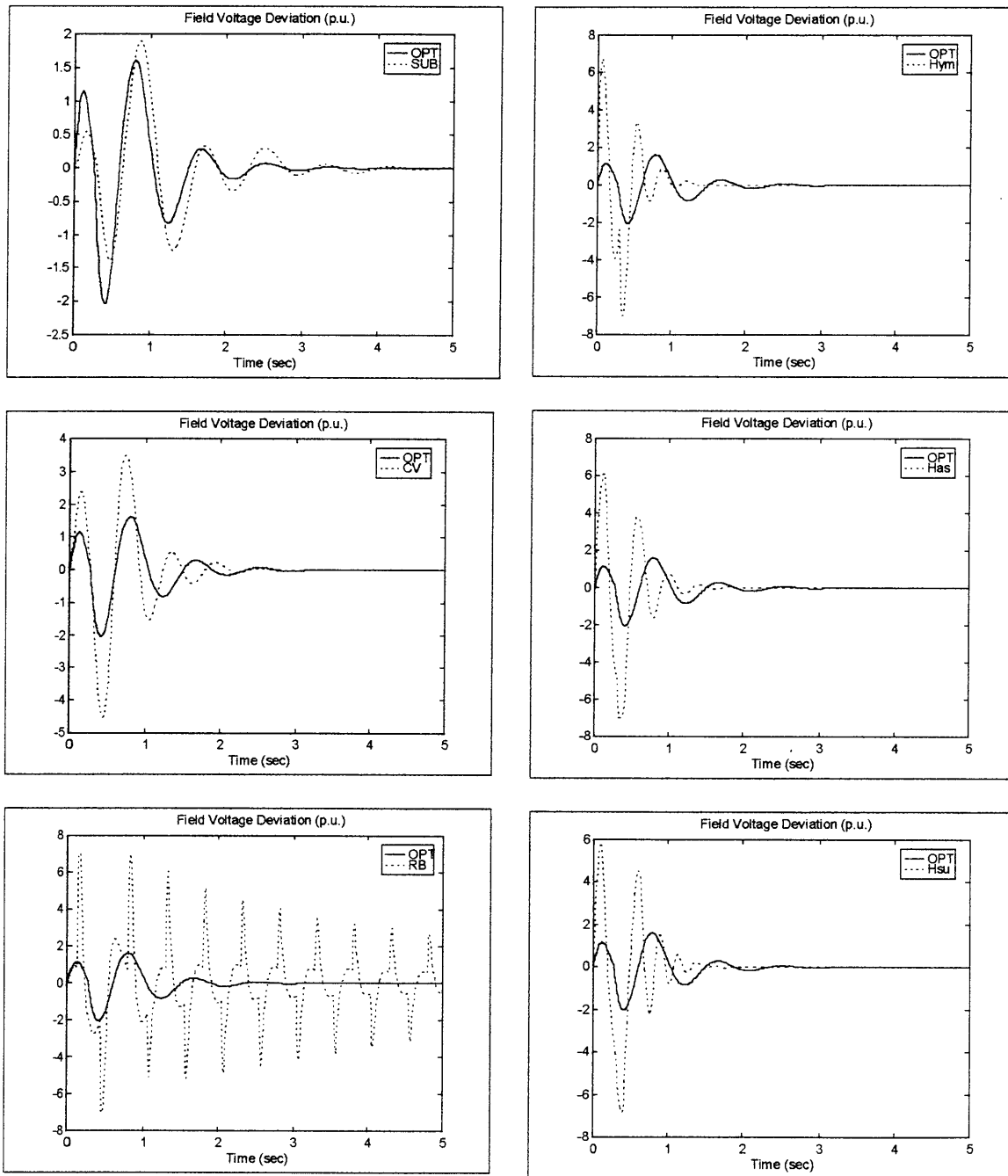


Fig. 3.20c Field voltage variations following 0.1 p.u. change in input mechanical power with inertia constant reduced by 50% from nominal.

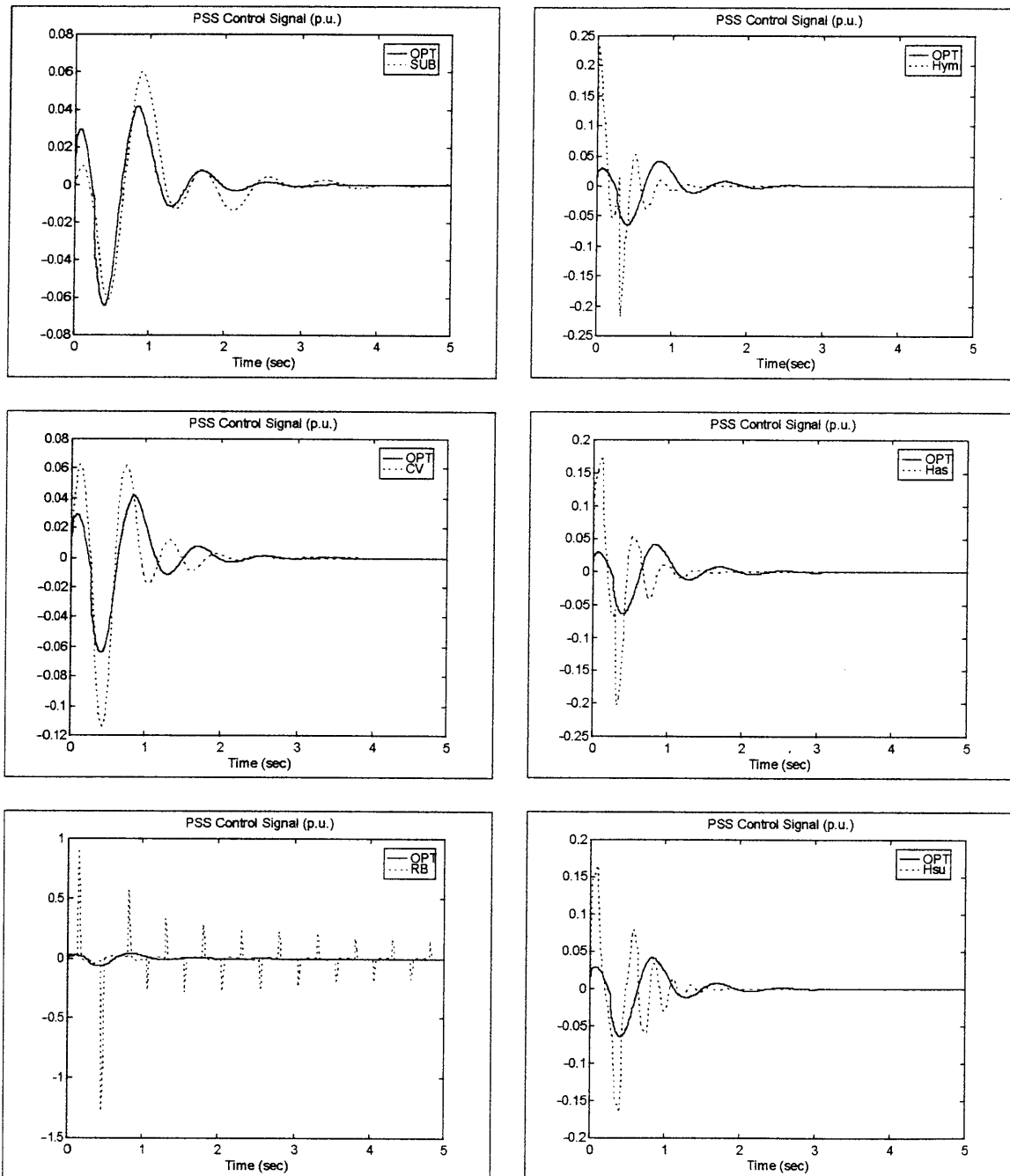


Fig. 3.20d PSS control signal variations following 0.1 p.u. change in input mechanical power with inertia constant reduced by 50% from nominal.

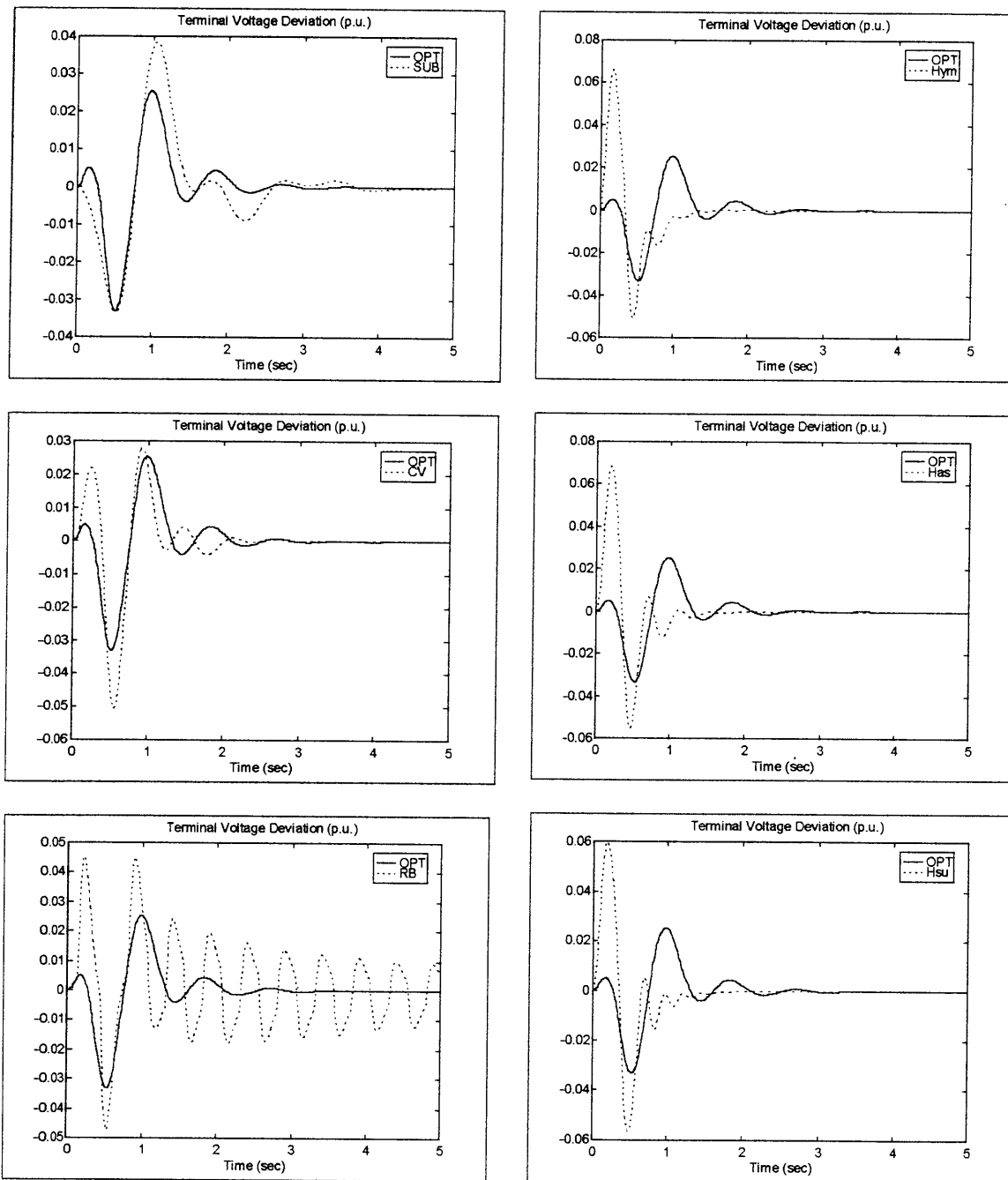


Fig. 3.20e Terminal voltage variations following 0.1 p.u. change in input mechanical power with inertia constant reduced by 50% from nominal.

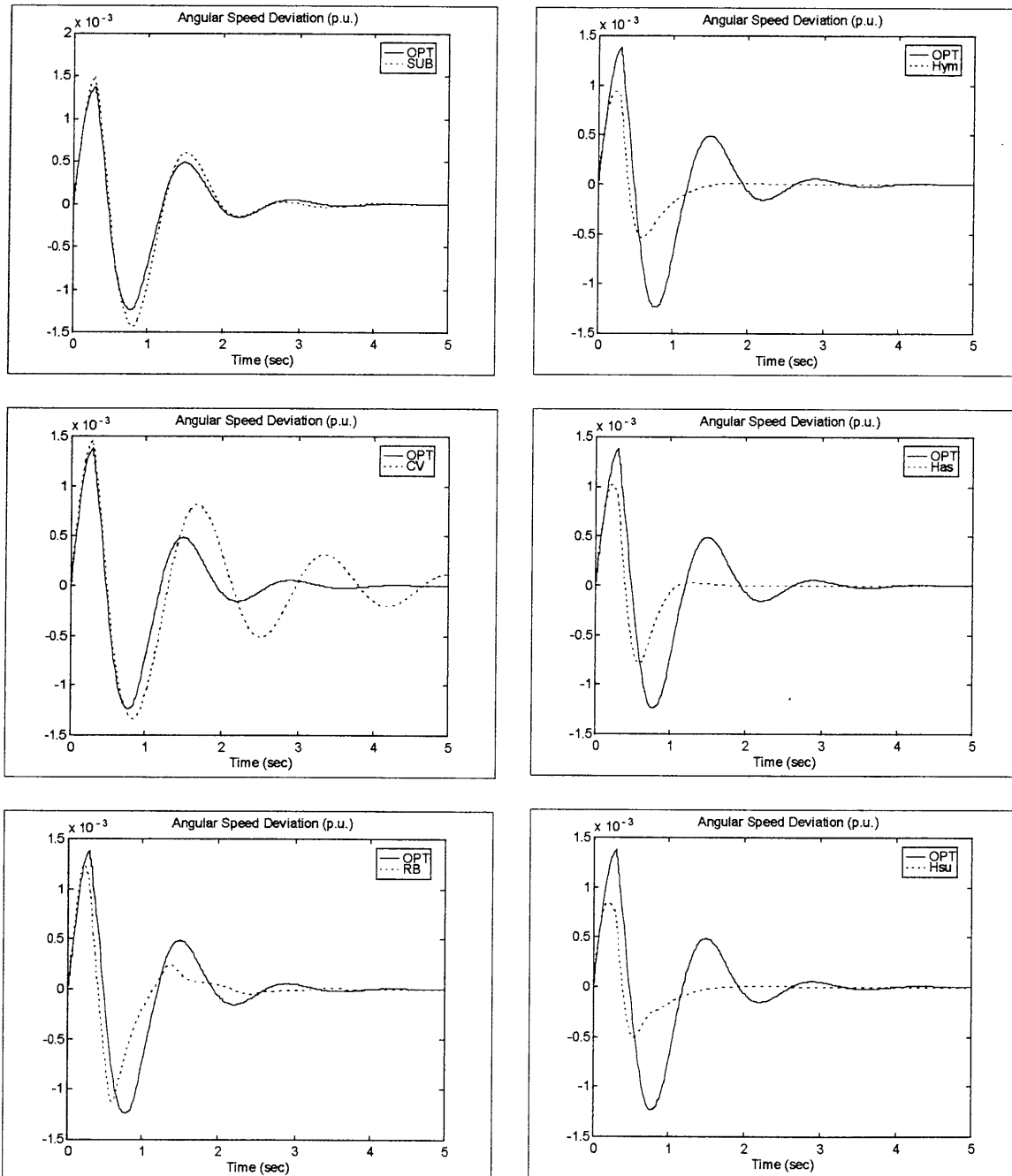


Fig. 3.21a Angular speed variations following 0.1 p.u. change in input mechanical power with inertia constant increased by 50% from nominal.

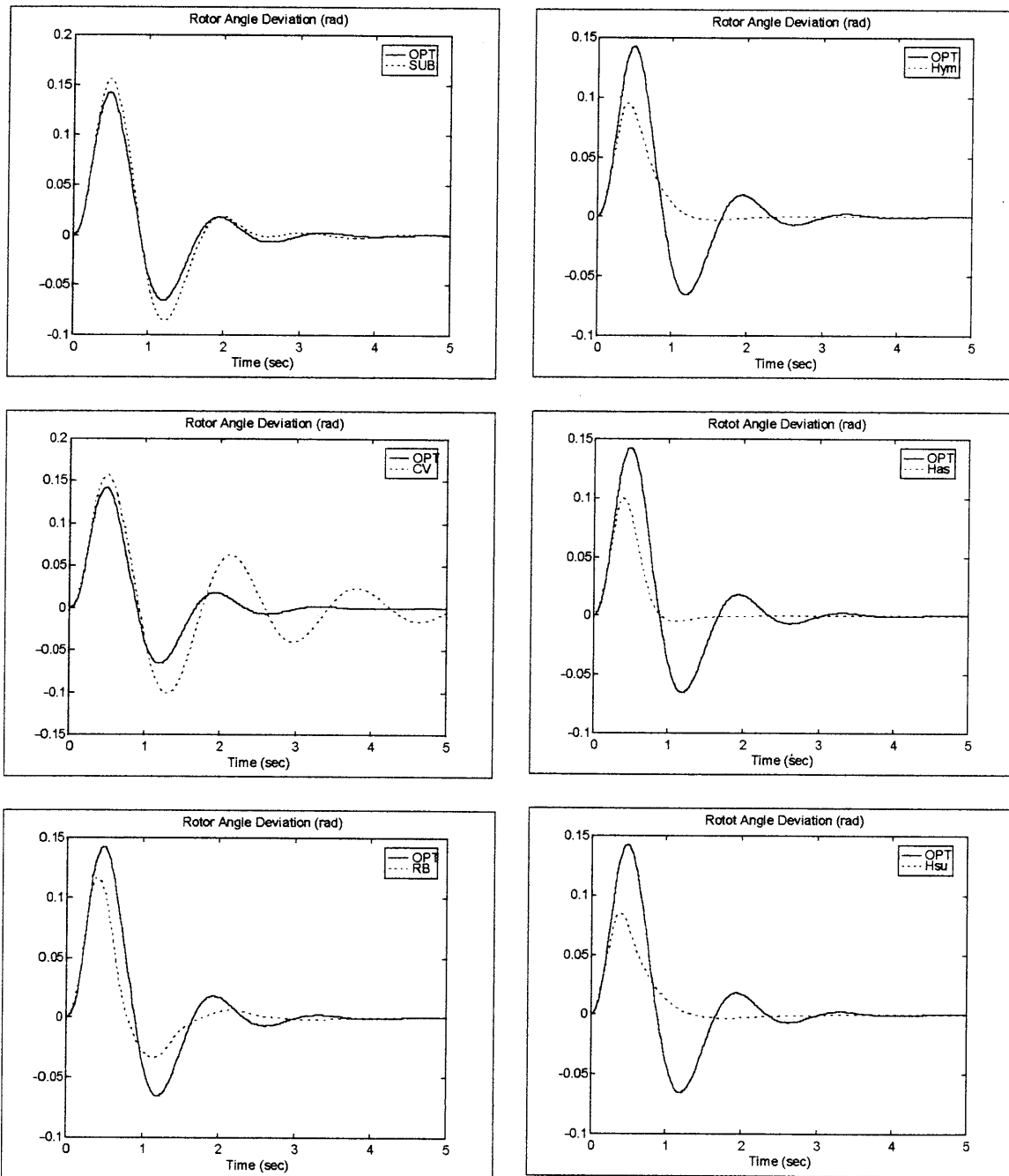


Fig. 3.21b Rotor angle variations following 0.1 p.u. change in input mechanical power with inertia constant increased by 50% from nominal.

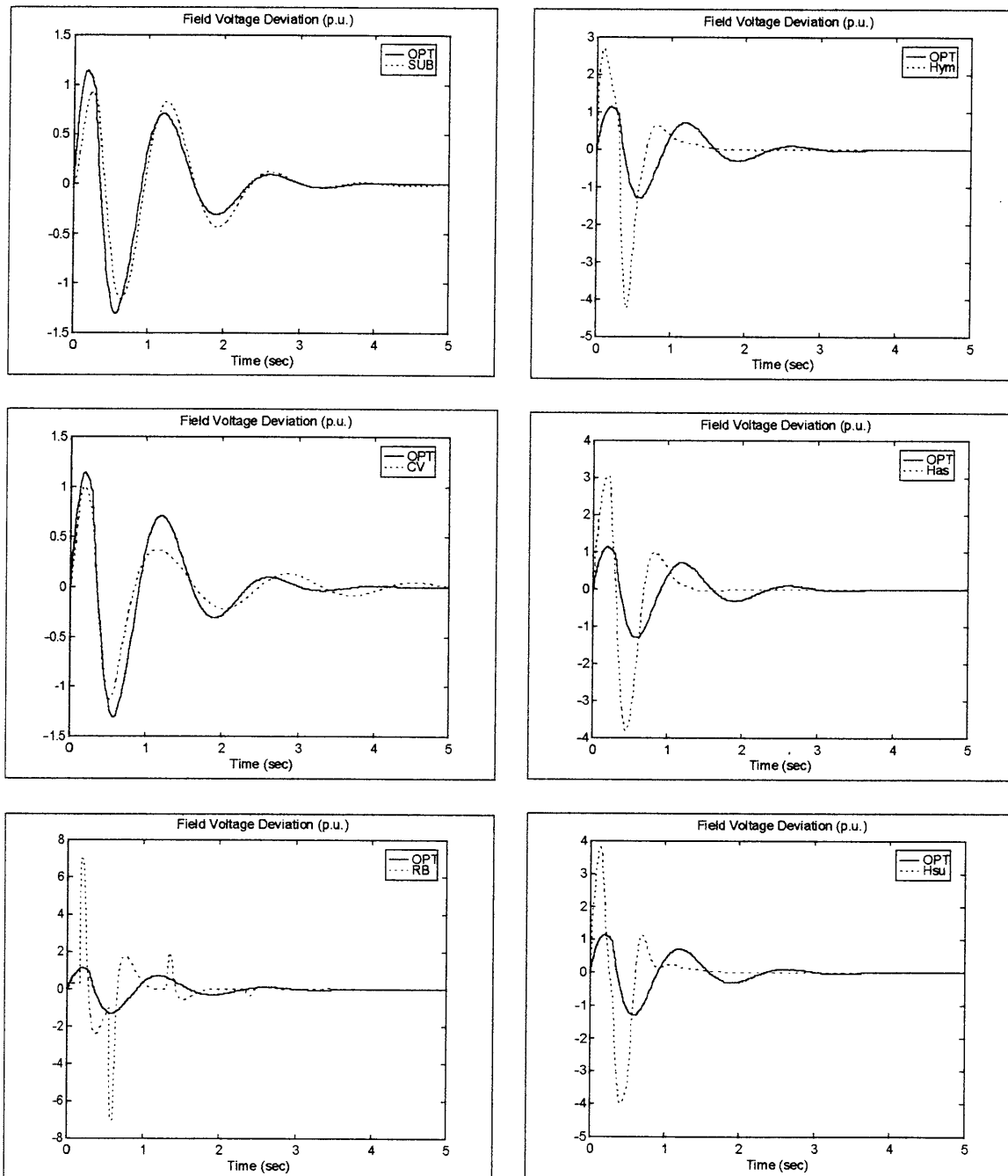


Fig. 3.21c Field voltage variations following 0.1 p.u. change in input mechanical power with inertia constant increased by 50% from nominal.

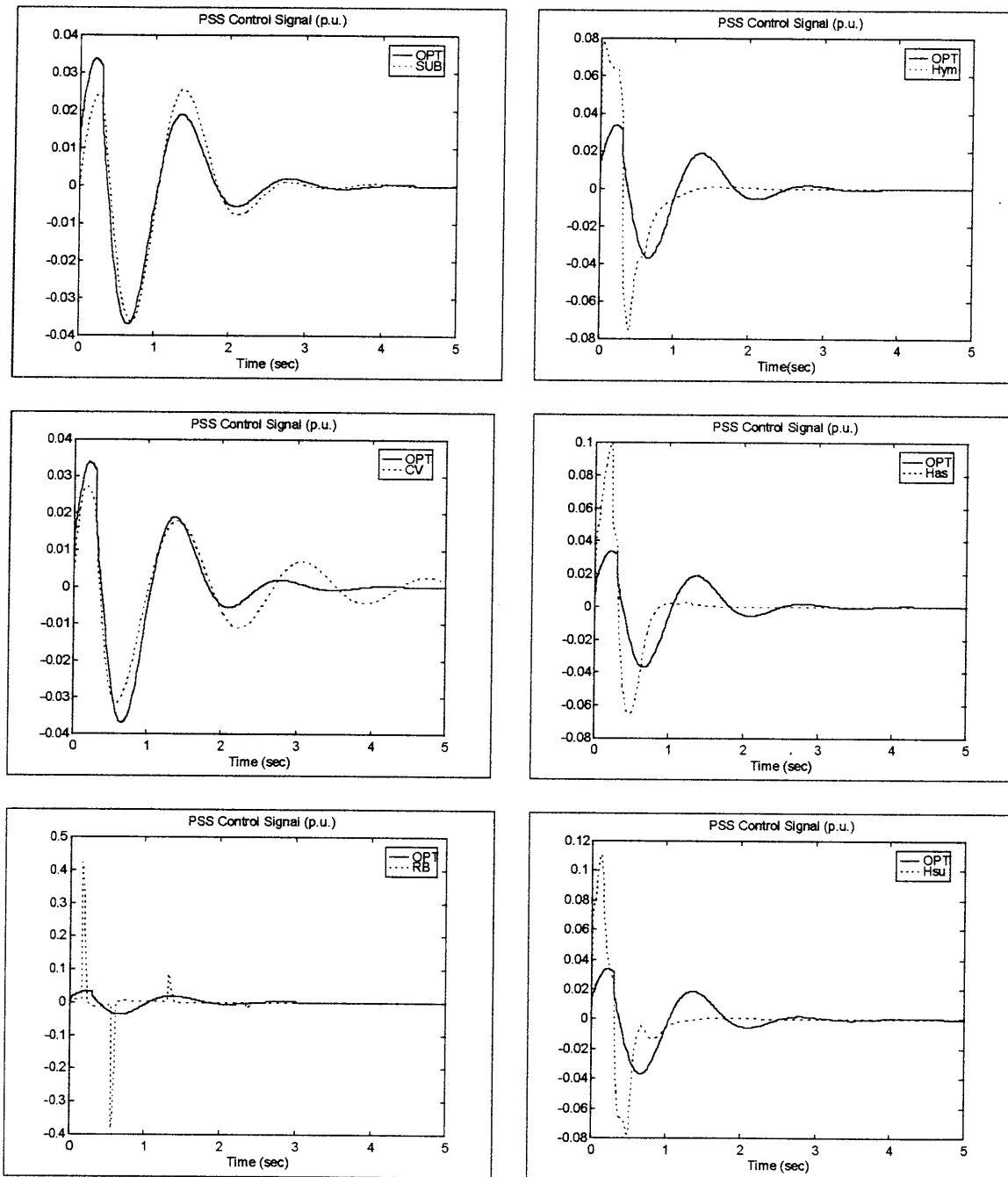


Fig. 3.21d PSS control signal variations following 0.1 p.u. change in input mechanical power with inertia constant increased by 50% from nominal.

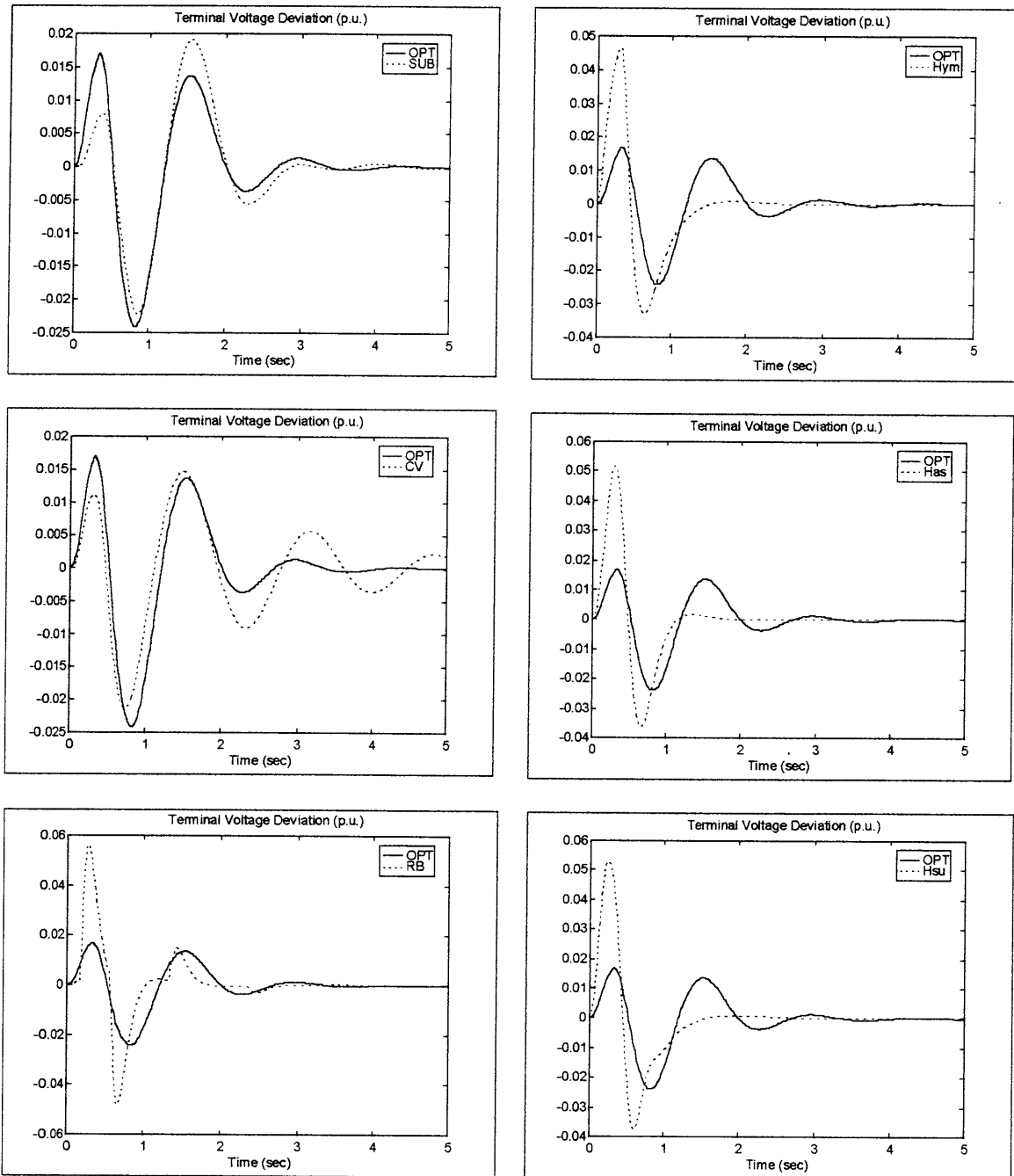


Fig. 3.21e Terminal voltage variations following 0.1 p.u. change in input mechanical power with inertia constant increased by 50% from nominal.

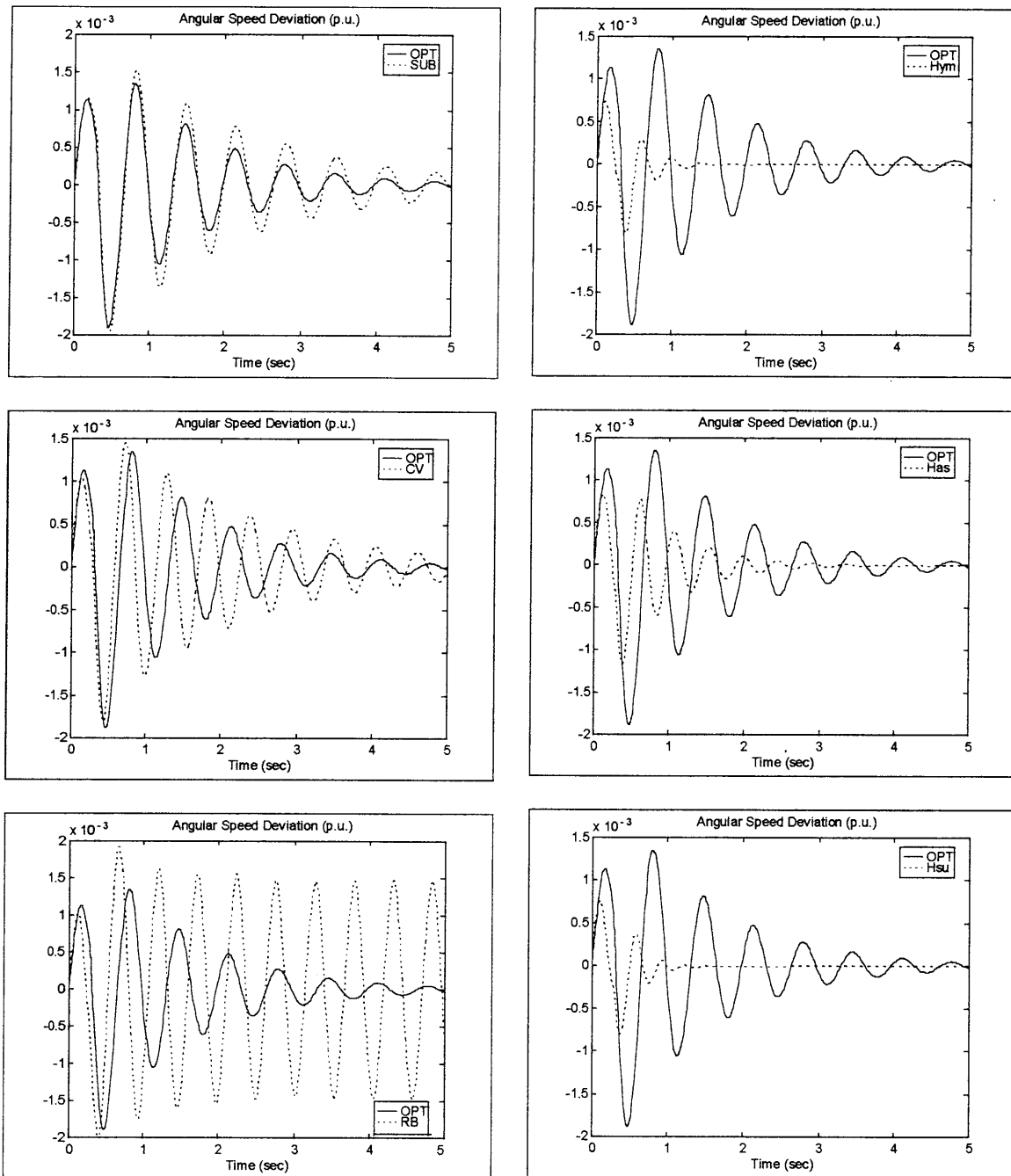


Fig. 3.22a Angular speed deviation following 0.1 step change in mechanical power with X_{TL} decreased by 90%.

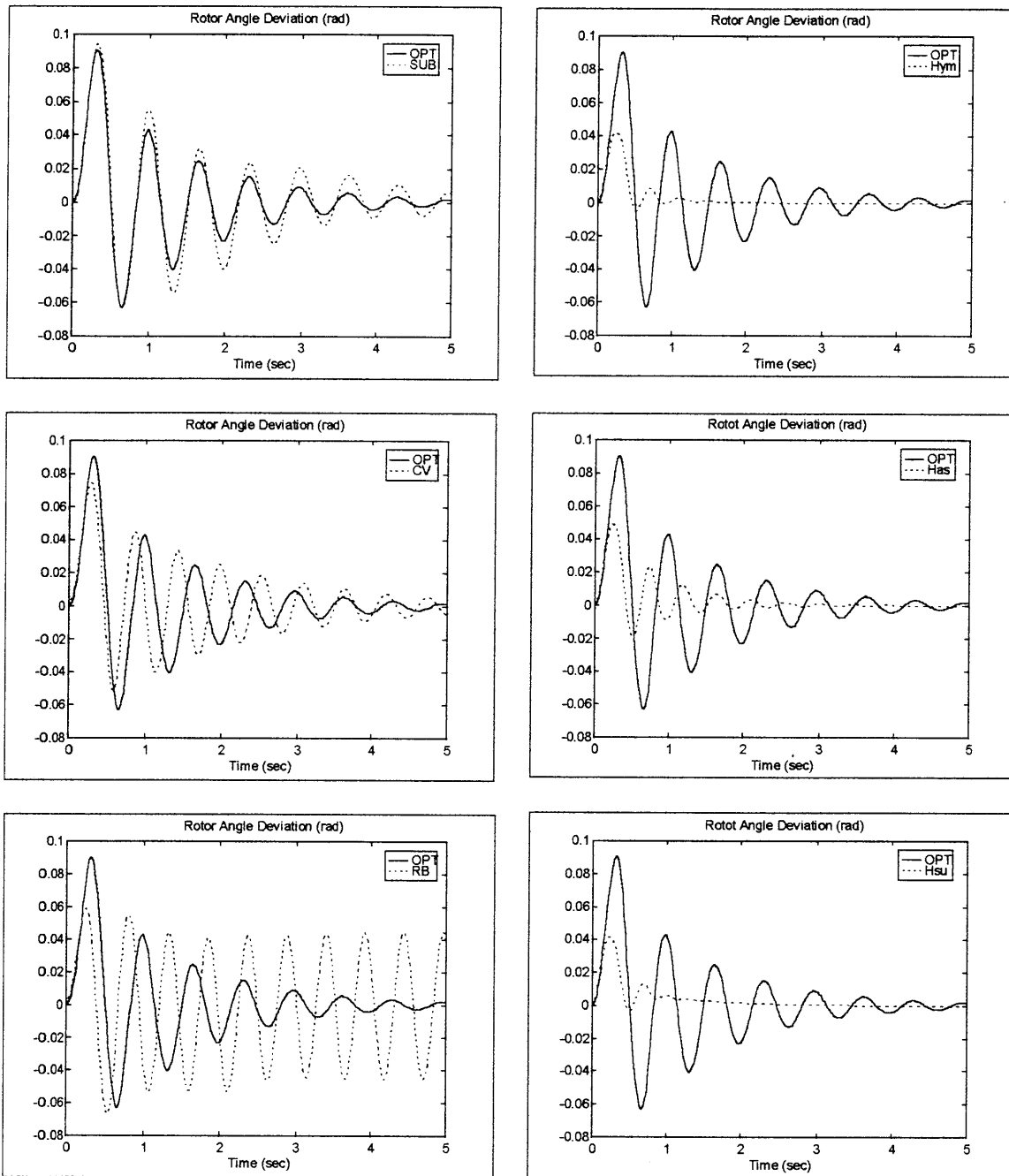


Fig. 3.22b Rotor angle deviation following 0.1 step change in mechanical power with X_{TL} decreased by 90%.

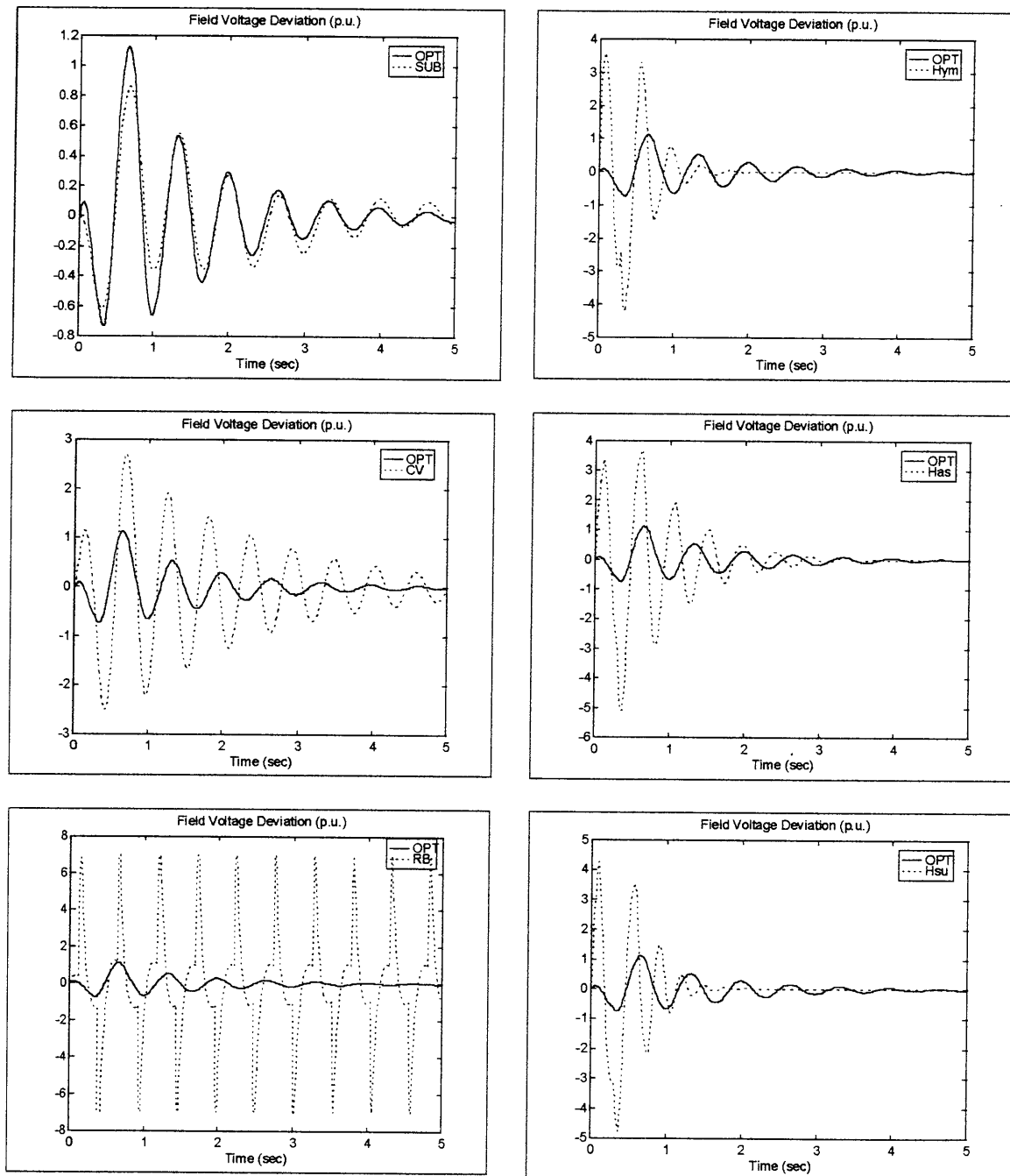


Fig. 3.22c Field voltage deviation following 0.1 step change in mechanical power with X_{TL} decreased by 90%.

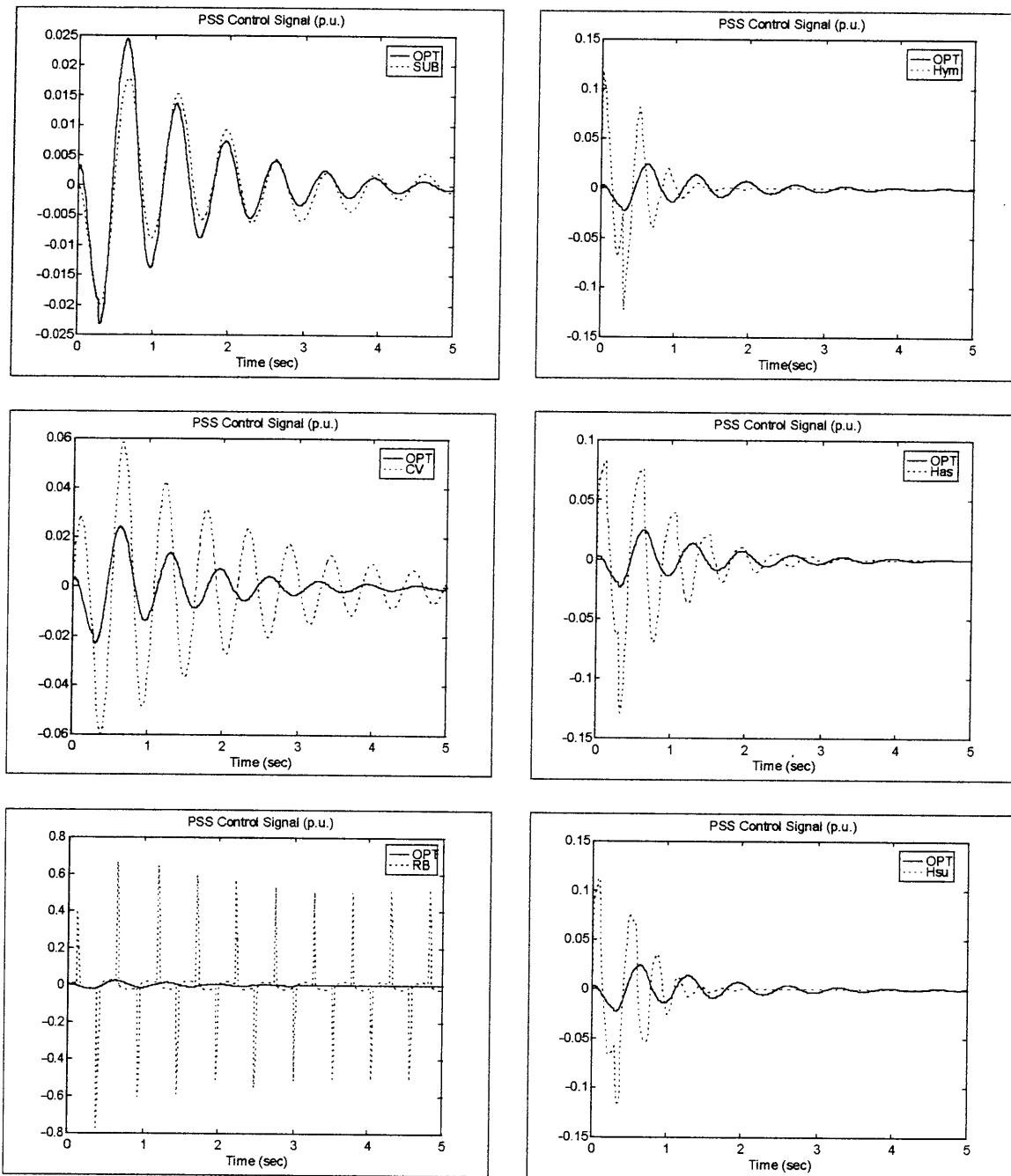


Fig. 3.22d PSS control signal variations following 0.1 step change in mechanical power with X_{TL} decreased by 90%.

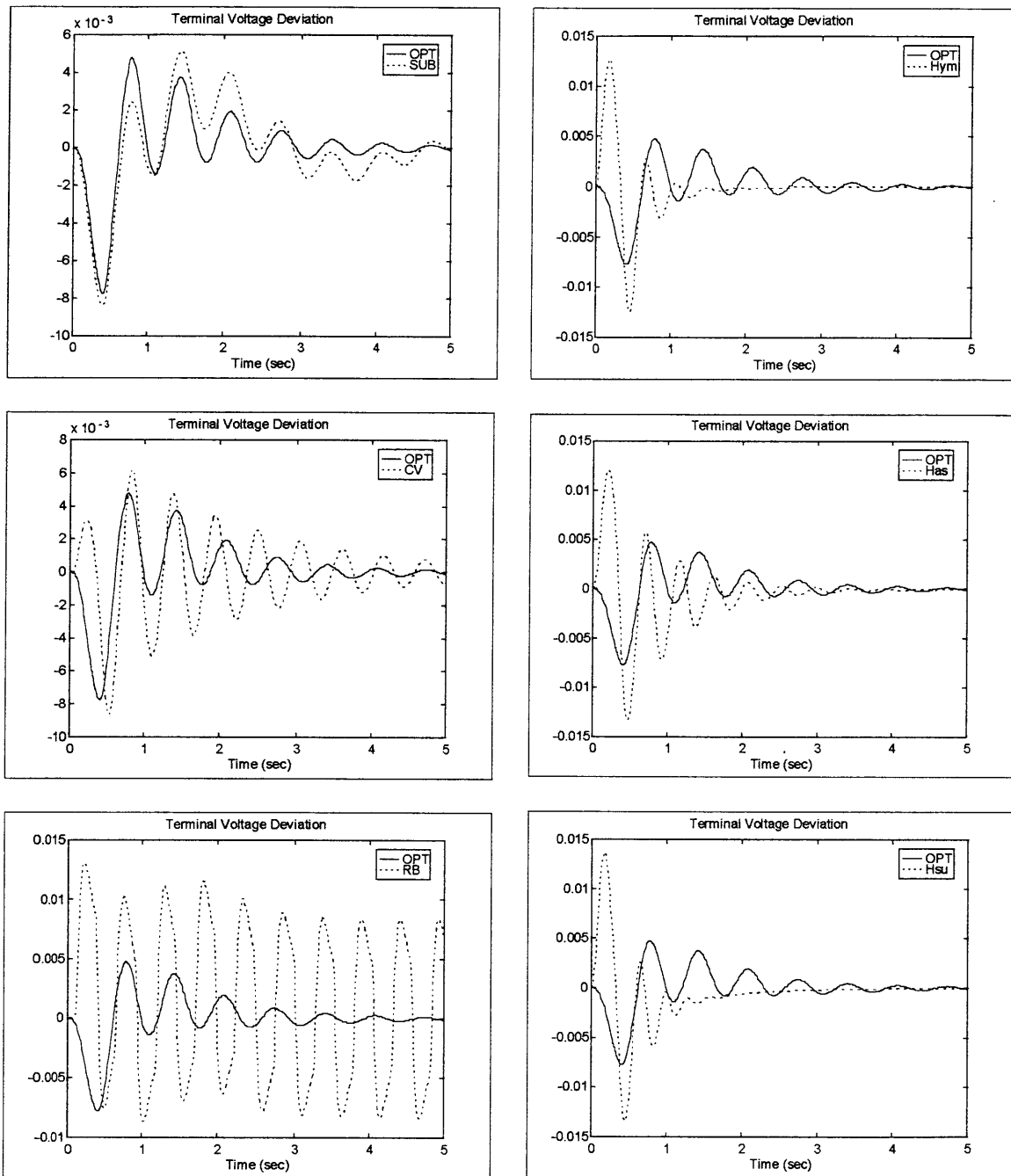


Fig. 3.22e Terminal voltage deviation following 0.1 step change in mechanical power with X_{TL} decreased by 90%.

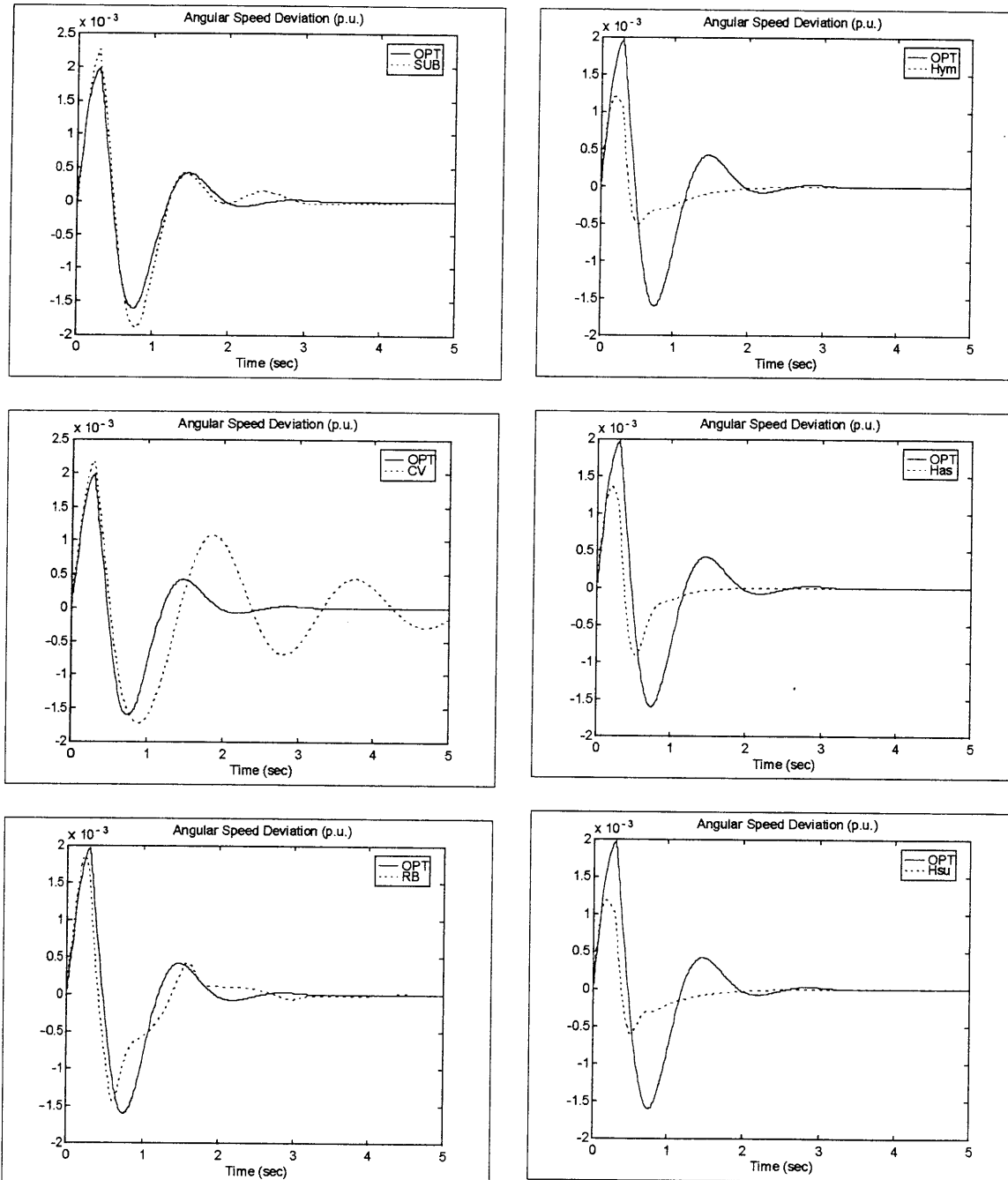


Fig. 3.23a Angular speed variations following 0.1 p.u. change in input mechanical power with X_{TL} increased by 50% from nominal.

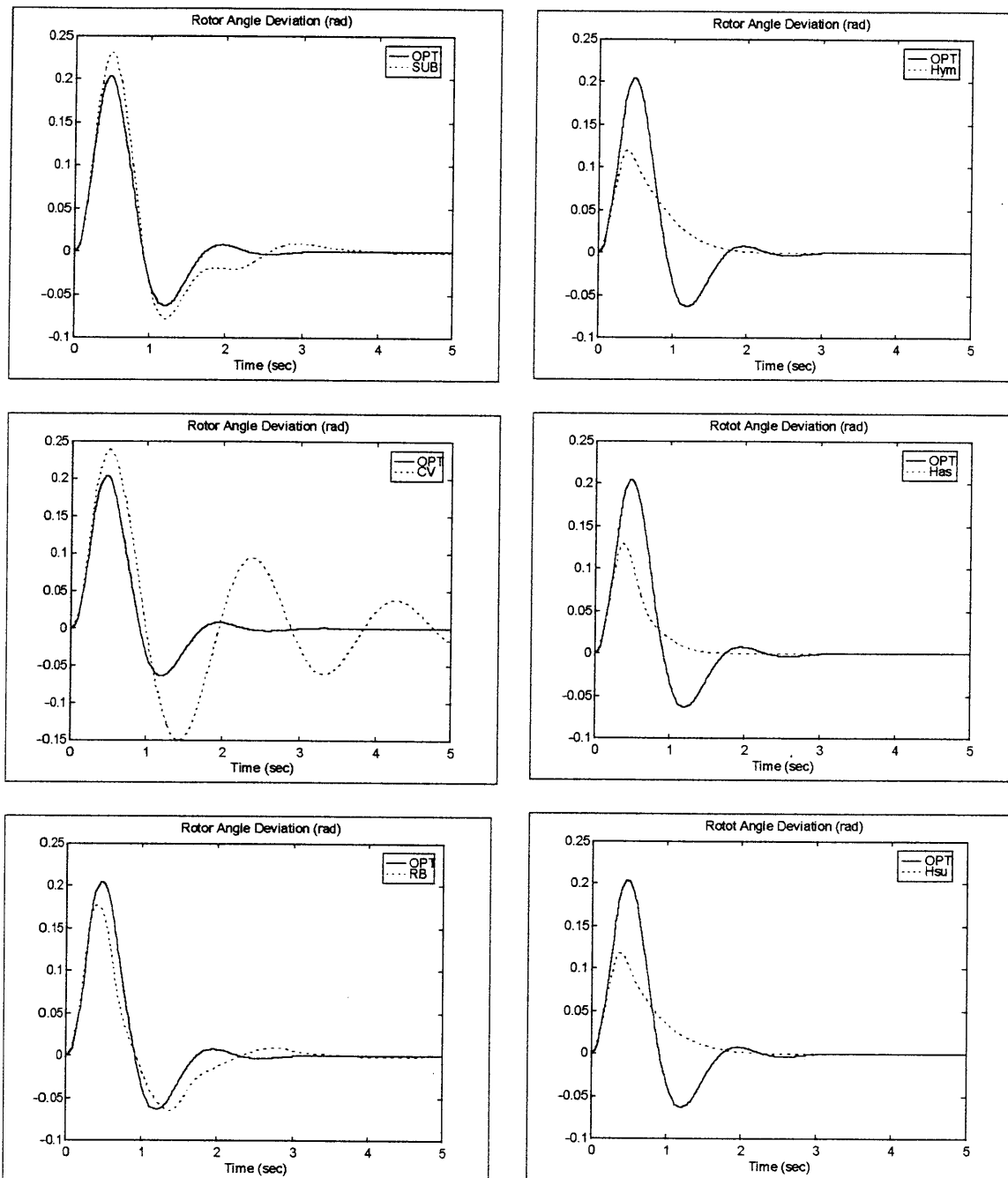


Fig. 3.23b Rotor angle variations following 0.1 p.u. change in input mechanical power with X_{TL} increased by 50% from nominal.

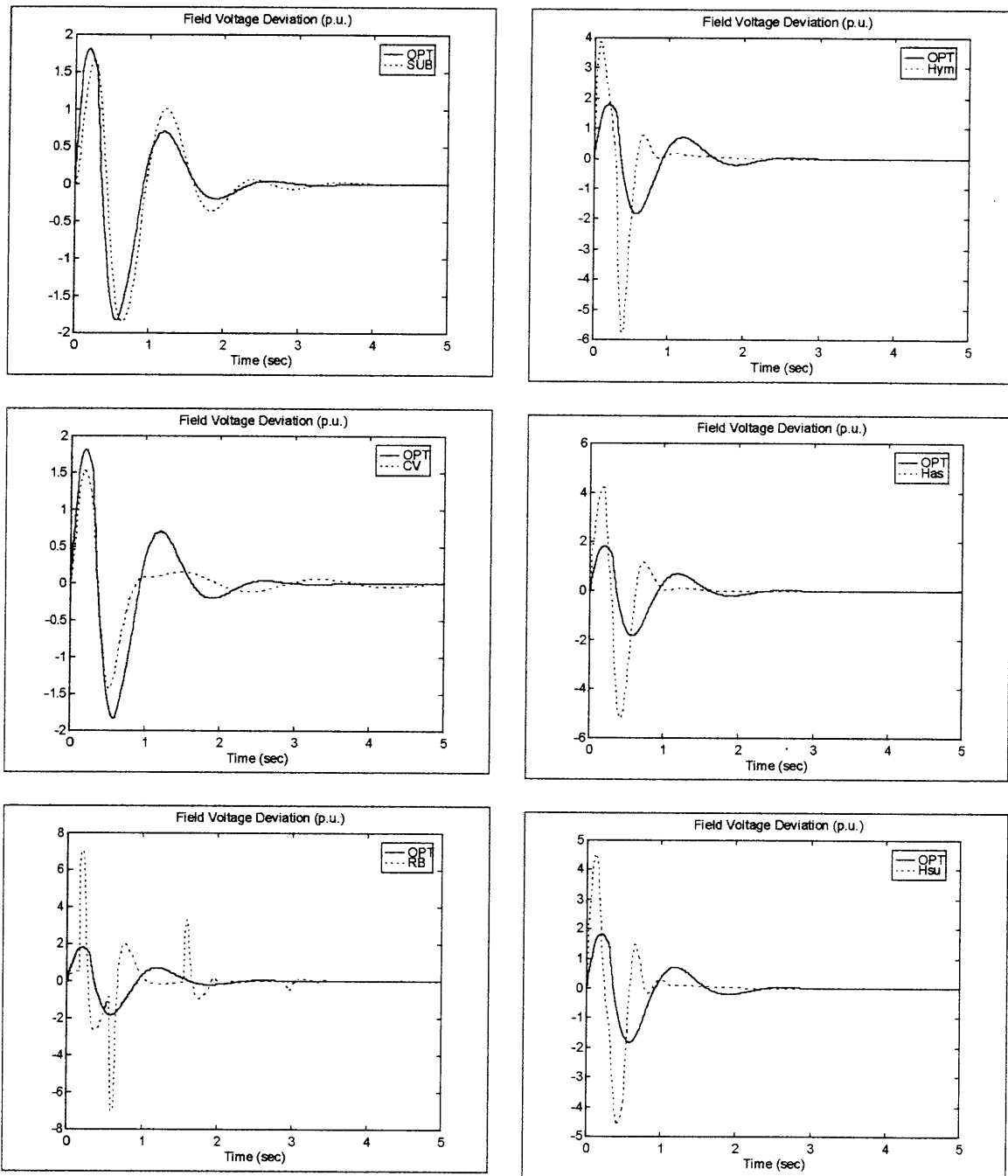


Fig. 3.23c Field voltage variations following 0.1 p.u. change in input mechanical power with X_{TL} increased by 50% from nominal.

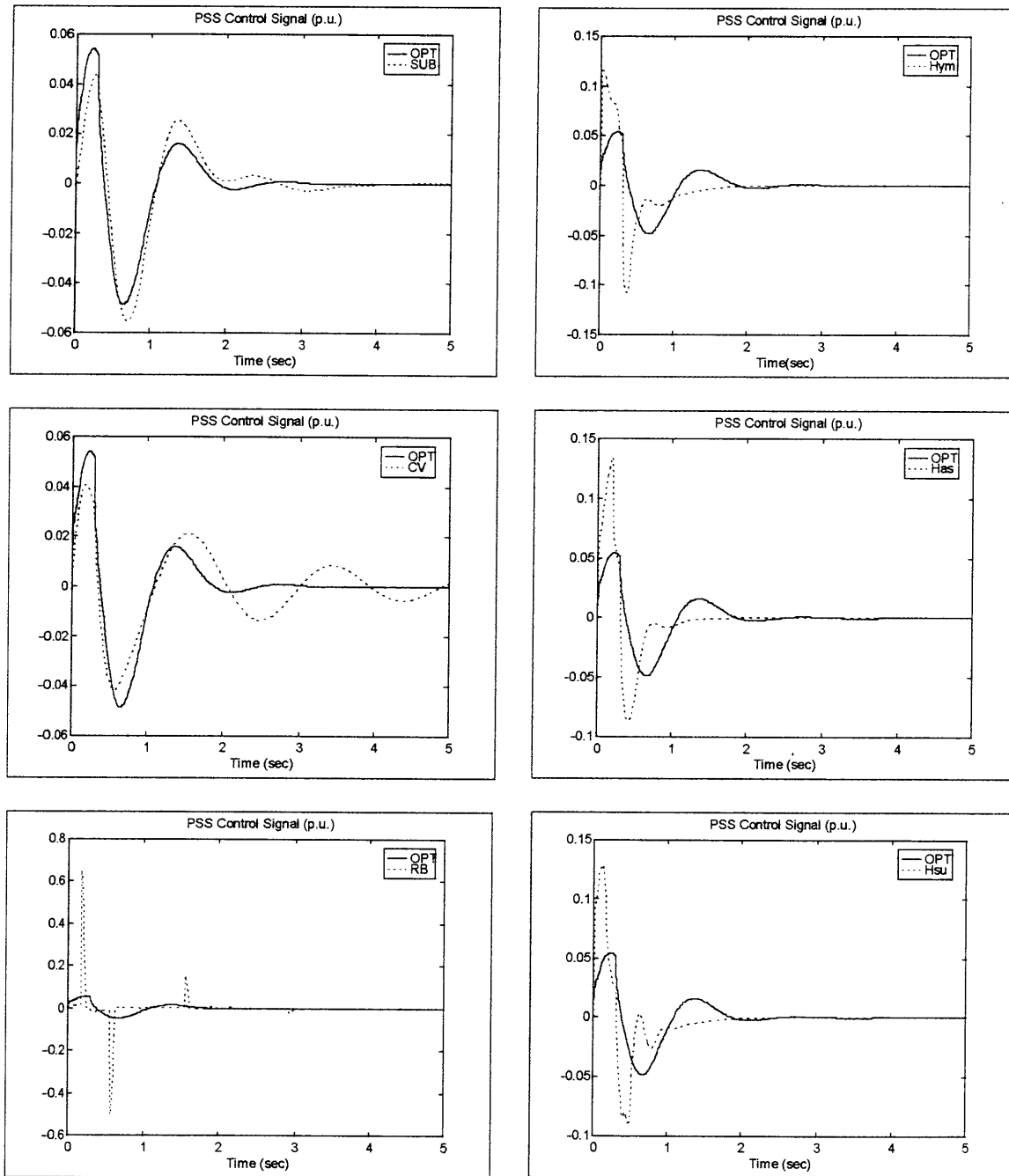


Fig. 3.23d PSS control signal variations following 0.1 p.u. change in input mechanical power with X_{TL} increased by 50% from nominal.

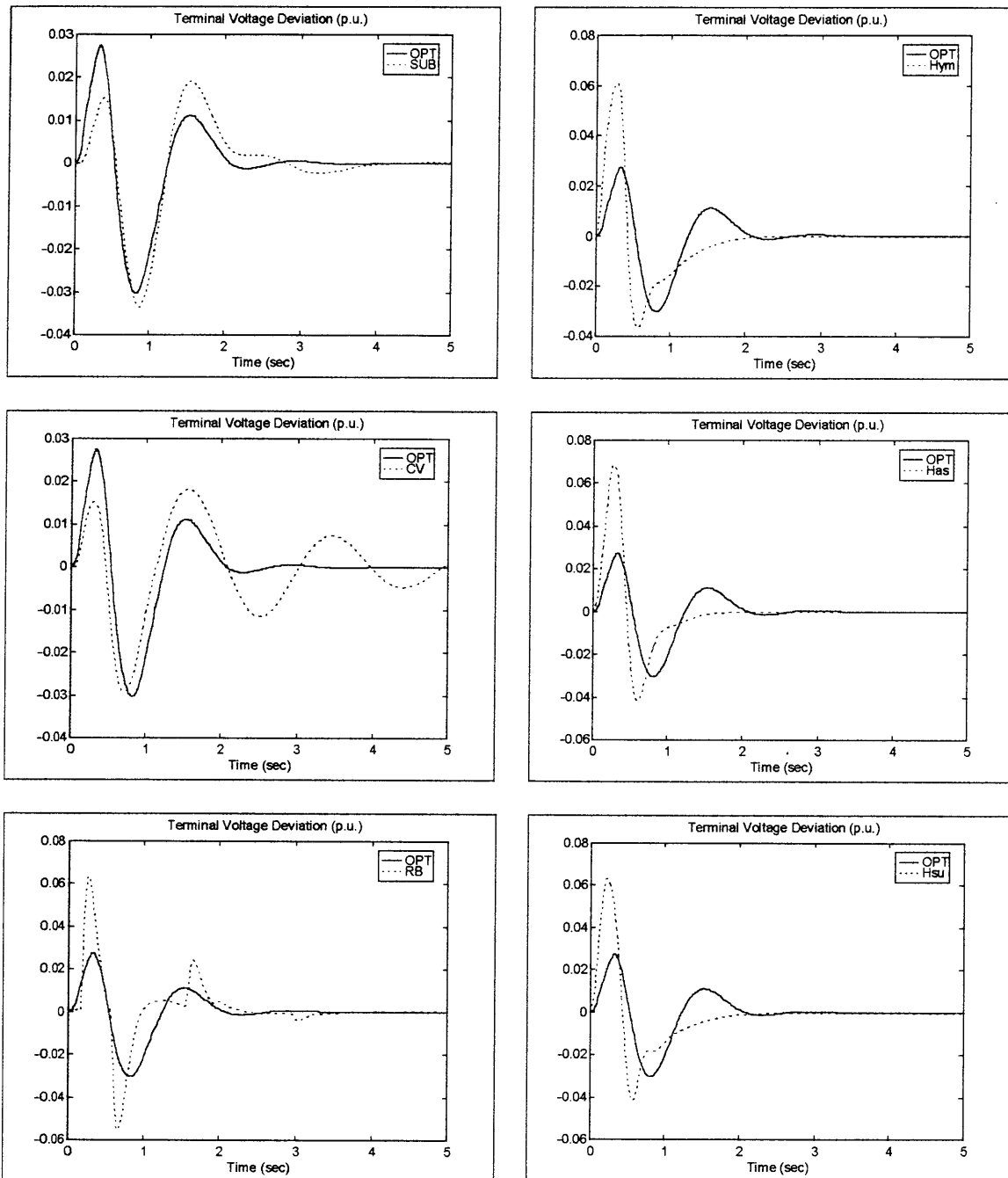


Fig. 3.23e Terminal voltage variations following 0.1 p.u. change in input mechanical power with X_{TL} increased by 50% from nominal.

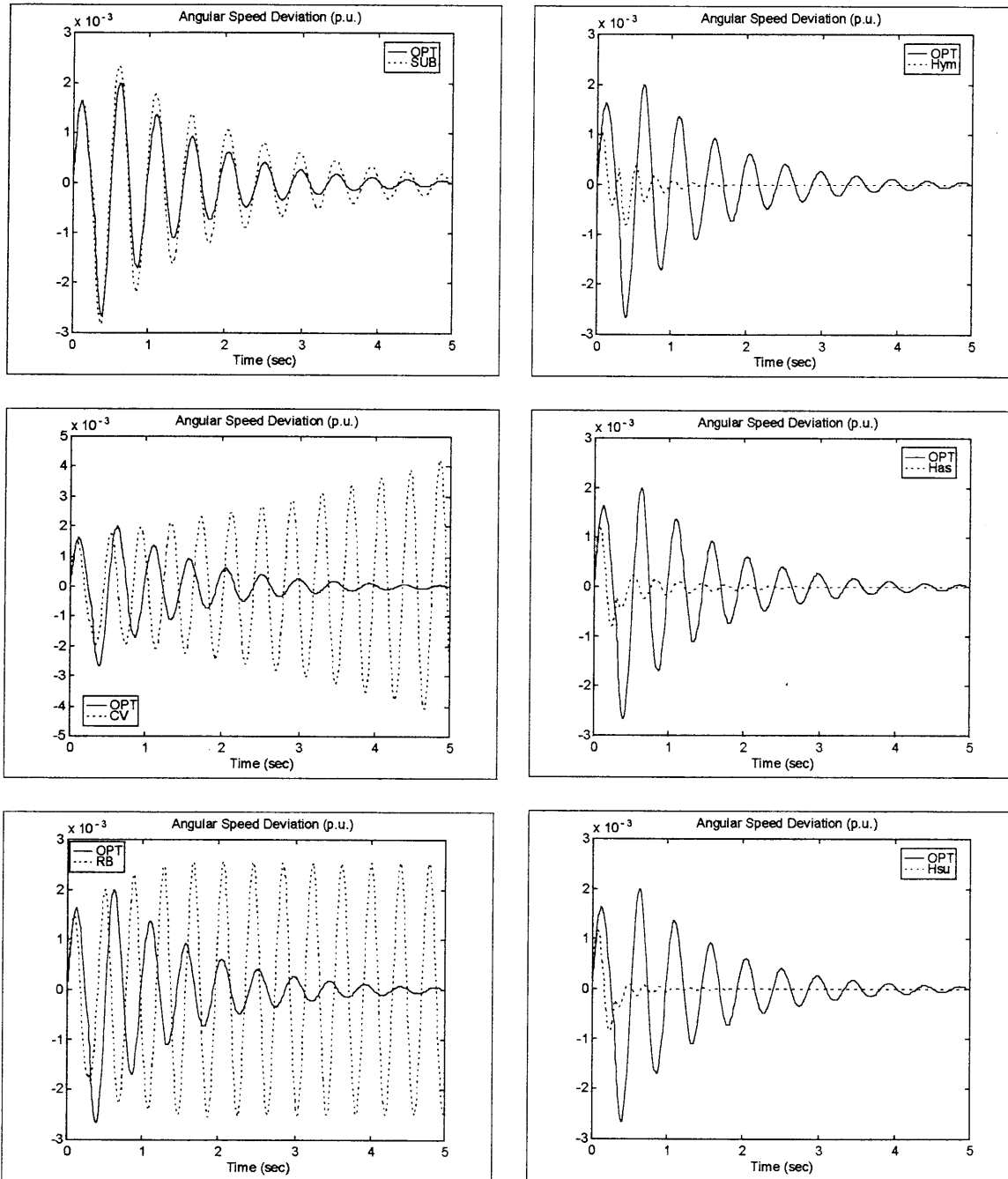


Fig. 3.24a Angular speed variations following 0.1 p.u. step change in input mechanical torque at leading p.f. operating point with system parameters changed to (inertia is reduced by 50%, and X_{TL} is reduced by 90%)

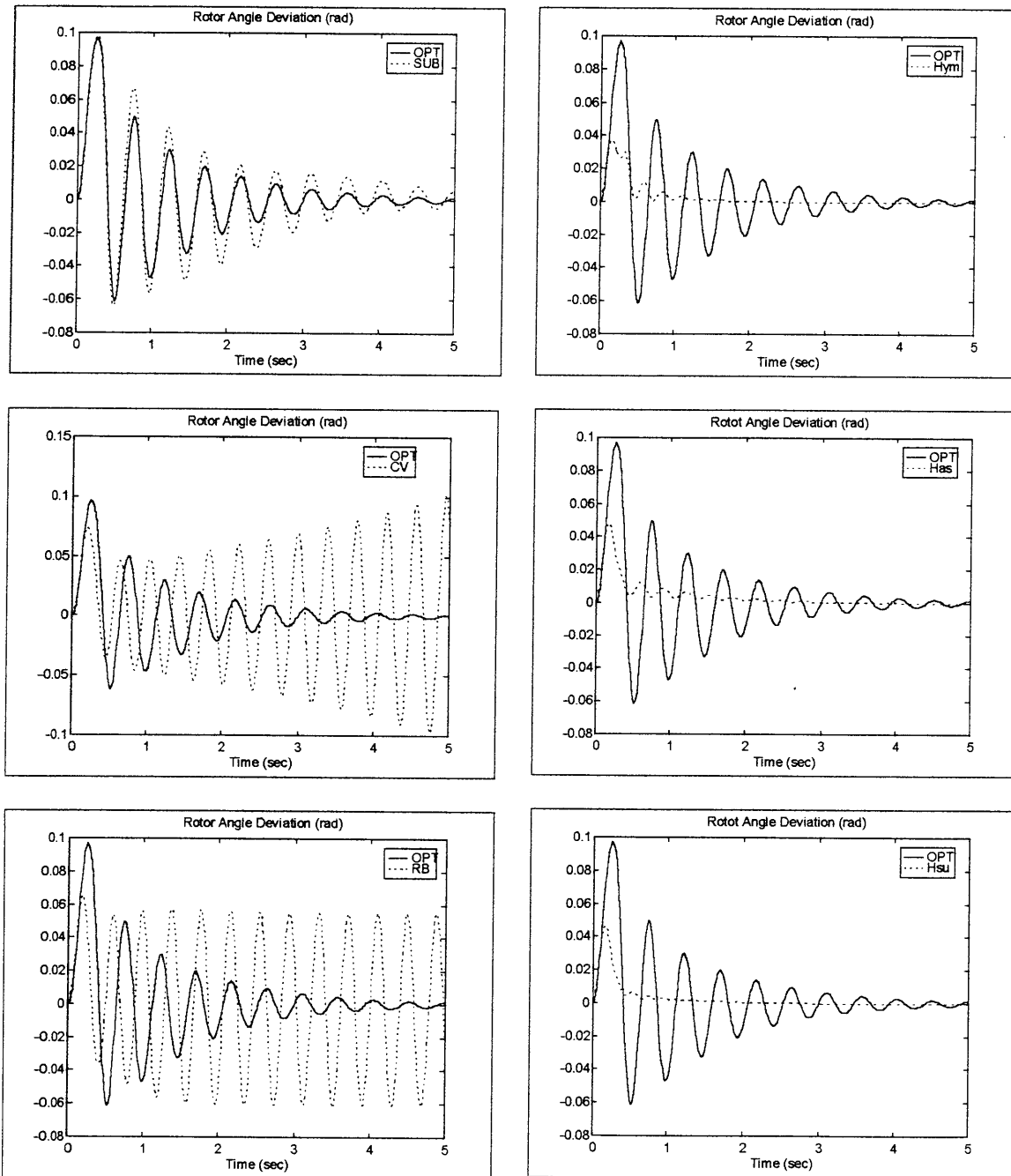


Fig. 3.24b Rotor angle variations following 0.1 p.u. step change in input mechanical torque at leading p.f. operating point with system parameters changed to (inertia is reduced by 50%, and X_{TL} is reduced by 90%)

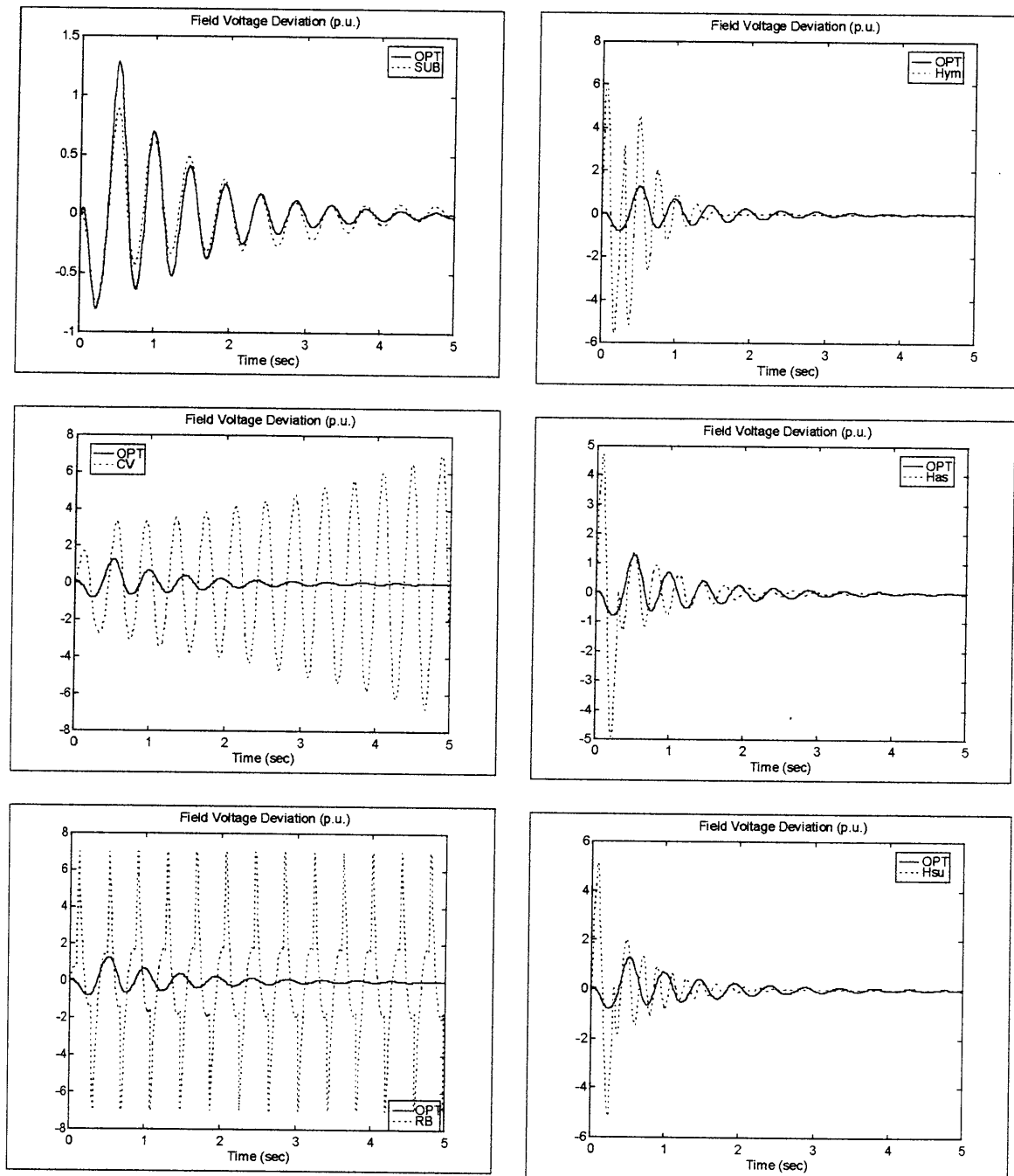


Fig. 3.24c Field voltage variations following 0.1 p.u. step change in input mechanical torque at leading p.f. operating point with system parameters changed to (inertia is reduced by 50%, and X_{TL} is reduced by 90%)

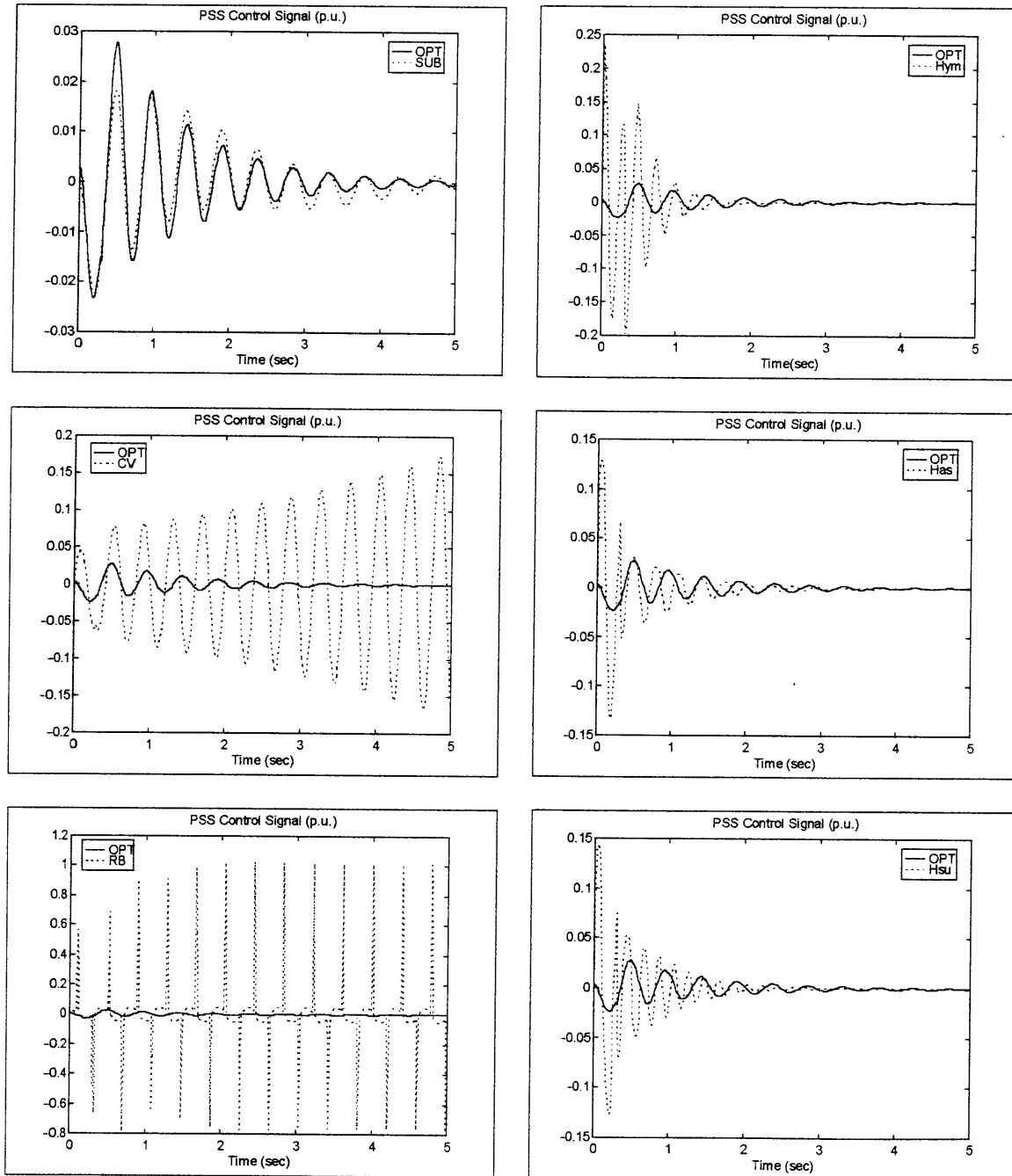


Fig. 3.24d PSS control signal variations following 0.1 p.u. step change in input mechanical torque at leading p.f. operating point with system parameters changed to (inertia is reduced by 50%, and X_{TL} is reduced by 90%)

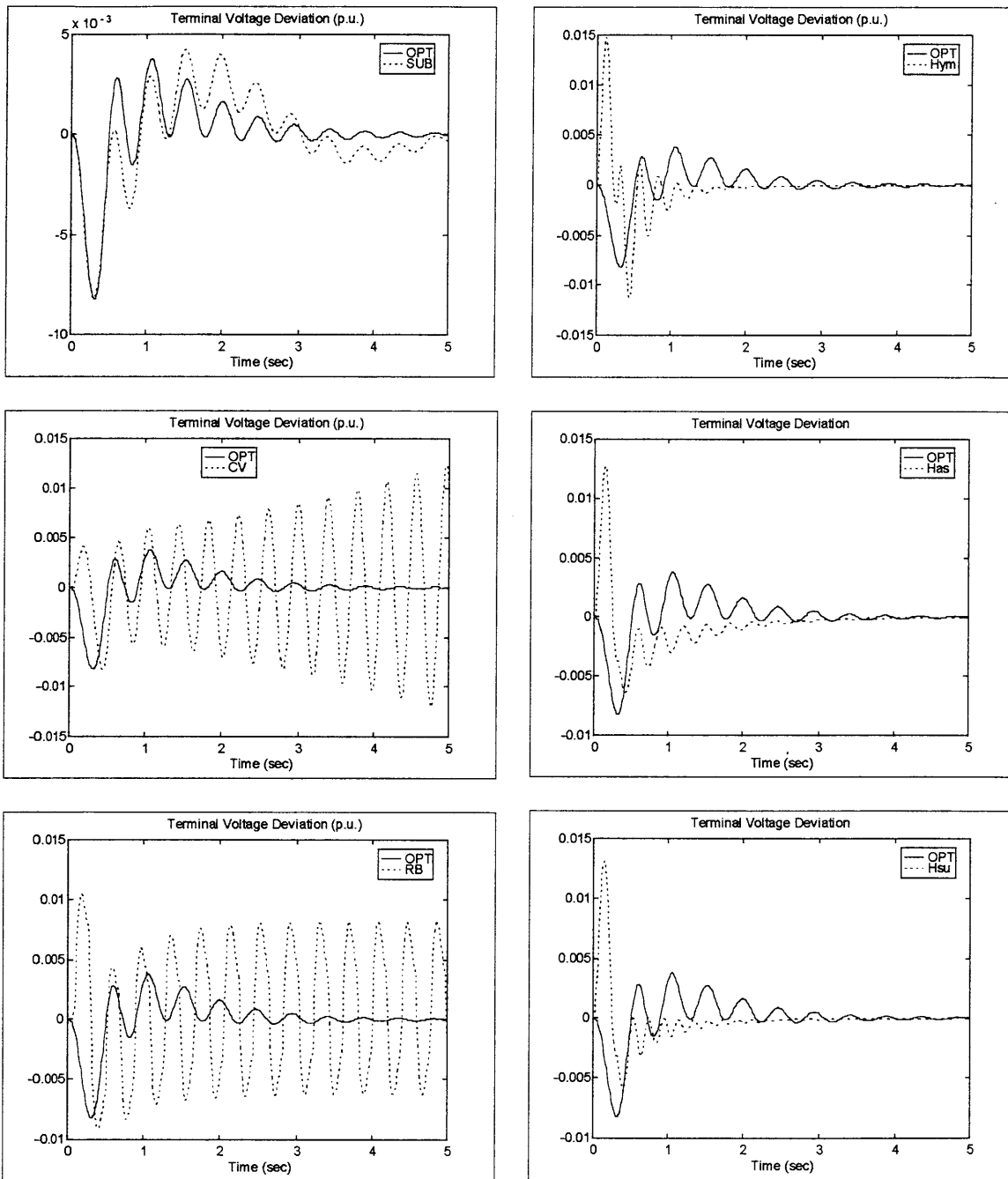


Fig. 3.24e Terminal voltage variations following 0.1 p.u. step change in input mechanical torque at leading p.f. operating point with system parameters changed to (inertia is reduced by 50%, and X_{TL} is reduced by 90%)

CHAPTER 4

LOAD FREQUENCY CONTROL

In this part of the thesis, another control problem in the area of power system operation and control will be considered. The Load Frequency control (LFC) problem or more recently termed as the Automatic Generation Control (AGC) will be the subject of investigation.

4.1 INTRODUCTION

A large scale power system is normally divided into a number of control areas or regions each representing a coherent group of generators. The various areas are generally interconnected through tie-lines. The tie-lines are utilised for contractual energy exchange between the areas and provide inter-area support in case of abnormal conditions. Fig. 4.1 shows a hypothetical two area interconnected by a tie-line. A sudden loss of a generating unit in one area or a block of loads is added to the system, leads to a power mismatch between generation and load demand. The power mismatch is initially compensated by an extraction of kinetic energy from the system inertia storage which causes a declining system frequency. As the frequency decreases, the power taken by the load decreases. Equilibrium for large systems is often obtained when the frequency sensitive reduction in loads balances the output power of the tripped unit or that delivered to the added block of load at the resulting (new) frequency. Output of generating units will be increased by governor action, if the mismatch is large enough to cause the frequency to deviate beyond the governor

deadband of the generating units throughout the interconnected system. For such mismatches, an equilibrium is obtained when the reduction in the power taken by loads plus the increased generation due to governor action compensates for the mismatch at the new frequency. This compensation is referred to as the power system natural response. The new frequency and tie-line power flows obtained at the new equilibrium state have to be corrected by supplementary control so that each area can be brought back to normal frequency and agreed tie-line power exchange with other areas.

In view of the above, the Load Frequency Control (LFC) of interconnected systems is defined as; the regulation of the power output of the electrical generators within a prescribed area, in response to change in system frequency, tie-line loading, or the relation of these to each other; so as to maintain the scheduled system frequency and/or the established interchange with other areas within predetermined limits [68].

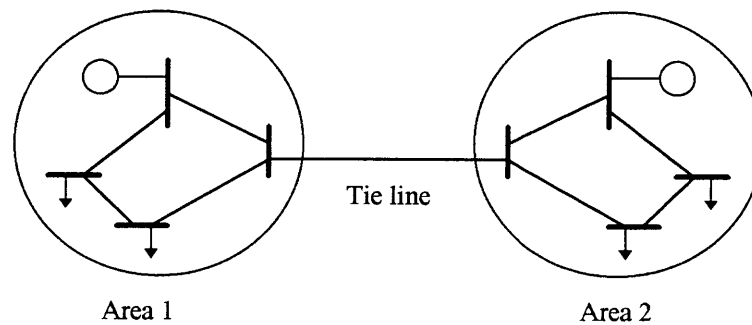


Fig. 4.1 Two-area system.

Many investigation in the subject area of LFC problem of interconnected power systems have been reported over the past six decades [68-76]. A number of control strategies have been employed in the design of load frequency controllers in order to achieve better dynamic performance. Among the various types of load frequency controllers, the most widely employed one is the conventional proportional-integral (PI) controller [68-70,75-76,94]. The PI controller is simple for practical

implementation but it generally results in a large frequency deviation when the system is subjected to load disturbance [85]. A number of state feedback controllers based on the linear optimal control theory have been proposed to achieve better dynamic performance [96, 77-78,95]. State feedback controllers require the transfer of information from all parts of the system to a central facility for processing, which for large-scale interconnected power systems, could prove to be difficult for practical implementation and uneconomical. An alternative and more practical forms of feedback controllers such as output feedback and decentralised controllers have been the subject of extensive investigations [79-80]. As these controllers only use a subset of the state vector for feedback purposes, they are simpler, more practical and easier to implement than the full state feedback controllers.

Both the conventional PI controller and the linear optimal controllers mentioned above, are fixed gain controllers which are designed based on a fixed-parameter model of the system derived by a linearization around a nominal operating point. However, power system parameters are function of the operating points and hence fixed gain controllers fails to provide best control performance over a wide range of operating conditions. So, to keep the system performance near its optimum, it is desirable to track the operating conditions and use the updated parameters to compute the control. In view of this, adaptive controllers [81-84] with self-adjusting gain settings have been proposed for LFC of interconnected power systems. Despite the promising results achieved by these adaptive controllers which offer better dynamic performance than the fixed-gain LFC, the control algorithms appear to be too complicated and require on-line system model identification in real time [84].

Recently, artificial neural networks and fuzzy systems have been successfully applied to LFC problem with rather promising results [85-89]. The salient feature of these techniques that distinguish them from the traditional control approaches is that they provide a model-free description of the control systems and hence no need for system model identification.

The first fuzzy logic based LFC is proposed by Hsu et. al. on 1991, [85]. In this controller, both the frequency deviation and its derivative have been used as the input signals. The proposed controller offered better dynamic performance than the conventional PI controller. However, the proposed controller has been tested when installed on only one of the areas of a two-area interconnected system while a PI controller installed on the other area. It has not been tested when both areas are controlled by the fuzzy controller.

The second fuzzy logic based LFC has been proposed by Indulkar et. al. [86] and published in march 1995 in which the calculated values of the area control error (ACE) and its change have been used as the input signals. The proposed controller has been installed on both areas of an interconnected system and its performance has been compared with a classical integral controller. The results show that the proposed fuzzy controller has a smaller settling time for the steady state frequency deviations of both areas. However, it has not been possible to reduce the steady state error of the tie-line power flow deviations using the proposed fuzzy controller.

The third fuzzy logic based LFC has been proposed by Djukanovic et. al. in June, 1995 [87] in which the calculated values of the ACE and its integral have been used as input signals to the fuzzy controller. The proposed fuzzy controller has been tested on a two-area system and its dynamic performance has been compared with a full state feedback linear optimal regulator. The result shows a close agreement of the fuzzy controller performance with the optimal controller. However, the proposed controller has been only tested at nominal operating conditions at which it is destined.

As has been demonstrated, the history of application of fuzzy logic to the LFC problem is very short, and according to my knowledge, these are the only three papers published on this subject, [85-87]. This motivates further work on this area, and a number of new fuzzy logic based load frequency controllers are proposed in this thesis.

4.2 MULTI-AREA CONTROL

When any area in a multi-area interconnection system is exposed to any load-generation imbalance, a frequency deviation occurs. When the frequency changes from the scheduled frequency F_s , all areas of the interconnection respond to stabilize the frequency through load and turbine governor changes. Load changes are directly proportional to frequency change while turbine generator governor change is inversely proportional to frequency change. The total of these two actions representing the system natural response (primary control) referred to as the System Response to frequency deviation Characteristic (SRC) or some times called Area Frequency Response Characteristic (AFRC). The SRC action will stabilize the frequency at a deviated value from the scheduled value and will not return the frequency to the scheduled value which will also lead to tie-line flows deviation from the scheduled . These deviations will remain until supplementary control action takes place to return the frequency and tie-line flows to their scheduled values by the control area with generation surplus or deficiency. Thus, when systems are interconnected, tie-line flows as well as frequency must be controlled by a load frequency controller which must fulfils some control specifications for successful multi-area system operation.

4.2.1 Specifications of Control

Since the basic function of the load frequency controller is to control the real power output of electrical generators under disturbance conditions in order to maintain system frequency and tie-line exchange within predetermined limits, the design of any controller for LFC problem should consider the following specifications [68,76]:

- (a) The steady-state frequency error following a step load change should vanish. The magnitude of the transient frequency deviation should be minimised. (This magnitude depends, of course, upon the magnitude of the load change).

- (b) The static change in the tie-line power following a step load change in either area must be zero, provided each area can accommodate its own load change. This requirement guarantees that each area, in steady-state, absorbs its own load changes.
- (c) Any area in need of power during emergency should be obtained from other areas.

4.2.2 Modes of Tie-Line Operation

To achieve the above control specifications, a variety of control philosophies for multi-area system have been examined [71,90-92] some of which are :

- 1- Flat (constant) frequency control.
- 2- Flat (constant) tie-line control.
- 3- Tie-line frequency bias control.

- ***Flat frequency control:***

In this type of control mode, area control respond only to frequency changes from scheduled value F_s shown in Fig. 4.2-a and does not respond to tie-line flow changes. The operation of such interconnection under this control mode would face a severe problem if the areas attempting to control frequency had measurement errors. For example, an area would reduce its generation if it measures the frequency at a value higher than others. While others will raise their generation, attempting to force the frequency (as they all measure it) to the scheduled value. This type of control is suitable for isolated systems because frequency is the only quantity that is affected when load changes.

- ***Flat tie-line control:***

In this control scheme, each area controls the sum of its tie-line power flows to match with its scheduled value i.e. responds to tie-line flow changes only and does not respond to frequency changes as shown in Fig. 4.2-b. In other words, each area generates enough power to serve its internal load and losses, plus the total scheduled power interchange " T_s " with other areas. However, if every area operates with this objective, for reasons described below, the interconnection might not be able to operate satisfactorily. Consider a system comprising two areas, 1 and 2, and suppose area 1 measures its interchange several MW below the actual, and area 2 measures its own correctly, then both areas will continuously raise their generation and no equilibrium can ever be reached. Alternately, assume area 1 uses a wrong interchange schedule whose magnitude is higher than that used by area 2 for its purchase. The same instability occurs, even in the absence of the mentioned errors, this method of control is unable to provide satisfactory operation because it results in several depressed frequency when either area is not able to produce its share of generation. As area 2 will attempt to maintain its interchange at the schedule, the system may collapse if a large unit is tripped in area 1.

Therefore, neither of the above two modes of operation satisfies all of the three conditions (specifications) previously listed as desirable for successful interconnected operation. As a result, an alternative control philosophy named tie-line frequency bias control was developed in the mid thirties.

- ***Tie-Line Frequency Bias Control:***

When a system is operating with tie-line bias control, it will respond to both frequency errors and tie-line-flow errors and will assist in achieving the objective of having each control area matches its generation with its load and scheduled tie-line exchange. In addition, when some areas are unable, for whatever reasons, to match

generation with their demands, other areas will provide a sustained assistance according to a bias characteristic which in turn, prevents large deviations of the interconnection frequency, (see Fig. 4.2-c).

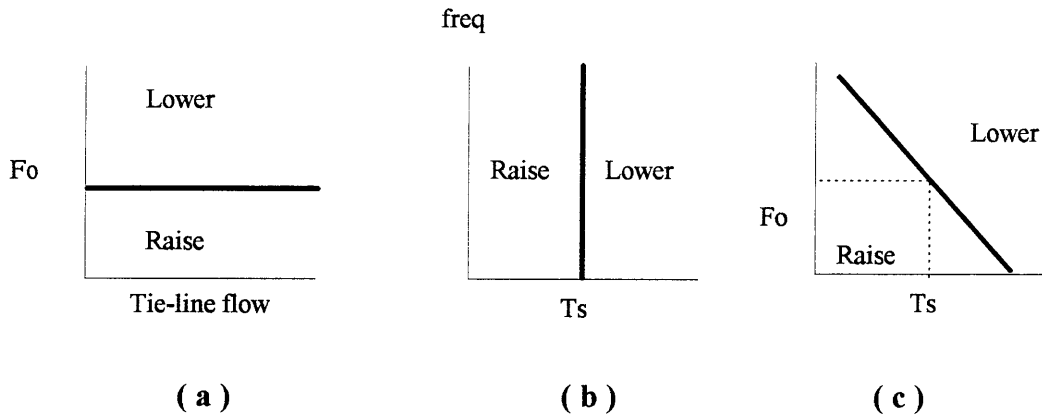


Fig. 4.2 Plots of frequency versus tie-line flows show controller balance points. Control types are: (a) constant frequency, (b) constant tie-line, (c) tie-line frequency bias; [90]

To understand the basis of the above control philosophy, assume the system pre-disturbance scheduled frequency is F_s , then as it mentioned earlier, when the system is subjected to load disturbance, the system natural response will act as a primary control to stabilize the system at a new frequency F_a . This response is conventionally expressed as $10\beta(F_a - F_s)$. The coefficient, β , referred to as (AFRC) or (SRC) and traditionally given in MW/0.1 Hz. It represents the combination of both load and governor sensitivity [71] to frequency. It can be clearly noticed that, the primary response due to the system natural response diminishes, as the system frequency returned to schedule i.e. $F_a = F_s$.

When the system operates as one control area, it benefits from primary response of the complete system until central (supplementary or secondary) control actions can fully compensate for the power upset. On the other hand, assume the same

system operates as two control areas and the location of the power upset is in area 1. It is desired, of course, to obtain a smooth restoration of frequency in this case also. Therefore, area 2 should, as before, assist area 1 with its natural response - a power comparable to its share of $10\beta (F_a - F_s)$. Thus, the LFC in area 2 should yield a generation trend which has an “acceptable match” with the area’s own load and losses, scheduled interchange (T_s), and the area contributed portion of $10\beta (F_a - F_s)$. This means that area 1 will obtain assistance from area 2 beyond the scheduled interchange when area 1 is not, for what ever reason, satisfying its obligations.

Since the system natural response coefficient, β , must be estimated because it is not a constant, it is not accurately obtainable nor predictable as it depends on the current status and governor response characteristics of the presently on-line units and the sensitivity of loads to frequency deviation, [71]. The closer the estimate B matches the SRC, β , of the control area, the better the control area LFC can separate internal imbalances from external ones and control to the internal ones [91]. This will reduce the number of unnecessary control actions and thereby prove better control. The North American Electric Reliability Council (NERC) Guidelines specifies using $10B (F_a - F_s)$ to represent the area portion of the frequency response term in area’s LFC process. The Guidelines allow the use of a constant for B which is to be estimated annually based on the average of apparent area β values as observed for disturbances that occurred during on-peak hours. (The sum of all area β values is system β). Guidelines alternatively allow using a variable B shown in Fig. 4.3 (b & c). So, the tie-line frequency bias curve is a control parameter which simulates the control area’s SRC in the control loop. Any tie-line frequency deviation point on the tie-line frequency bias curve will result in no control action. While for points above the curve the LFC will reduce generation and for points below the curve, the LFC will increase generation.

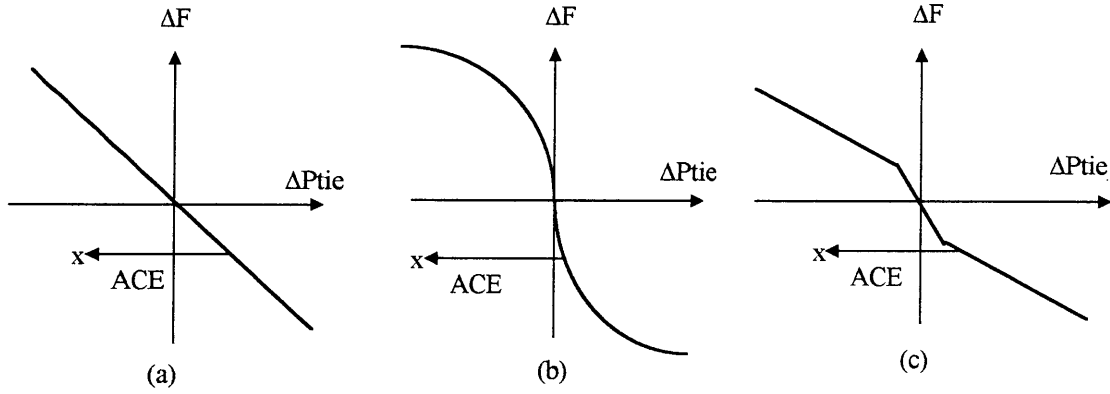


Fig. 4.3 Various frequency bias characteristics or zero ACE contours, presently in use : (a) constant B characteristic, (b)& (c) : non-linear B characteristic; [92]

Using B in place of area's β restates one of the major objectives of LFC - *it is desired that LFC in each control area provides a generation trend which has an acceptable match with that representing the sum of the area's own load and losses, $10B(F_a - F_s)$, and scheduled tie-line interchange (T_s), [71].* Generation in this area equals the sum of load and losses, and actual tie-line interchange (T_a). Therefore, the difference, called the *Area Control Error (ACE)* is given by:

$$ACE = (P_{tie,a} - P_{tie,s}) - 10B(F_a - F_s) \quad (4.1)$$

where

T_a = Measured net power interchange

T_s = Scheduled power interchange

$b = 10B$ = frequency bias coefficient (MW/Hz)

F_a = Measured system frequency

F_s = Nominal frequency

The above equation (4.1) can be rewritten as

$$ACE = \Delta P_{tie} - b\Delta F \quad (4.2)$$

where

$$\Delta P_{tie} = T_a - T_s ; \text{ Incremental change in tie-line power}$$

$$\Delta F = F_a - F_s ; \text{ Incremental frequency deviation}$$

The constant b , as used by most areas, is a fixed, linear value set in the LFC that remains the same throughout the year. The frequency bias factor, b , can be defined as:

$$b_i = D_i + \frac{I}{R_i} \quad (4.3)$$

where

$$D_i : \text{load frequency constant of } i^{\text{th}} \text{ area.}$$

$$R_i : \text{speed regulation of governor of } i^{\text{th}} \text{ area.}$$

Note from the above equation that the frequency bias factor (b) is sensitive to the status of generation (if a unit was committed or de-committed) and governor characteristics of units on-line (deadband estimation problem), as well as the total area load and its aggregate frequency response (D), all of which are widely variable. An area's frequency bias factor is also sensitive to the magnitude of upset from the pre-disturbance frequency [92]. In fact, the integral action of the supplementary controller will guarantee a reset of ACE to zero even when b is in error [69].

Fig. 4.3 shows different frequency bias characteristics. A fixed linear value of frequency bias factor is shown in Fig. 4.3-a. On the other hand, B can be used as variable and non-linear, as shown in Fig. 4.3-b & 4.3-c which reflect the fact that depending on the upset from the pre-disturbance frequency, the variable number of governors coming out of dead-band causes β to be highly sensitive to frequency upset size.

4.3 TWO-AREA MODEL

Two-area interconnected power system is considered as a study system for investigation of LFC problem. A block diagram of a two-area interconnected system area for the uncontrolled case is shown in Fig. 4.4 in which it has been assumed that each area is equipped with non-reheat steam turbines and there is no interaction between the power/frequency and the reactive-power/voltage control loops as the excitation system (AVR loop) acts much faster than the LFC system (due to the mechanical inertia in the later) and hence the AVR loop can be neglected in the development of the LFC problem. The mathematical model of the two-area power system for LFC problem will be developed in this section. The dynamic state-variable model for the ‘uncontrolled’ two area system shown in Fig. 4.4 can be developed as follows:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{L}\mathbf{d}(t) \quad (4.4)$$

where

$$\text{state vector} \quad : \quad \mathbf{x}(t) = [\Delta f_1, \Delta P_{g1}, \Delta P_{v1}, \Delta P_{tie}, \Delta f_2, \Delta P_{g2}, \Delta P_{v2}]^T$$

$$\text{control vector} \quad : \quad \mathbf{u}(t) = [u_1, u_2]^T = [\Delta P_{c1}, \Delta P_{c2}]^T$$

$$\text{disturbance vector} \quad : \quad \mathbf{d}(t) = [\Delta P_{d1}, \Delta P_{d2}]^T$$

The *system matrix* $\mathbf{A}$, the *input distribution matrix* $\mathbf{B}$, and the *disturbance distribution matrix* $\mathbf{L}$ are defined as follows:

$$\mathbf{A} = \left[\begin{array}{ccc|c|ccc} -\frac{I}{T_{p1}} & \frac{K_{p1}}{T_{p1}} & 0 & -\frac{K_{p1}}{T_{p1}} & 0 & 0 & 0 \\ 0 & -\frac{I}{T_{t1}} & \frac{I}{T_{t1}} & 0 & 0 & 0 & 0 \\ -\frac{I}{R_1 T_{g1}} & 0 & -\frac{I}{T_{g1}} & 0 & 0 & 0 & 0 \\ \hline T_{12} & 0 & 0 & 0 & -T_{12} & 0 & 0 \\ \hline 0 & 0 & 0 & \frac{K_{p2}}{T_{p2}} & -\frac{I}{T_{p2}} & \frac{K_{p2}}{T_{p2}} & 0 \\ 0 & 0 & 0 & 0 & 0 & -\frac{I}{T_{t2}} & \frac{I}{T_{t2}} \\ 0 & 0 & 0 & 0 & -\frac{I}{R_2 T_{g2}} & 0 & -\frac{I}{T_{g2}} \end{array} \right] \quad (4.5)$$

$$\mathbf{B} = \left[\begin{array}{ccc|c|ccc} 0 & 0 & \frac{1}{T_{g1}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{g2}} \end{array} \right]^T \quad (4.6)$$

$$\mathbf{L} = \left[\begin{array}{ccc|c|ccc} -\frac{K_{p1}}{T_{p1}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{K_{p2}}{T_{p2}} & 0 & 0 \end{array} \right]^T \quad (4.7)$$

The model description is incomplete unless we add the equation of the system output. Since the effectiveness of the LFC is judged in terms of the ACE, the system output can be expressed as:

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) \quad (4.8)$$

where

$$\mathbf{y}(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} ACE_1 \\ ACE_2 \end{bmatrix} \quad (4.9)$$

$$\mathbf{C} = \left[\begin{array}{ccc|c|ccc} b_1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & b_2 & 0 & 0 \end{array} \right] \quad (4.10)$$

where b_1 and b_2 are positive values.

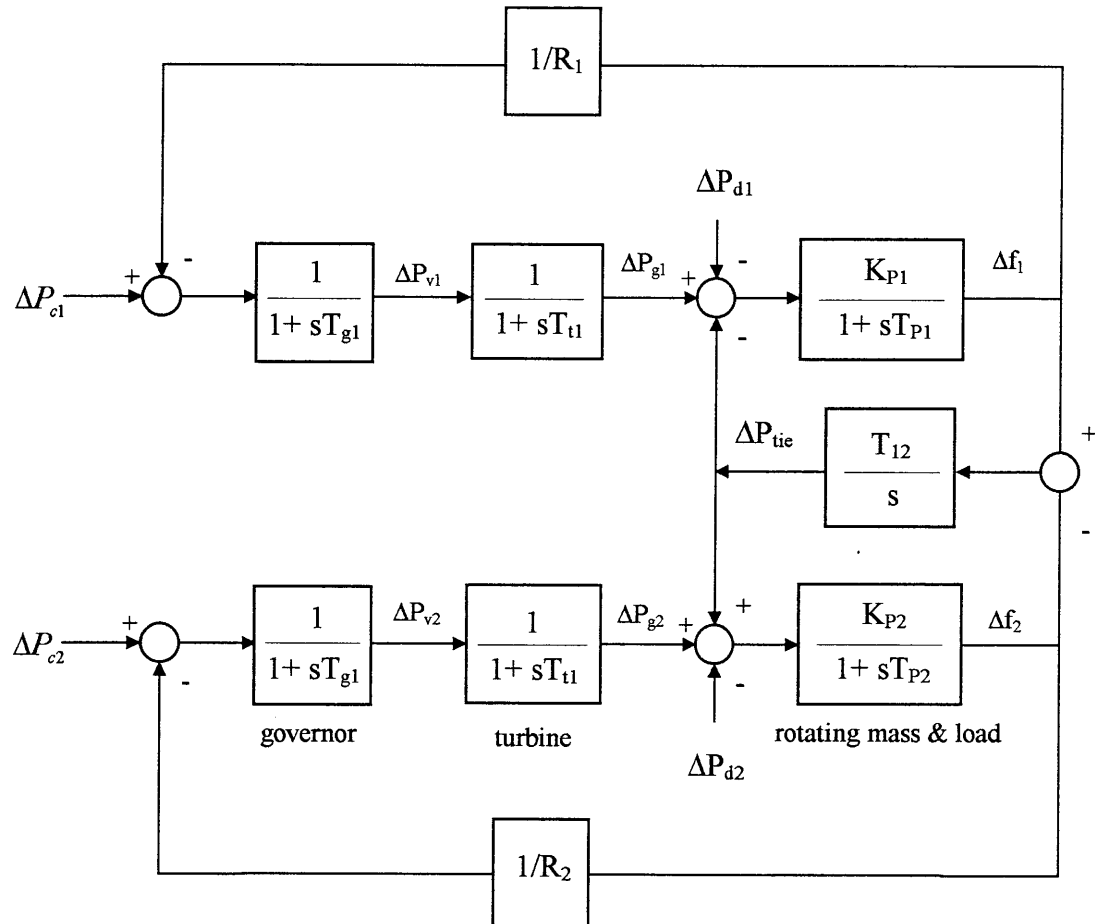


Fig. 4.4 Block diagram of two interconnected area.

4.4 DESIGN OF LOAD FREQUENCY CONTROLLERS

The task of the load-frequency controller is to generate a control signal u which will maintain both the system frequency of each area and the tie-line interchange within predetermined limits. Among the different control schemes that have been reported in literature to achieve the stated task, only three of them will be addressed in this thesis. These schemes are the conventional or classical control scheme (integral controller), the linear optimal control scheme and the fuzzy control scheme. In the fuzzy control scheme, there will be initially a survey of what has been reported in literature on the application of fuzzy controllers applied to LFC problem and finally new proposed fuzzy based load frequency controllers will be presented.

4.4.1 CONVENTIONAL CONTROL SCHEME

The common conventional control scheme is the integral controller shown in Fig. 4.5. From the figure, it is clear for each control area, that there are two feedback terms. The first one is proportional to the frequency deviation and the second one is proportional to deviation in tie-line power flow. The control inputs u_1 and u_2 are constructed as:

$$u_1 = -K_1 \int_0^{\tau} (ACE_1) dt = -K_1 \int_0^{\tau} (\Delta P_{tie1} + b_1 \Delta f_1) dt \quad (4.11a)$$

$$u_2 = -K_2 \int_0^{\tau} (ACE_2) dt = -K_2 \int_0^{\tau} (\Delta P_{tie2} + b_2 \Delta f_2) dt \quad (4.11b)$$

taking the derivative of the above two equations yield:

$$\dot{u}_1 = -K_1(ACE_1) = -K_1(\Delta P_{tie1} + b_1 \Delta f_1) \quad (4.12a)$$

$$\dot{u}_2 = -K_2(ACE_2) = -K_2(\Delta P_{tie2} + b_2 \Delta f_2) \quad (4.12b)$$

or in matrix form

$$\dot{\mathbf{u}} = -\mathbf{K}_I \mathbf{C} \mathbf{x} \quad (4.13)$$

where

$$\mathbf{K}_I = \begin{bmatrix} K_1 & 0 \\ 0 & K_2 \end{bmatrix} \quad (4.14)$$

combining equation (4.4) and equation (4.13), yields in the following augmented system

$$\dot{\mathbf{x}}_c = \mathbf{A}_c \mathbf{x}_c + \mathbf{L}_c \mathbf{d} \quad (4.15)$$

where

$$\mathbf{x}_c = \begin{bmatrix} \mathbf{x} \\ \mathbf{u} \end{bmatrix} ; \quad \mathbf{A}_c = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ -\mathbf{K}_I \mathbf{C} & \mathbf{0} \end{bmatrix} ; \quad \mathbf{L}_c = \begin{bmatrix} \mathbf{L} \\ \mathbf{0} \end{bmatrix} \quad (4.16)$$

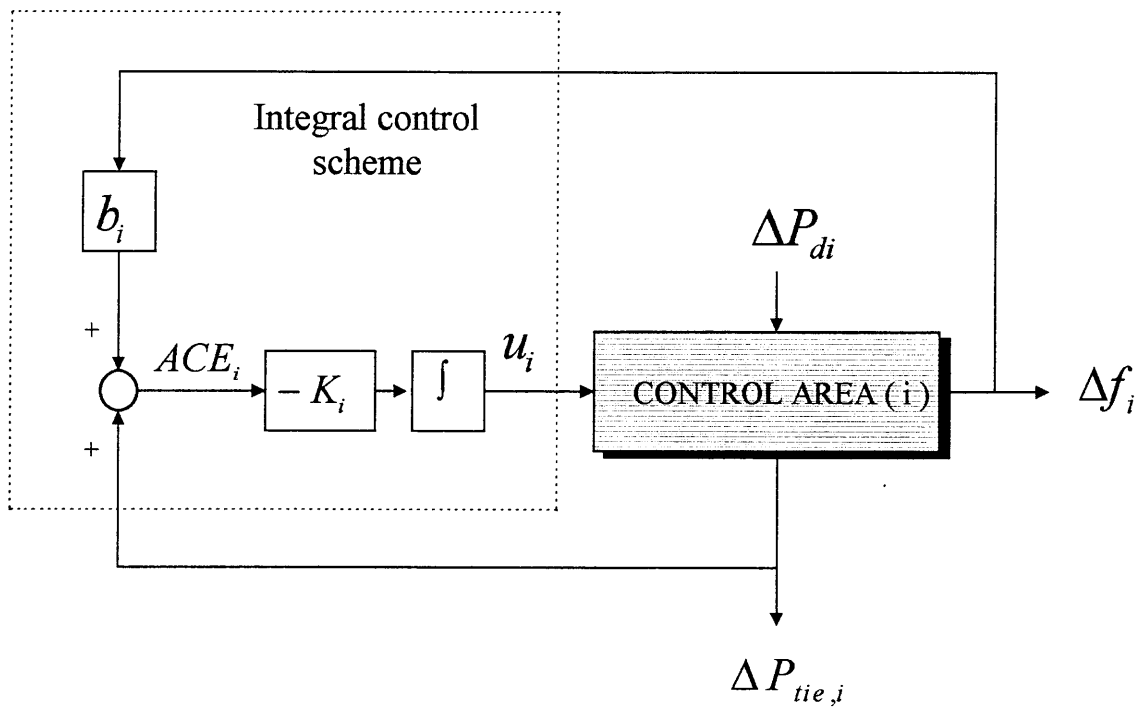


Fig. 4.5 Conventional integral controller installed on i^{th} area

4.4.2 OPTIMAL P-I CONTROLLER [96,77]

The Linear Quadratic Regulator (LQR) optimal theory may be utilized for the design of a suitable optimal LFC system if some modifications are first introduced. Let us, first introduce the state optimal regulator optimisation problem then the necessary modification will be introduced so that it can be applied for LFC.

Linear State Regulator problem:

Consider the linear time-invariant system

$$\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) ; \mathbf{x}(0) = \mathbf{x}^0 \quad (4.17)$$

$$\mathbf{y}(t) = \mathbf{C} \mathbf{x}(t) \quad (4.18)$$

In the optimal control scheme, the control vector $\mathbf{u} = [u_1 \ u_2]^T$ is generated by feeding back the states through feedback constants to be determined in accordance with an optimality criterion. For full state feedback, the control vector $\mathbf{u}$ is constructed as a linear combination of all the states, i.e.

$$\mathbf{u} = -\mathbf{K} \mathbf{x}(t) \quad (4.19)$$

The feedback matrix $\mathbf{K}$ is to be determined so that a certain *performance index* (J) is minimised in transferring the system from an arbitrary initial state $\mathbf{x}(0)$ to origin in infinite time ($\mathbf{x}(\infty) = 0$).

$$J = \frac{1}{2} \int_0^{\infty} (\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{u}^T \mathbf{R} \mathbf{u}) dt \quad (4.20)$$

where Q and R are positive semidefinite and positive definite constant matrices respectively. Determination of the feedback matrix K which minimises J is the *state-space optimal regulator problem* [96]. K is obtained from the solution of the algebraic matrix Riccati equation as:

$$A^T S + SA - SBR^{-1}B^T S + Q = 0 \quad (4.21)$$

$$K = R^{-1}B^T S \quad (4.22)$$

Thus, the closed-loop system is described by the equation

$$\dot{\mathbf{x}}(t) = (A - BK) \mathbf{x}(t) \quad (4.23)$$

At steady-state, $\dot{\mathbf{x}} = 0$ and therefore, $\lim_{t \rightarrow \infty} \mathbf{x}(t) \rightarrow 0$.

However, the above optimal control will not suit a system subjected to unknown external disturbance signal as in LFC problem where load may change during the day cycle which in turn can lead to a non-zero steady-state. So, some modifications will be introduced to solve the disturbance rejection problem.

Application of the LQR to the LFC:

Recall that that the LFC system needs to be designed so as to ensure that the deviations in the area frequencies and the tie-line power flows go to zero asymptotically after the system has been subjected to a step change in power demand in one of the areas. So, equation (4.17) must be replaced with

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{L}\mathbf{d} \quad (4.4)$$

where $\mathbf{d}$ is a load disturbance (assumed to be a constant step) vector.

The closed-loop system with the control law (4.19) is described by the equation

$$\dot{\mathbf{x}}(t) = (\mathbf{A} - \mathbf{BK})\mathbf{x}(t) + \mathbf{L}\mathbf{d} \quad (4.24)$$

At steady-state, $\dot{\mathbf{x}} = 0$ and the system state reaches a non-zero state $\mathbf{x}_{ss}$ governed by the relation

$$0 = (\mathbf{A} - \mathbf{BK})\mathbf{x}(t) + \mathbf{L}\mathbf{d} \quad (4.25)$$

This gives

$$\mathbf{x}_{ss} = -(\mathbf{A} - \mathbf{BK})^{-1} \mathbf{L}\mathbf{d} \quad (4.26)$$

Thus, the disturbance $\mathbf{d}$ will result in an off-set in the system's steady-state by an amount governed by equation (4.26). It can be seen that the magnitude of the off-set depends upon the magnitude of the disturbance and hence, the off-set will shift from one value to another with changes in the step value of the disturbance. Therefore, a modification is needed to suppress this off-set.

One obvious approach to suppressing this off-set that was proposed initially by Porter [93] and implemented in LFC by Reddoch et. al. [77] is to add new system variables “integral states” $\mathbf{q}$ defined as

$$\mathbf{q}(t) = \int \mathbf{y}(t) dt = \int \mathbf{C}\mathbf{x}(t) dt \quad ; \quad \mathbf{q}(0) = \mathbf{q}^0 \quad (4.27)$$

Since $\mathbf{q}$ satisfy the following equation,

$$\dot{\mathbf{q}} = \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) \quad (4.28)$$

Combining equation (4.4) and (4.18) with (4.28) yields in the following state equation

$$\dot{\mathbf{x}}_a = \mathbf{A}_a \mathbf{x}_a + \mathbf{B}_a \mathbf{u} + \mathbf{L}_a \mathbf{d} \quad (4.29)$$

$$\mathbf{y}_a(t) = \mathbf{C}_a \mathbf{x}_a(t) \quad (4.30)$$

where

$$\mathbf{x}_a(t) = \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{q}(t) \end{bmatrix} \quad ; \quad \mathbf{y}_a(t) = \begin{bmatrix} \mathbf{y}(t) \\ \mathbf{q}(t) \end{bmatrix} \quad ; \quad \mathbf{x}_a(0) = \begin{bmatrix} \mathbf{x}(0) \\ \mathbf{q}(0) \end{bmatrix} \quad (4.31)$$

$$\mathbf{A}_a = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{C} & \mathbf{0} \end{bmatrix} ; \quad \mathbf{B}_a = \begin{bmatrix} \mathbf{B} \\ \mathbf{0} \end{bmatrix} ; \quad \mathbf{L}_a = \begin{bmatrix} \mathbf{L} \\ \mathbf{0} \end{bmatrix} ; \quad \mathbf{C}_a = \begin{bmatrix} \mathbf{C} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \quad (4.32)$$

It was shown in [93] that the linear quadratic (LQ) optimal control law for ensuring that $\mathbf{x}_a(t)$ goes to zero in the presence of an unknown constant $\mathbf{d}$ is the same as that obtained by solving the LQR problem for disturbance free augmented system.

$$\dot{\mathbf{x}}_a = \mathbf{A}_a \mathbf{x}_a + \mathbf{B}_a \mathbf{u} \quad (4.33)$$

Choosing the quadratic performance index for the augmented system as;

$$J_a = \frac{1}{2} \int_0^{\infty} (\mathbf{x}_a^T \mathbf{Q}_a \mathbf{x}_a + \mathbf{u}^T \mathbf{R} \mathbf{u}) dt \quad (4.34)$$

then, a unique optimal solution to this problem may be found so that J_a is minimized.

The solution to this problem is given by:

$$\mathbf{u} = -\mathbf{K}_a \mathbf{x}_a(t) \quad (4.35)$$

where the optimal feedback matrix $\mathbf{K}_a$ is defined as:

$$\mathbf{K}_a = \mathbf{R}^{-1} \mathbf{B}_a^T \mathbf{S} \quad (4.36)$$

where $\mathbf{S}$ is the steady-state solution to the Matrix Algebraic Riccati equation:

$$\mathbf{A}_a \mathbf{S} + \mathbf{S} \mathbf{A}_a - \mathbf{S} \mathbf{B}_a \mathbf{R}^{-1} \mathbf{B}_a^T \mathbf{S} + \mathbf{Q}_a = \mathbf{0} \quad (4.37)$$

Once the feedback matrix $\mathbf{K}_a$ is found, the control law of equation (4.35) may be partitioned into its proportional and integral components as follows:

$$\mathbf{u} = \mathbf{K}_p \mathbf{x} + \mathbf{K}_i \mathbf{q} \quad (4.38)$$

where $\mathbf{K}_P$ and $\mathbf{K}_I$ are the proportional and integral feedback gain matrices respectively; i.e. $\mathbf{K}_a = [\mathbf{K}_P \quad \mathbf{K}_I]$. That is why this LFC is referred to as *Optimal P-I State Feedback Controller*. In the design of this optimal controller, the state and control weighting matrices (Q_a and R) for the combined system are given in appendix B as proposed by Reddoch et. al. [77].

4.4.3 FUZZY CONTROL SCHEMES

Different fuzzy LFC's that have been reported in literature will be covered and then the new proposed fuzzy-based load frequency controllers will be presented.

The First Application of Fuzzy Set Theory to LFC Problem [85]:

The first application of fuzzy set theory to LFC problem of power system was developed by Hsu et. al., [85]. In the Hsu proposed fuzzy load frequency controller shown in Fig. 4.6, the input signals are the measured system frequency deviation (Δf) and its derivative ($\dot{\Delta f}$) which is computed using the measured signals. These signals are first expressed in some linguistic variables using fuzzy set notations before they are processed by the fuzzy controller. A set of decision rules expressed in linguistic variables are established to relate input signals with output (control) signal. These decision rules, which are summarised by a fuzzy relation matrix using membership functions, form the basis for the fuzzy logic operations performed by a fuzzy controller to reach a proper control signal. Finally the control signal is converted from linguistic term to numerical value, using a conversion table, before it is fed into the system. This controller has been tested on a single area and a two-area interconnected system. The results show that the transient performance has been significantly

improved by the fuzzy controller as compared to the conventional PI controller. However, the proposed fuzzy controller of the two-area system was installed on a single area while the other area equipped with a conventional PI controller. In this thesis, Hsu fuzzy controller has been tested for a case where both areas are equipped simultaneously with the fuzzy controller. The result reveals the ineffectiveness of Hsu fuzzy controller in such situation.

The design steps of Hsu fuzzy load-frequency controller is similar to what has been already explained in subsection 3.3.5 of chapter 3 for the design of one of the fuzzy logic power system stabilizers proposed. Thus, for more details, please refer to subsection 3.3.5 of the previous chapter. The decision rules shown in Table 4.1, are similar to what was previously given in Table 3.1. The input variables (Δf , $\dot{\Delta f}$) are quantized into seven linguistic sets each described by a membership function shown in Fig. 4.2. In order to convert the linguistic output of the fuzzy controller, the conversion table shown in Table 4.3 is used.

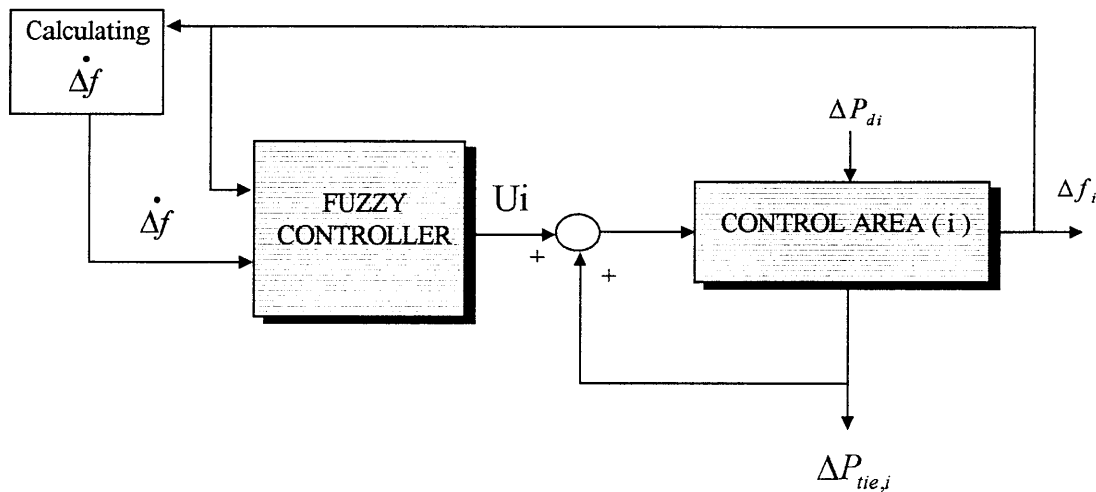


Fig. 4.6 Fuzzy load frequency controller proposed by Hsu [85].

Table 4.1 The decision table.

		Frequency Deviation rate ($\dot{\Delta f}$)						
		LN	MN	SN	VS	SP	MP	LP
frequency deviation Δf	LP	VS	SP	MP	LP	LP	LP	LP
	MP	SN	VS	SP	MP	MP	LP	LP
	SP	MN	SN	VS	SP	SP	MP	LP
	VS	MN	MN	SN	VS	SP	MP	MP
	SN	LN	MN	SN	SN	VS	SP	MP
	MN	LN	LN	MN	MN	SN	VS	SP
	LN	LN	LN	LN	LN	MN	SN	VS

Table 4.2 Membership functions for the controller inputs

normalized inputs	membership functions						
(Δf_u or $\dot{\Delta f}_u$)	LN	MN	SN	VS	SP	MP	LP
-1.0	1	0.7	0.5	0.3	0	0	0
-0.2	1	0.9	0.7	0.5	0.2	0	0
-0.1	0.8	1	0.9	0.7	0.4	0.2	0
-0.05	0.6	0.8	1	0.9	0.6	0.4	0.2
0	0.4	0.6	0.8	1	0.8	0.6	0.4
0.05	0.2	0.4	0.6	0.9	1	0.8	0.6
0.1	0	0.2	0.4	0.7	0.9	1	0.8
0.2	0	0	0.2	0.5	0.7	0.9	1
1.0	0	0	0	0.3	0.5	0.7	1

Table 4.3 Conversion table from linguistic variables to numerical values.

	LN	MN	SN	VS	SP	MP	LP
U	-3.6	-2.4	-1.2	0	1.2	2.4	3.6

The input factors (Sf_1 and Sf_2) and output scaling factor (Sf_3) which are not shown on figure 4.6, have been selected such the following performance index is minimized.

$$J = \sum [t(k)\Delta f(k)]^2 \quad (4.39)$$

where k : positive integer.
 $t(k)$: time at k^{th} sample.
 Δf : area frequency deviation at $t(k)$.

The Second Fuzzy Load Frequency Controller Proposed in the Literature:

Indulkar et. al. [86] have proposed a fuzzy load frequency controller in which they used the ACE and its change as input signals to the fuzzy controller. The proposed fuzzy controller have been tested on a two-area system. The simulation results show that the proposed controller has a smaller settling time as compared to the classical integral controller. However, it has not been possible to reduce the steady-state error in the tie-line power flow deviations to zero using their proposed fuzzy controller.

In order to solve the drawback of Indulkar fuzzy controller, a new fuzzy load frequency controller is proposed in this thesis using the same input signals used in Indulkar fuzzy controller but has the following main differences:

- i- Different rules have been used which are shown in Table 4.5.
- ii- The Centroid defuzzification method is used instead of max. defuzzification method used in Indulkar fuzzy controller.

The structure of the proposed controller is shown in Fig. 4.7. As can be seen from Fig. 4.7, there are three scaling factors corresponding respectively to the ACE, its change and output control signals. These scaling factors are required to be tuned to obtain the best system dynamic performance. This can be accomplished by minimising a certain performance index (cost function) such as that defined by equation (4.39).

Table 4.4 Fuzzy rules used by Indulkar fuzzy controller [86]

		ACE change						
		NB	NM	NS	ZO	PS	PM	PB
ACE	PB			NM	NB	NB	NB	NB
	PM			NM	NB	NB	NB	NB
	PS	PS	PS	NM	NM	NM	NM	NM
	PO			PS		NS	NM	NM
	NO			PS		NS	NM	NM
	NS	PM	PM	PM	PM		NS	NS
	NM	PB	PB	PB	PB	PM		
	NB	PB	PB	PB	PB	PM		

where B= Big, M= medium, S= Small, ZO= Zero, P= Positive, N= Negative.

Table 4.5 Fuzzy rules used in the proposed controller.

		ACE rate of change						
		LN	MN	SN	VS	SP	MP	LP
ACE	LP	VS	SN	SN	MN	LN	LN	LN
	MP	SP	VS	SN	MN	MN	LN	LN
	SP	MP	SP	VS	SN	SN	MN	LN
	VS	MP	MP	SP	VS	SN	MN	MN
	SN	LP	MP	SP	SP	VS	SN	MN
	MN	LP	LP	MP	MP	SP	VS	SN
	LN	LP	LP	LP	LP	MP	SP	VS

where L=Large, M= Medium, S= Small, N= Negative, P= Positive, V= Very.

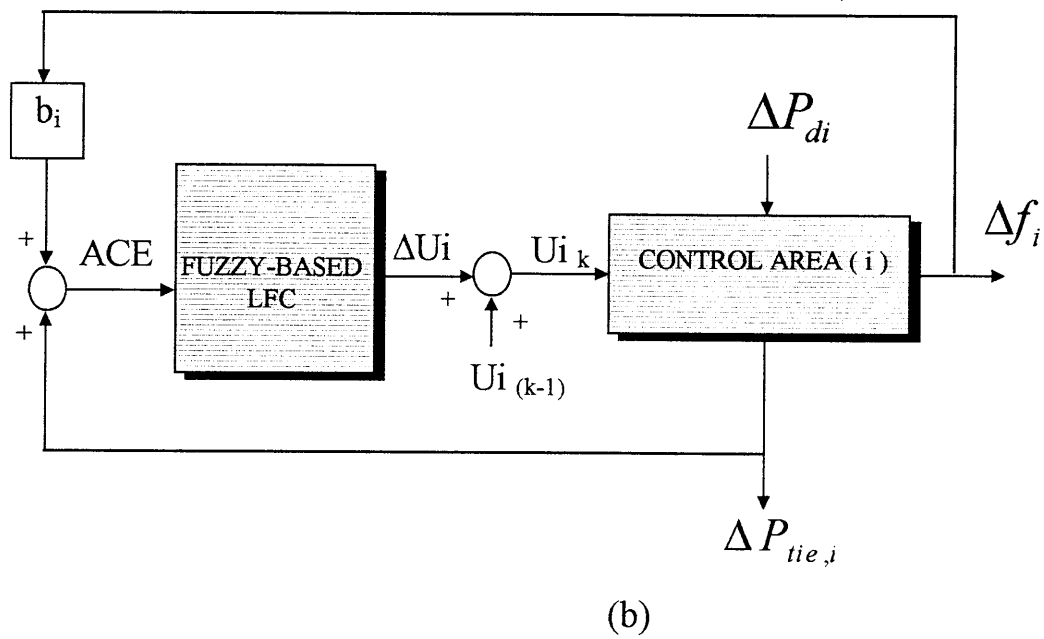
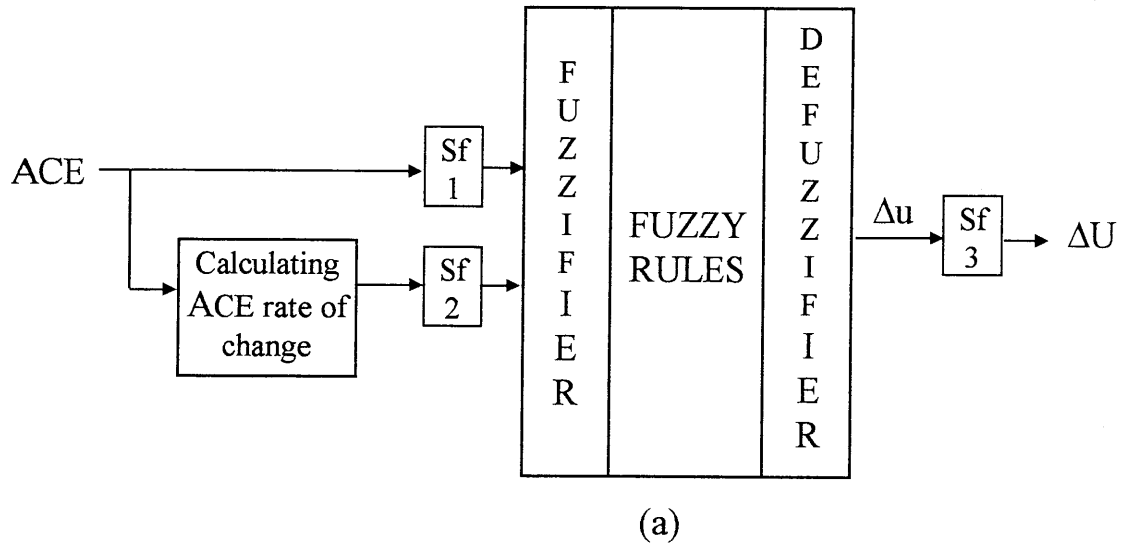


Fig. 4.7 (a) Proposed fuzzy LFC, (b) Application to i^{th} area

Second New Proposed Fuzzy controller:

The design of this fuzzy-based LF controller for two-area system is based on the concept of identifying the location of disturbance from which the area control action (increase, decrease or no change in area generation) can be decided. This can be realised based on the sign of both area frequency change and tie-line power flow change. As an example, consider a two-area system shown in Fig. 4.8.

- i) If frequency decreases and net interchange power leaving the system increases, then a load increase has occurred outside the area and therefore no change in area generation is required.
- ii) If frequency decreases and net interchange power leaving the system decreases, a load has occurred inside the system and therefore an increase in area generation is required to compensate for the load increase.

This can be extended to cases where frequency increases. Making the following definitions.

P_{gen} = area power generation

ΔP_{d1} = Load change in area 1.

ΔP_{d2} = Load change in area 2.

ΔP_{tie} = Change in tie-line power flow from area 1 to area 2.

(+ for power leaving the area; - for power entering)

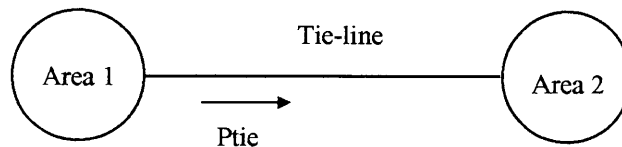


Fig. 4.8 Two-area system

Then a summary of area control action can be given as in Table 4.6.

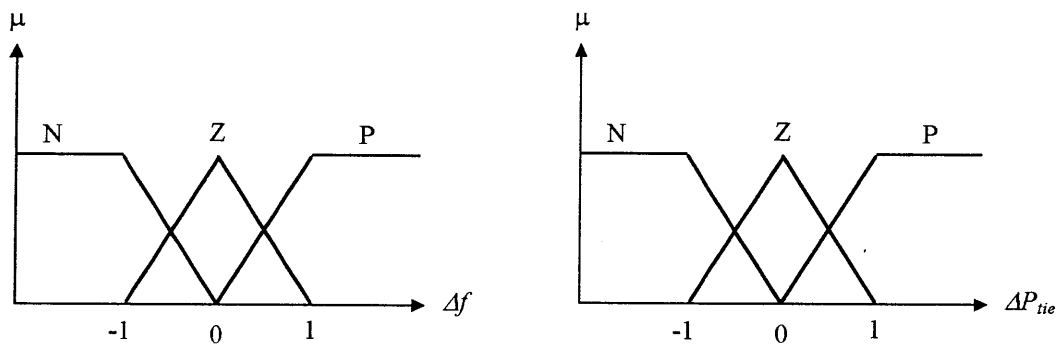
Table 4.6 Tie-line frequency control action for two area system

Frequency change (Δf)	Tie-line flow change (ΔP_{tie})	Load Change ΔP_d	Resulting control action
-	-	ΔP_{d1} + ΔP_{d2} 0	<i>Increase P_{gen} in area 1</i>
+	+	ΔP_{d1} - ΔP_{d2} 0	<i>Decrease P_{gen} in area 1</i>
-	+	ΔP_{d1} 0 ΔP_{d2} +	<i>Increase P_{gen} in area 2</i>
+	-	ΔP_{d1} 0 ΔP_{d2} -	<i>Decrease P_{gen} in area 2</i>
-	0	ΔP_{d1} + ΔP_{d2} +	<i>Increase P_{gen} in area 1 & 2</i>
+	0	ΔP_{d1} - ΔP_{d2} -	<i>Decrease P_{gen} in area 1 & 2</i>
0	-	0	<i>Increase P_{gen} in area 1</i>
0	+	0	<i>Decrease P_{gen} in area 1</i>
0	0	0	<i>No change in generation</i>

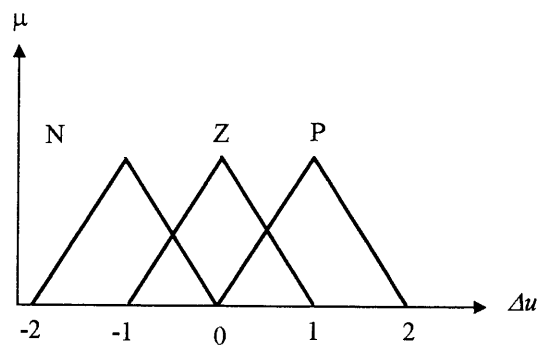
This can lead us to the rules shown in Table 4.7 which represent the rule base of the fuzzy controller relating its inputs (frequency change and tie-line power change) and output (control action or command). The output of the fuzzy controller is a fuzzy linguistic variable. Both the fuzzy input and output variables are represented (quantized) by three fuzzy sets (Positive “P”, Negative “N” and Zero “Z”) shown in Fig. 4.9.

Table 4.7 Fuzzy rule base.

		ΔP_{tie}		
		N	Z	P
Δf	N	<i>P</i>	<i>P</i>	<i>Z</i>
	Z	<i>P</i>	<i>Z</i>	<i>N</i>
	P	<i>Z</i>	<i>N</i>	<i>N</i>



(a) Membership functions of the input



(b) Membership functions of the output variable

Fig. 4.9 Fuzzy input/output normalized membership functions

The block diagram of this fuzzy-based load frequency controller and its application to i^{th} area are shown in Fig. 4.10 where Sf_1 , Sf_2 and Sf_3 are the scaling factors for the frequency change, tie-line change and incremental output respectively. These scaling factors are to be tuned according to the cost index defined in equation (4.39).

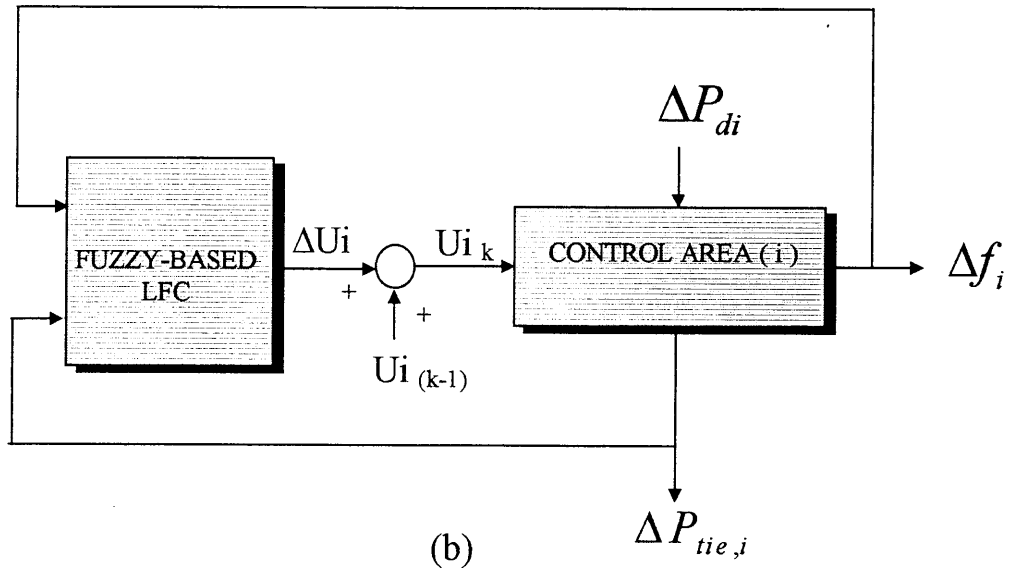
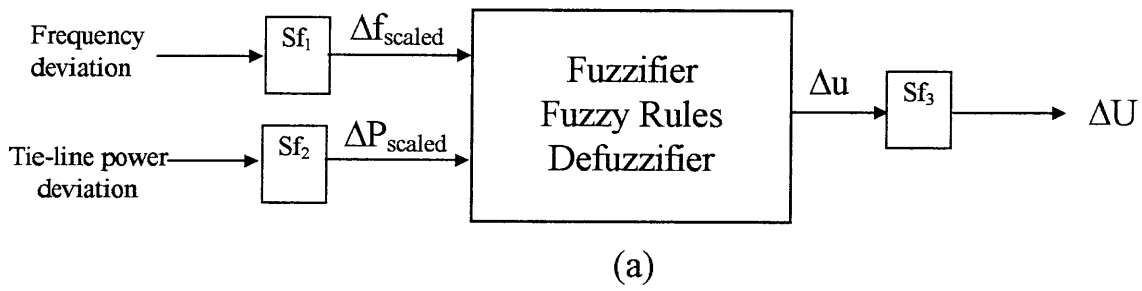


Fig. 4.10 (a) Proposed fuzzy LFC, (b) Application to i^{th} area

4.4.4 ADAPTIVE FUZZY GAIN SUPERVISOR/SCHEDULER

The main drawback of fixed gain controllers is that their performance deteriorates as a result of changes in system operating conditions due to load changes, unit commitment changes, or unpredictable disturbances such as generator outages. In order to maintain desired quality of the system dynamics over a wide range of operating conditions, it is highly desirable to be able to adapt the controller gains according to the on-line information.

In view of the above, Djukanovic et. al. [87-88] used Artificial Neural Networks (ANN) for adaptation of elements of the feedback gain matrix K of a state space optimal load frequency controller as shown in Fig. 4.11. In his approach, three parameters have been monitored and used as inputs to the neural net based adaptive controller. Two of the parameters are used to monitor the power system operating conditions through the power system time constant, T_P and the synchronising coefficient, T_{12} where:

$$T_{12} = 2\pi \frac{V_1 V_2}{X_{12} P_{r1}} \cos(\delta_1^o - \delta_2^o)$$

$$T_p = \frac{2H}{Df^o}$$
(4.40)

The third monitored parameter is the frequency bias setting b where:

$$b = D_i + 1/R_i$$
(4.41)

These parameters activate many individual neural-nets (SL1, SL2, ..., SLN) trained with supervised learning for cases in which one of the three monitored parameters varies and two parameters are set fixed. The training set of patterns are generated by solving the state-space optimal regulator problem (using solutions of the algebraic Riccati matrix equation (4.36,4.37) for different values of power system time constant-

T_p (13-27s), synchronising coefficient- T_{12} (0.18127-0.36254) and frequency bias settings- b (0.343-0.425). Each training pattern contains 3 input features and 18 output features (2x9 dimension of feedback matrix $\mathbf{K}$). A feed-forward neural-net with two hidden layers (30 nodes in the first hidden layer and 20 nodes in the second hidden layer) were used. The results of the comparison between the dynamic performance of Djukanovic proposed neural-net based controller and the state space optimal regulator shows that neural-net is capable of providing optimal control which closely agrees with the optimal control calculated off-line using the solution of the Riccati matrix equation.

The strengths of ANN lie in their capability to learn adaptively from a body of examples and in synthesising the non-linear and complex relations [88]. Neural-nets do not require a priori formulation of rules for the system application which is a serious limitation for successful applications of expert systems. However, this technology is characterised by some inherent shortcomings. If the training data set contains a large number of patterns, then an algorithm, such as backpropagation, goes slowly unless implemented in expensive hardware. Furthermore, a criterion for how to select the optimum number of nodes in the hidden layers should be developed, which significantly affect the learning rate as well as classification performances.

In our proposed scheme, we have used a Sugeno type fuzzy system to replace the neural nets proposed in [88]. The advantage is that the design is simpler and fewer training patterns are required (only 27 instead of 399 used in case of neural-net) and hence avoiding the excessive training time using neural nets. The Sugeno type fuzzy inference system is used because it is extremely well suited to the task of smoothly interpolating linear gains across the input space. So, we could build a fuzzy system that switches smoothly between several linear controllers as a very non-linear system moves around in its operating space. Consequently, two new fuzzy based adaptive load frequency controllers are proposed in this thesis. The first is an optimal load frequency controller with fuzzy gain scheduling and the second is a conventional integral load frequency controller with fuzzy gain scheduling.

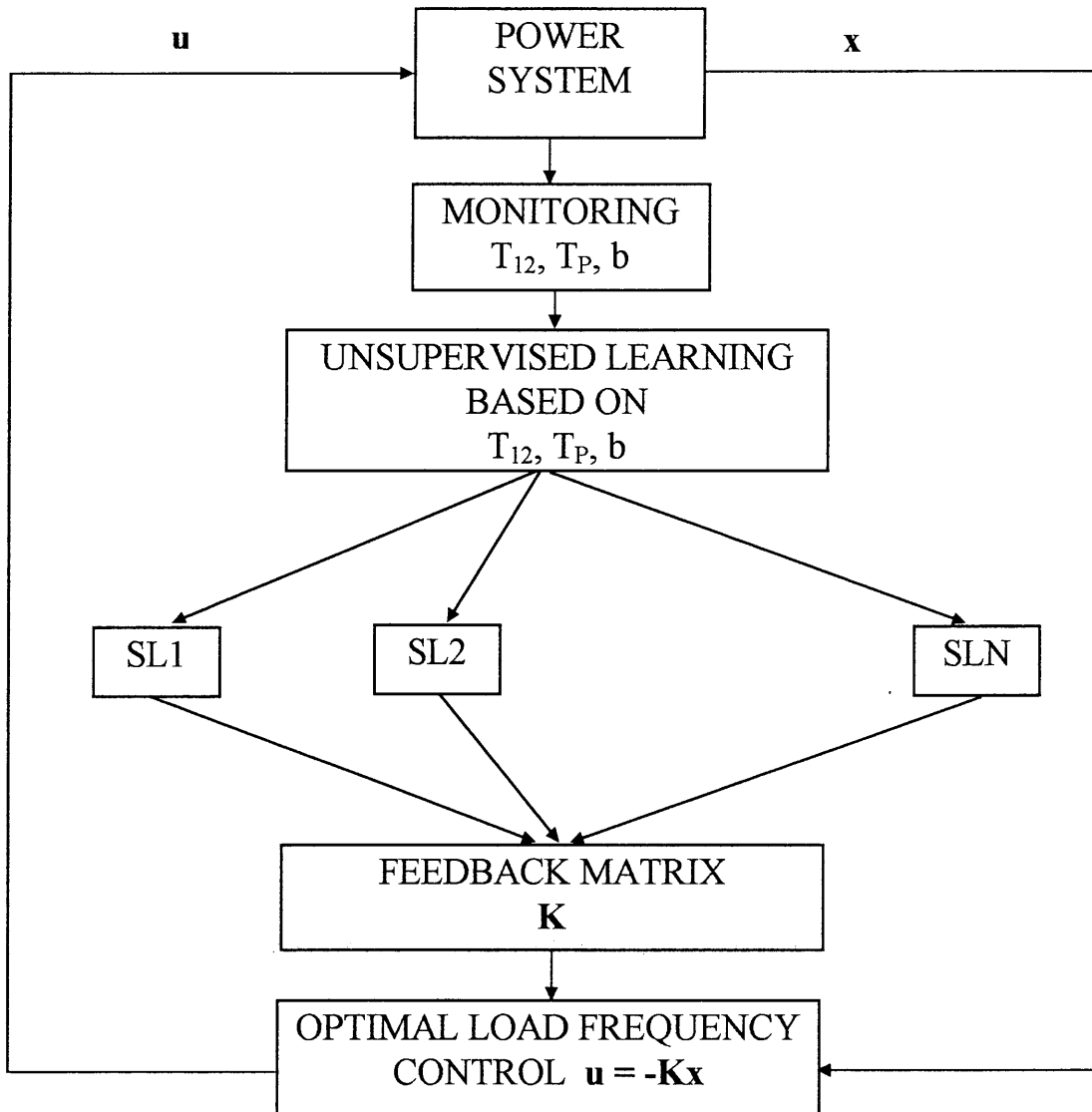


Fig. 4.11 Block diagram optimal neural-net based load frequency control system proposed by [87-88].

Optimal Controller with Fuzzy Gain Scheduling:

The linear optimal PI controller designed in section (4.4.2) will be modified in such a way that its feedback gain K elements are adapted by means of a fuzzy gain supervisor according to on-line system information (T_p, T_{12}, b) . The proposed fuzzy-based state-space optimal load frequency controller is shown schematically as in the block diagram of Fig. 4.12. It can be clearly seen that the structure of the proposed controller is similar to that proposed in [87-88] except that the neural net block (acting as adaptive gain scheduler) is replaced by an adaptive fuzzy gain scheduler. Unlike the neural-net approach wherein a large number of training patterns are required, we need only fewer number of patterns in the fuzzy approach (only 27 combinations of the system monitored parameters were used).

Each of the three monitored parameters is divided into three fuzzy sets (Small-Medium-Large) represented by a membership function as shown in Fig. 4.13. Then, each pattern (T_p, T_{12}, b) and corresponding optimal feedback gain matrix obtained by solving the algebraic matrix Riccati equation) will be represented by a sugeno type fuzzy rule such as:

$$\text{IF } (T_p \text{ is } A_1^i) \text{ AND } (T_{12} \text{ is } A_2^i) \text{ AND } (b \text{ is } A_3^i) \text{ THEN optimal gain} = K^i \quad (4.42)$$

where T_p, T_{12}, b : monitored parameters representing a particular system operating condition.

A_1^i, A_2^i, A_3^i : fuzzy sets of the i th rule.

K^i : optimal gain matrix of the i th rule.

Since there are a total of 27 patterns, then there will be 27 rules. The output of the fuzzy gain scheduler is a gain that corresponds to an operating condition that lies in the domains of the monitored parameters.

$$K_{scheduled} = \frac{\sum_{i=1}^{27} w^i K^i}{\sum_{i=1}^{27} w^i} \quad (4.43)$$

where w^i is the firing strength of the i^{th} rule which can be obtained as:

$$w^i = \min \{ \mu(A_1^i), \mu(A_2^i), \mu(A_3^i) \}. \quad (4.44)$$

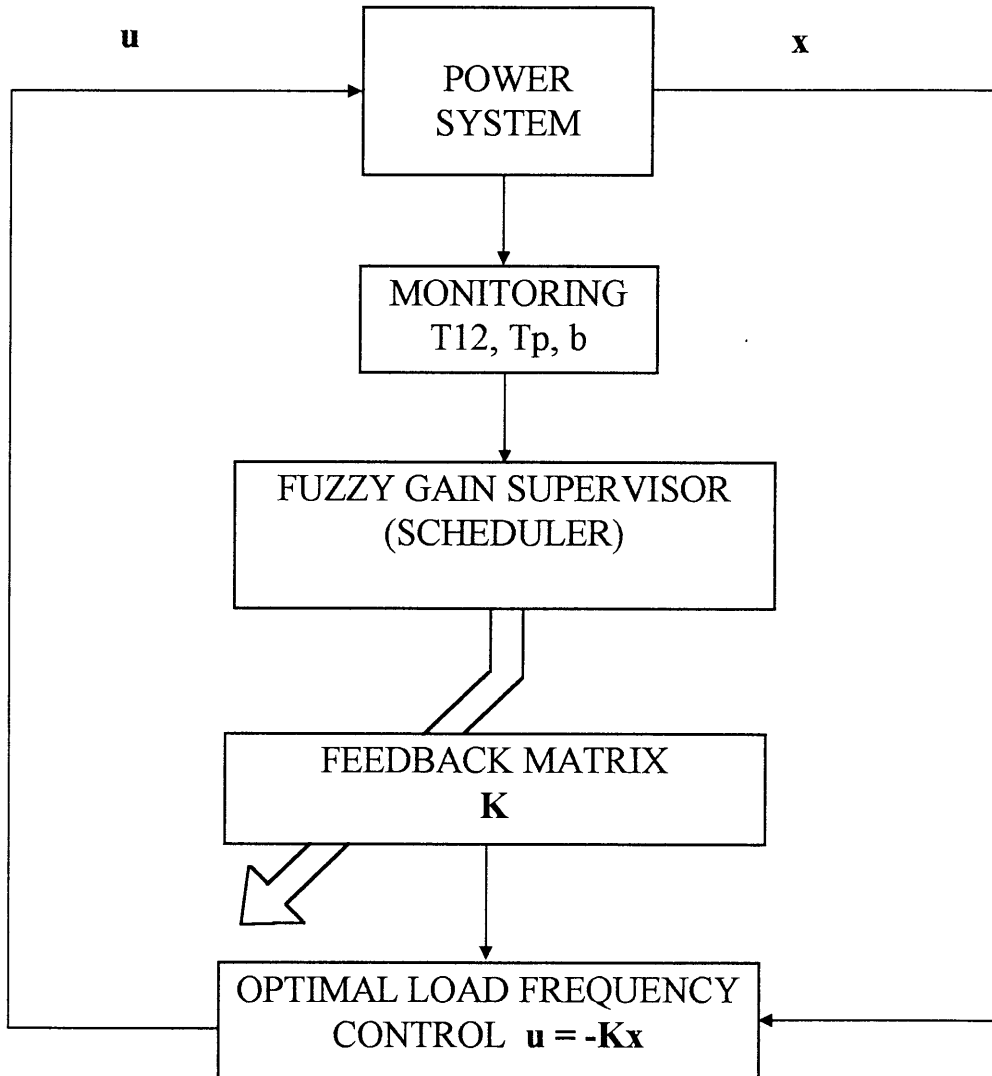


Fig. 4.12 The new proposed adaptive fuzzy-based optimal load frequency control system.

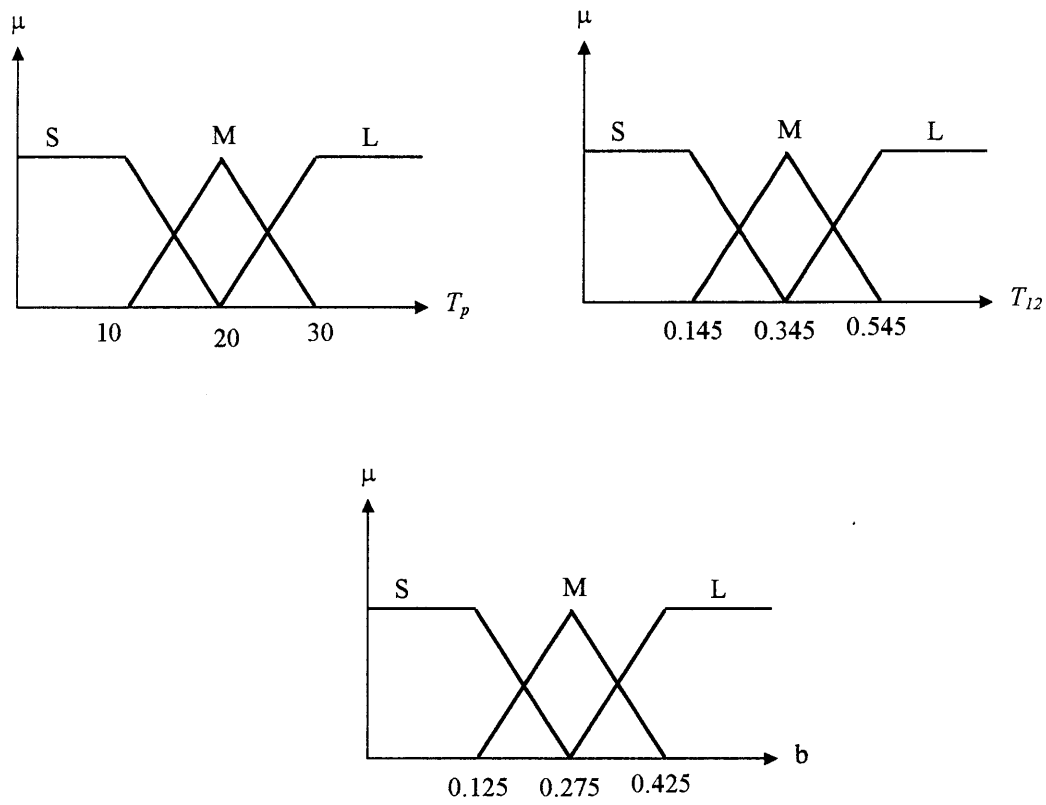


Fig. 4.13 Membership functions of the monitored parameters variable

Conventional Integral Control With Fuzzy Gain Scheduling:

The same concept of fuzzy gain scheduling applied to the optimal controller may also be applied for the adaptation of the conventional integral controller gain according to the system operating condition. The basic structure of this new proposed controller is shown in Fig. 4.14.

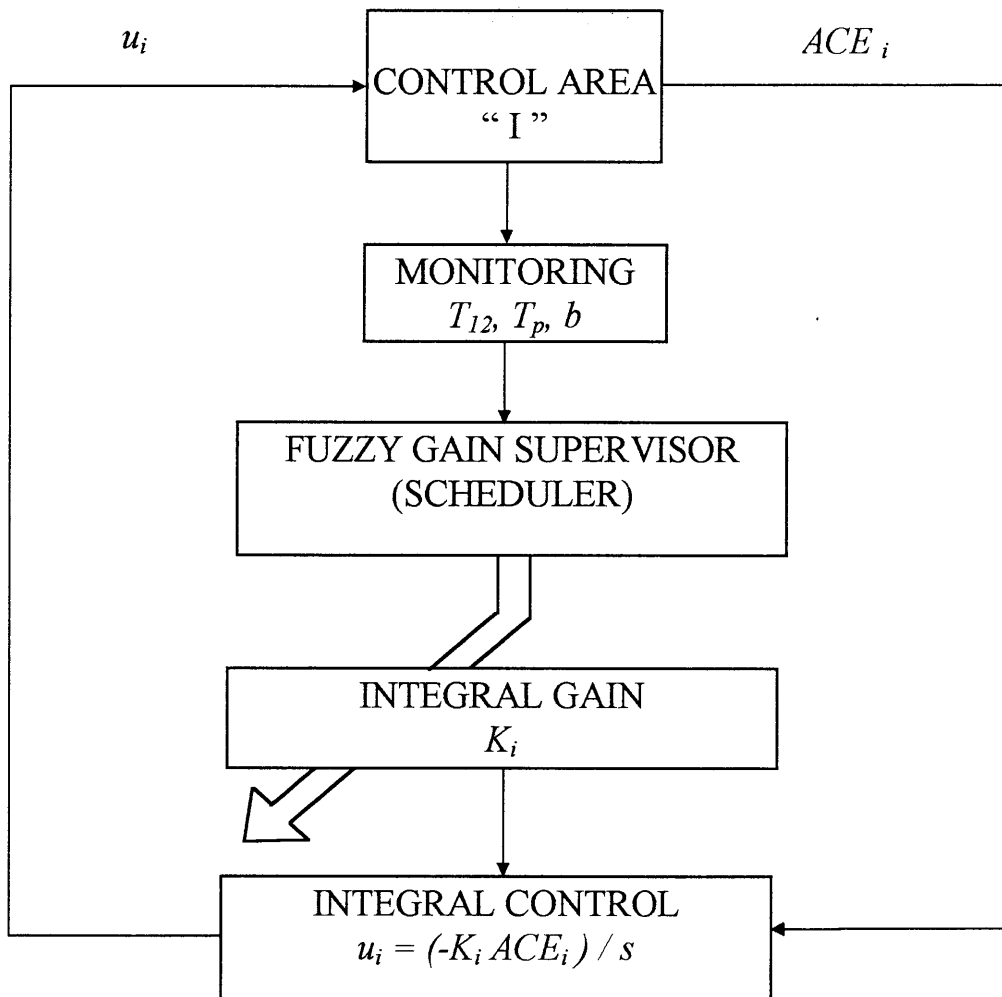


Fig. 4.14 The new proposed fuzzy-based conventional integral LFC system applied on the i^{th} area.

The design of the fuzzy control part of this controller is exactly similar to that designed for the optimal controller except that the calculated optimal gain matrices are replaced with integral gains calculated at different operating conditions. The calculated integral gains corresponding to the same 27 operating conditions are listed in Table 4.8. The integral gains shown in Table 4.8 are calculated such as to minimise the cost function (4.39) when a two identical area system is subjected to a 0.01 p.u. step load change in area 1.

Table 4.8 Calculated integral gain at different operating condition

PATTERN	OPERATING CONDITION			INTEGRAL GAIN
	T_p	T_{I2}	b	K_i
1	10	0.145	0.125	1.46
2	10	0.145	0.275	0.65
3	10	0.145	0.425	0.44
4	10	0.345	0.125	1.41
5	10	0.345	0.275	0.63
6	10	0.345	0.425	0.41
7	10	0.545	0.125	1.12
8	10	0.545	0.275	0.51
9	10	0.545	0.425	0.33
10	20	0.145	0.125	1.33
11	20	0.145	0.275	0.72
12	20	0.145	0.425	0.52
13	20	0.345	0.125	1.37
14	20	0.345	0.275	0.78
15	20	0.345	0.425	0.53
16	20	0.545	0.125	1.29
17	20	0.545	0.275	0.72
18	20	0.545	0.425	0.49
19	30	0.145	0.125	1.09
20	30	0.145	0.275	0.66
21	30	0.145	0.425	0.49
22	30	0.345	0.125	1.05
23	30	0.345	0.275	0.71
24	30	0.345	0.425	0.52
25	30	0.545	0.125	1.01
26	30	0.545	0.275	0.68
27	30	0.545	0.425	0.49

4.5 SIMULATION AND RESULTS

Matlab is used in as a software package for the design and simulation of the load frequency controllers. In order to evaluate the effectiveness and validity of the new proposed load frequency controllers, a digital computer simulations of a two-area power system following a step change in the load demand of area 1 is considered. The two-areas are assumed to be identical for which the system parameters are given in Appendix B. For the purpose of comparison, the dynamic response of the conventional integral control, the state-space optimal control, and the proposed fuzzy based controllers is analysed. All of the mentioned load frequency controllers have been initially designed to give the best system dynamic response at the nominal operating system condition given in Appendix B. The effect of change in certain important system parameters such as , power system time constant (T_P), synchronising coefficient (T_{12}) and frequency bias (b), on the performance of the designed load frequency controllers is highlighted. The effect of the amount of load disturbance on the load frequency controllers has been also investigated. In the following graphs, the following notations are considered:

- CLFC : Conventional Integral load frequency controller (LFC).
- OPTLFC : Optimal full-state feedback P-I LFC.
- PFLFC1 : First proposed fuzzy LFC designed in section (4.4.3) which is a modification to the fuzzy LFC proposed by Indulkar [86] .
- PFLFC2 : Second proposed Fuzzy LFC designed in section (4.4.3) with 9 rules.
- CLFCGS : Proposed conventional integral LFC with fuzzy-Gain Scheduling.
- OPTLFCGS: Proposed Optimal LFC with Fuzzy-Gain Scheduling.
- NC : Nominal system operating condition characterised by ($T_{12}=0.545$, $T_P=20$, $b=0.425$) at which the various LFC's have been designed.
- ON : off-nominal system operating Condition characterised by ($T_{12}=0.5$, $T_P=12$, $b=0.12$).

4.5.1 The Uncontrolled Case:

The uncontrolled two-area system case will be considered first. This means that we do not change the speed changers position i.e. $u_1 = u_2 = 0$. In this case, if the two area system were subjected to a load disturbance in either area, then the system natural response will act immediately to bring the system at equilibrium state at new frequency. For the two-area system considered in this thesis, the system response following a step change of 0.01 p.u. load demand in area 1 for uncontrolled case is shown in Fig. 4.15. The deviation of both frequency and tie-line power flow from their schedule values (set points) can be clearly seen from the figure. It can also be noticed that the amount of tie-line power flow from area 1 to area 2 decreased by about 0.05 p.u. which is half of the load disturbance (0.01 p.u.) that occurred in area 1. This means that area 2 has assisted area 1 with equal share of power as they are assumed to be identical. Frequency and tie-line power flow will remain deviated from schedule until a supplementary control action is taken by the control area within which load disturbance has occurred.

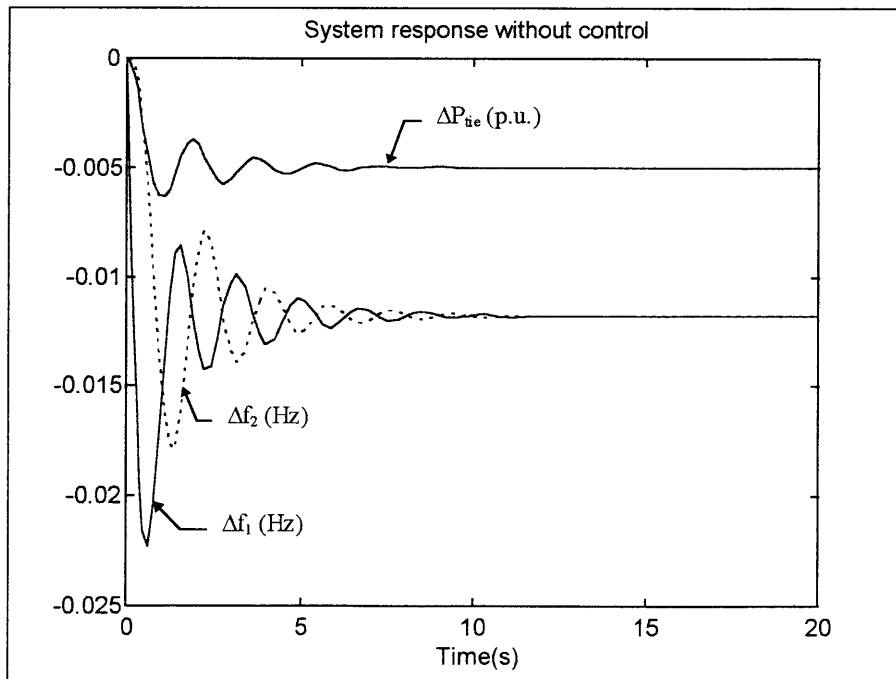


Fig. 4.15 Power system dynamic responses after step load change (0.01 p.u.) in area 1 for No Control Case.

4.5.2 The Controlled Case:

In this case, the load frequency controllers designed earlier will be added as a supplementary controller to both areas in order to restore the frequency and tie-line power to their scheduled values. The parameters of the load frequency controllers are tuned at the nominal operating condition and the final settings used in the computer simulations are as follows:

- (1) Integral LFC (CLFC): Integral gain (K)= 0.49.
- (2) Hsu LFC: $Sf_1 = 60$, $Sf_2 = 6$, $Sf_3 = 2.5 \times 10^{-5}$.
- (3) Djukanovic LFC: $Sf_1 = 1$, $Sf_2 = 1$, $Sf_3 = 0.5$.
- (4) FLFC1: $Sf_1 = 100$, $Sf_2 = 10$, $Sf_3 = 6 \times 10^{-5}$.
- (5) FLFC2: $Sf_1 = 40$, $Sf_2 = 100$, $Sf_3 = 2.7 \times 10^{-5}$.
- (6) OPTLFC: Q and R matrices are given in Appendix B.

The effect of changing the operating conditions on the performance of the conventional integral load frequency controller (CLFC) following a step change of 0.01 p.u. in load demand in area 1 is shown in Fig. 4.16. It can be seen from this figure that when system operates at off-nominal condition, the system response becomes sluggish and non-zero steady state error exist for both frequency and tie-line power flow. This is because the integral gain of CLFC's were tuned in the design stage to give the best system performance at a particular operating condition (NC). The fuzzy LFC proposed by Djukanovic et. al. [87], is applied and the system response following 0.01 p.u. step load change is not satisfactory as can be seen from Fig. 4.17. Similarly, when the fuzzy LFC proposed by Hsu et. al. [85] installed on both areas, there exist a persisting steady state error in the tie-line power flow as the system disturbed by 0.01 p.u. step load change in area 1 as shown in Fig. 4.18. That is because the inputs of the fuzzy LFC proposed by Hsu depends solely on the frequency deviations and does not includes the tie-line power deviations as input signal which represent an essential parameter to be controlled in two area system. For that reason, several trial are made to design a fuzzy logic based LFC which could overcome the drawback of the above mentioned LFC's and consequently four new load frequency controllers are proposed

in this thesis. The response of the two new proposed adaptive LFC are shown in Fig. 4.19 and Fig. 4.20. In Fig. 4.19, the proposed conventional LFC with fuzzy gain scheduler is compared with the classical integral LFC at the off-nominal system operating condition. That is because, at nominal condition, both show the same response characteristic. A comparison is also made between the optimal LFC with and without fuzzy gain scheduling as shown in Fig. 4.20. From Fig. 4.19 and 4.20, it can be seen that the new proposed controllers with fuzzy gain scheduling have improved the system steady state error in frequency of both interconnected areas.

Table 4.9 shows the comparison of feedback matrix $\mathbf{K}$ and system eigenvalues obtained using the fuzzy optimal gain scheduler and Riccati matrix equation for new operating condition characterised by $T_P = 10$ s, $T_{12} = 0.5$, $b = 0.12$. By comparing the eigenvalues given in Table 4.9 of the fuzzy based optimal controller (state-space optimal controller with fuzzy gain scheduling) and state-space optimal controller without gain scheduling, it can be concluded that the fuzzy based optimal controller is capable of providing the optimal control which closely agrees with the optimal control calculated off-line at the new operating condition using the solution of the Riccati equation.

All the above aforementioned LFC's including the other two proposed fuzzy based LFC's (FLFC1 and FLFC2) are compared at the nominal and off-nominal operating conditions following a 0.01 p.u. step load change in area 1 as shown respectively in Fig. 4.21 and 4.22. It can be depicted from Fig. 4.21 that the response of the conventional LFC without gain scheduling (CLFC) and with fuzzy gain scheduling (CLFCGS) are similar at nominal operating condition. This is also the case for the optimal LFC without gain scheduling (OPTLFC) and with fuzzy gain scheduling (OPTLFCGS). Unlike the fuzzy LFC proposed by Hsu and Indulkar which are associated with steady state error problem, the two proposed controllers (FLFC1 and FLFC2) overcome this problem. Furthermore, the response of the optimal controllers (OPTLFC and OPTLFCGS) are superior over the other controllers at nominal operating condition. However, when the system operating at off-nominal

condition, the response of the optimal LFC and the conventional LFC are worsen while the proposed controllers (FLFC2, CLFCGS, OPTLFCGS) shows distinct robustness as shown in Fig. 4.22a. In addition, the control effort of the proposed fuzzy LFC with the nine rules (FLFC2) is smaller than the other loaf frequency controllers as shown in Fig. 4.22c.

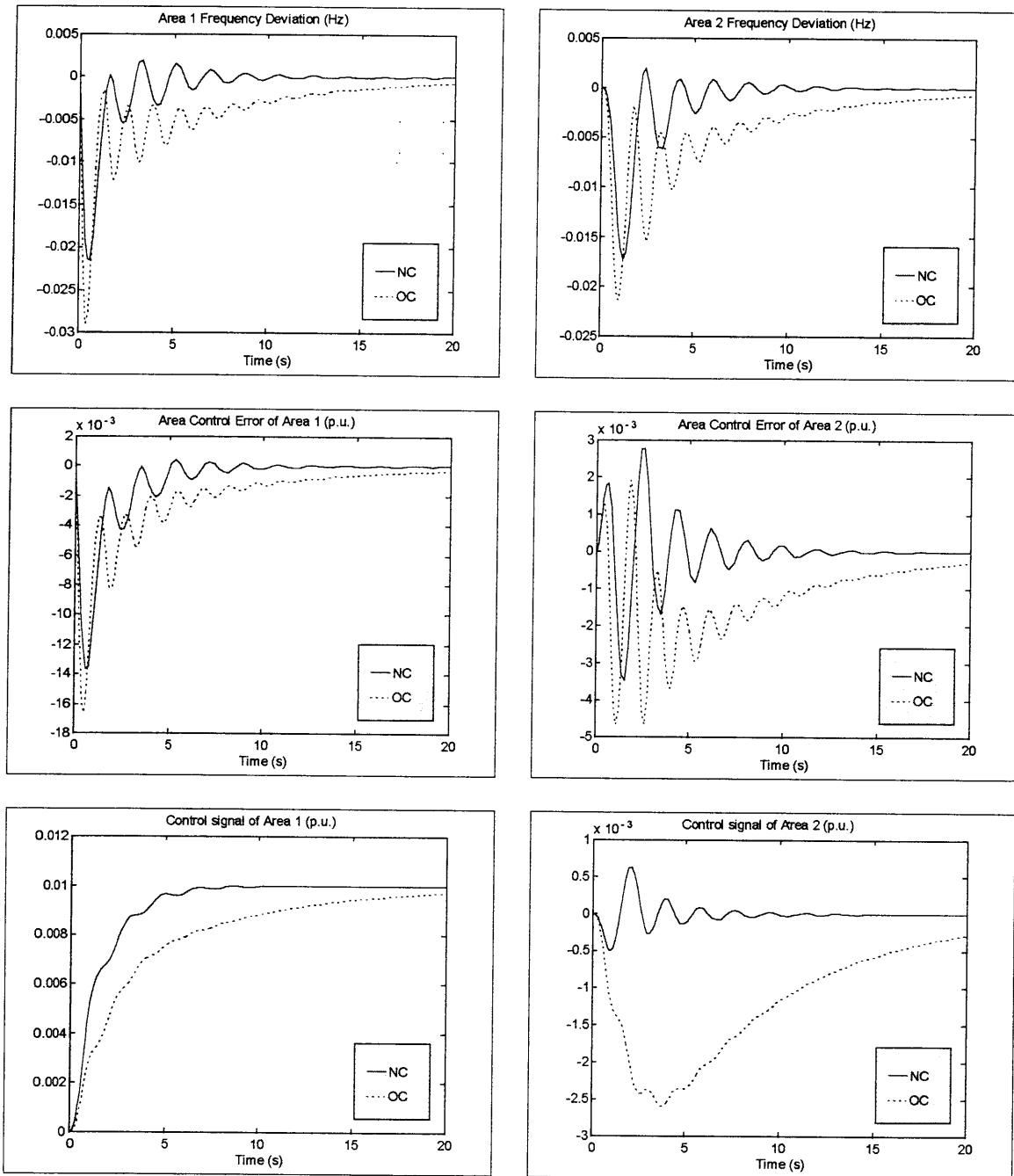


Fig. 4.16 (a) Frequency deviation, area control error, control signal of Area 1 and 2, following 0.01 p.u. step load change in area 1 at nominal and off-nominal system operating conditions.

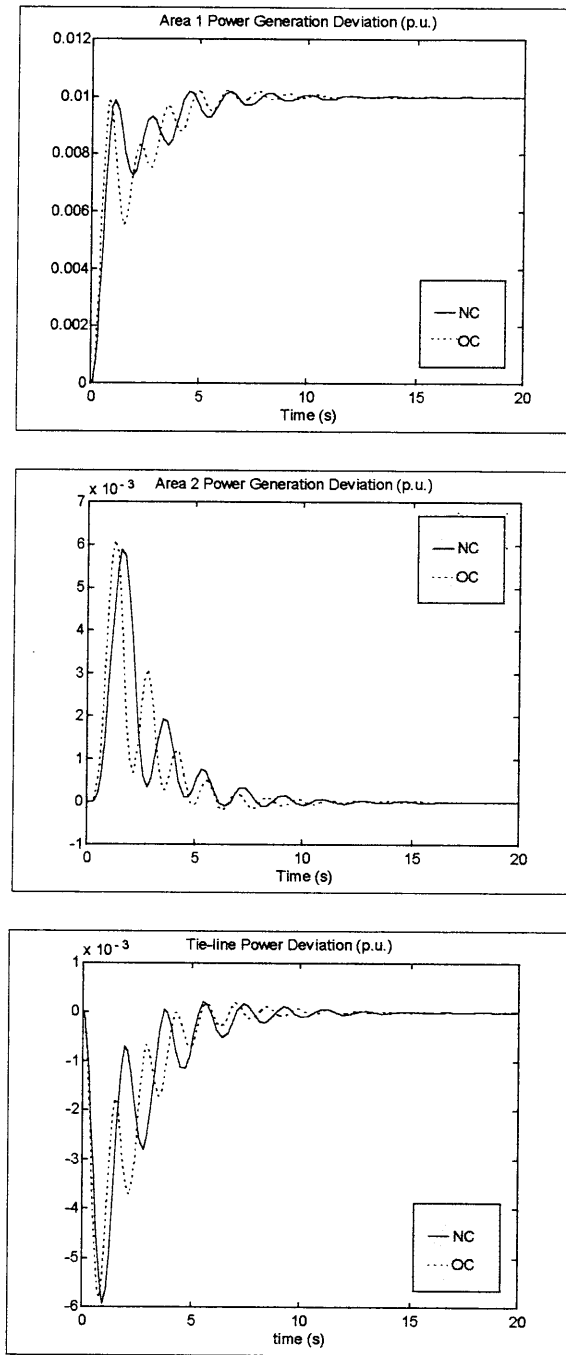


Fig. 4.16 (b) Area Power generation and tie-line power flow following 0.01 p.u. step load change in area 1 at nominal and off-nominal system operating conditions.

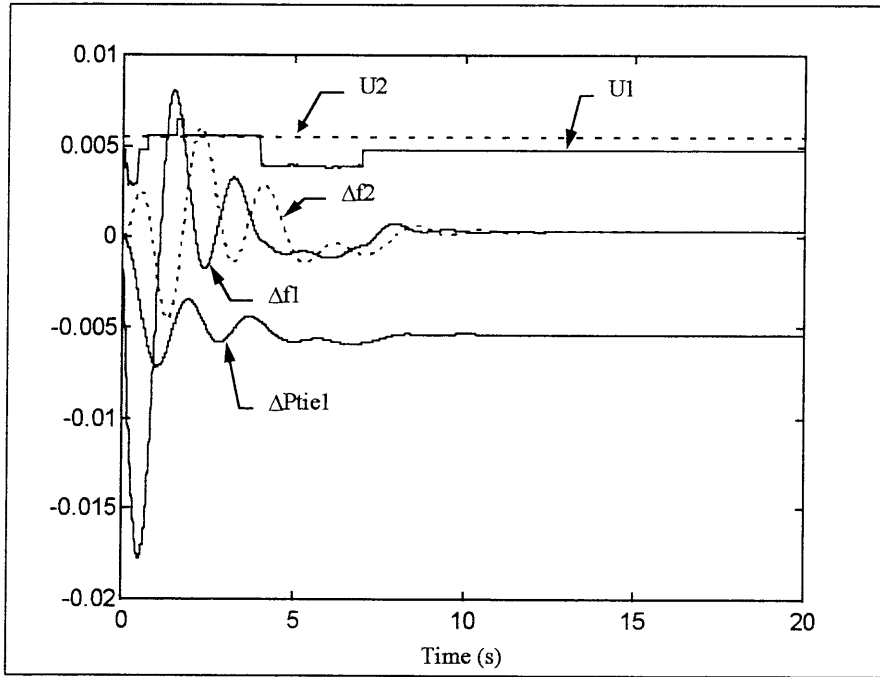


Fig. 4.17 System response following 0.01 p.u. step load change in area 1 with Djukanovic et. al. fuzzy LFC [87].

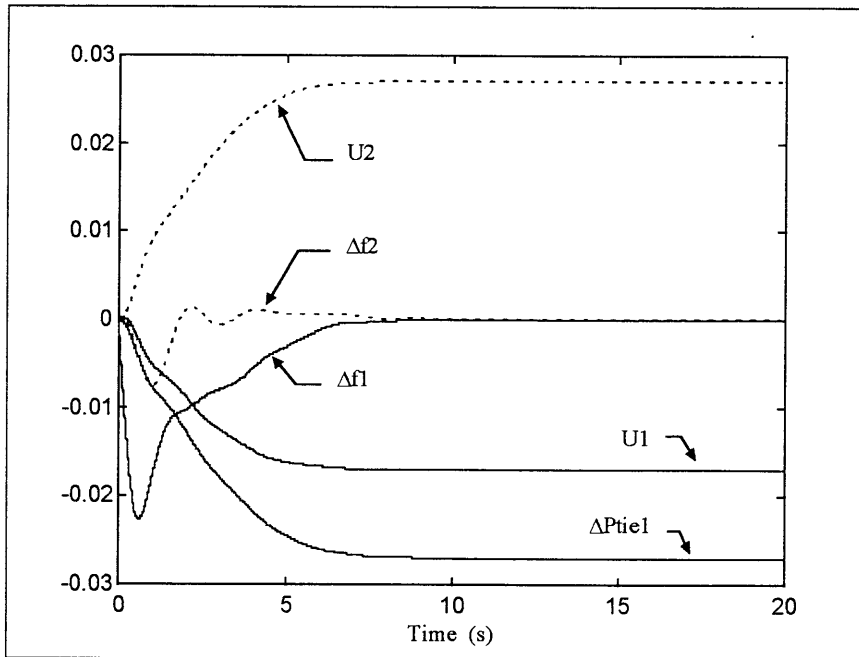


Fig. 4.18 System response following 0.01 p.u. step load change in area 1 with Hsu et. al. fuzzy LFC [85]

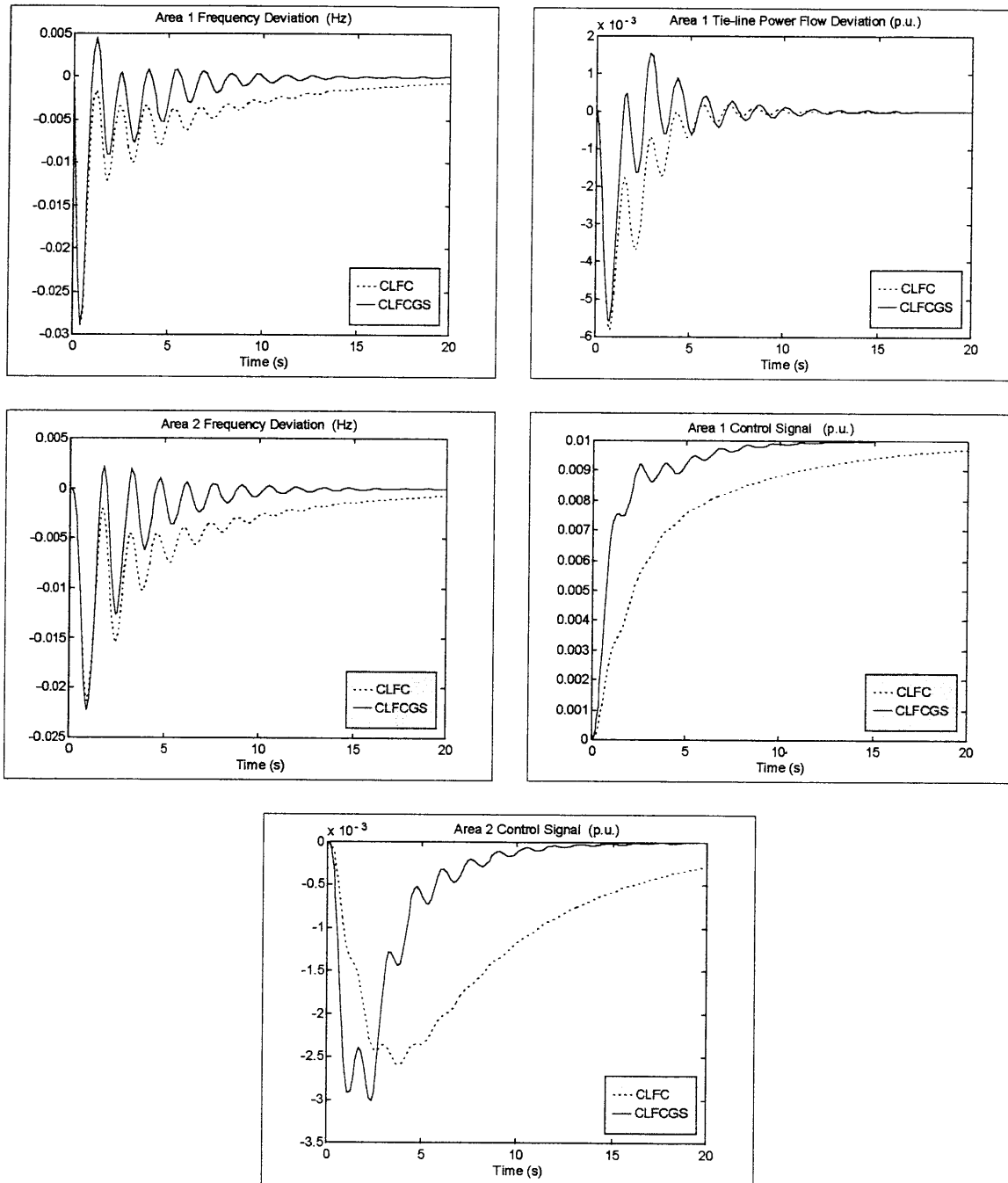


Fig. 4.19 Performance comparison between the CLFC and CLFCGS at off-nominal operating condition and following 0.01 p.u. step load change in area 1.

Table 4.9 Comparison of feedback matrix **K** and system eigenvalues obtained using the fuzzy optimal gain scheduler and Riccati matrix equation for operating conditions characterised by $T_p = 10$ s, $T_{12} = 0.5$, $b = 0.12$.

FEEDBACK MATRIX K^T OBTAINED FROM				SYSTEM EIGENVALUES OBTAINED USING	
SOLUTION OF RICCATI EQUATION		FUZZY GAIN SCHEDULER		SOLUTION OF RICCATI EQUATION	FUZZY GAIN SCHEDULER
0.1859	-0.0459	0.1378	-0.0860	-13.6737	-13.6268
0.0514	-0.1309	0.3849	-0.2242	-13.7269	-13.6735
0.1283	-0.0309	0.0964	-0.0544	$-0.8380 \pm j 4.7389$	$-0.604 \pm j 4.7572$
-0.1399	0.1399	0.1726	-0.1726	$-1.2438 \pm j 3.5353$	$-0.835 \pm j 3.3319$
-0.0459	0.1859	-0.086	0.1378	-1.843	-2.4171
-0.1309	0.5136	-0.2242	0.3849	-0.7139	-0.5501
-0.0309	0.1283	-0.0544	0.0964	-0.9185	-1.0977
1	0	1	0		
0	1	0	1		

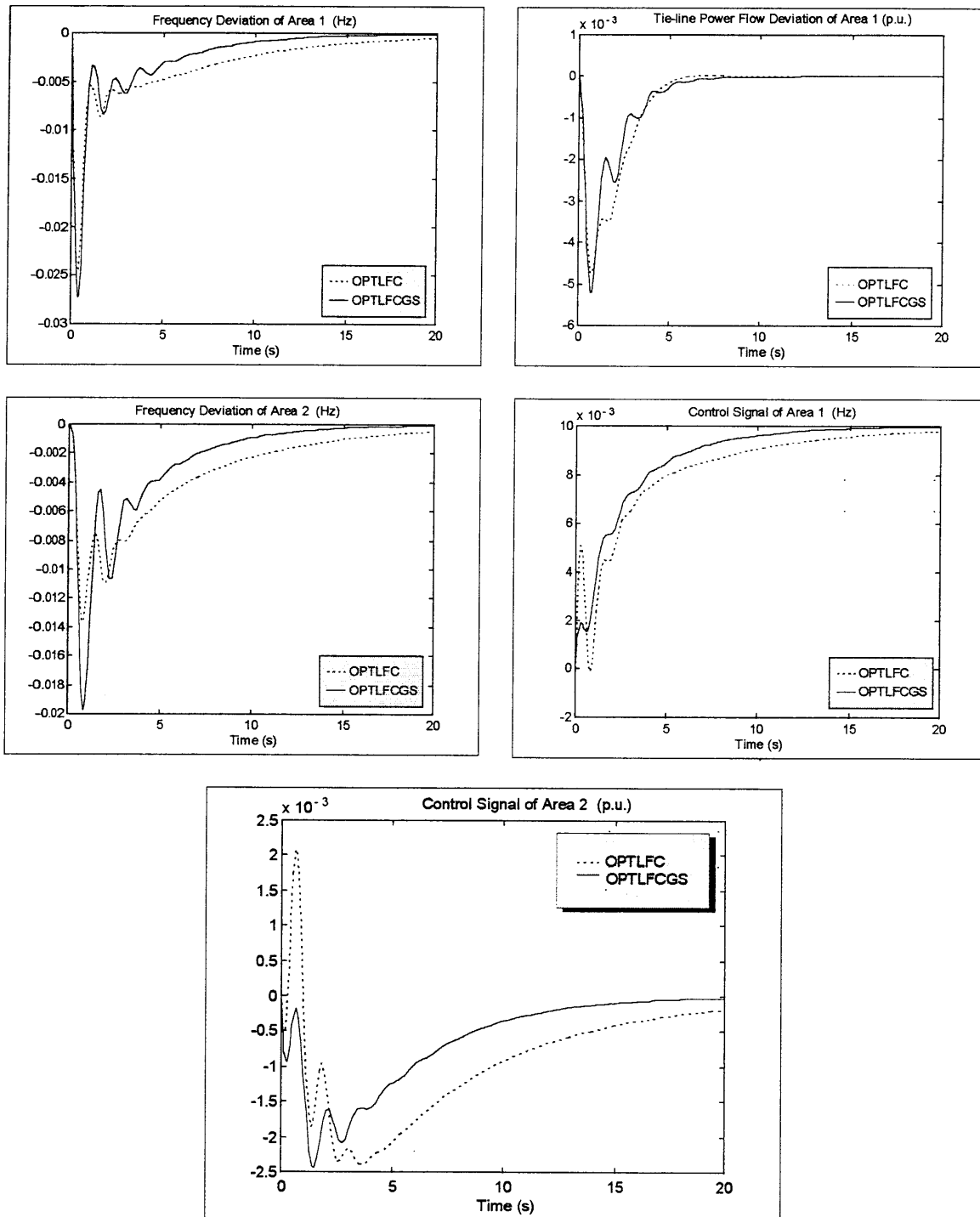


Fig. 4.20 Performance comparison between the OPTLFC and OPTLFCGS at off-nominal operating condition and following 0.01 p.u. step load change in area 1.

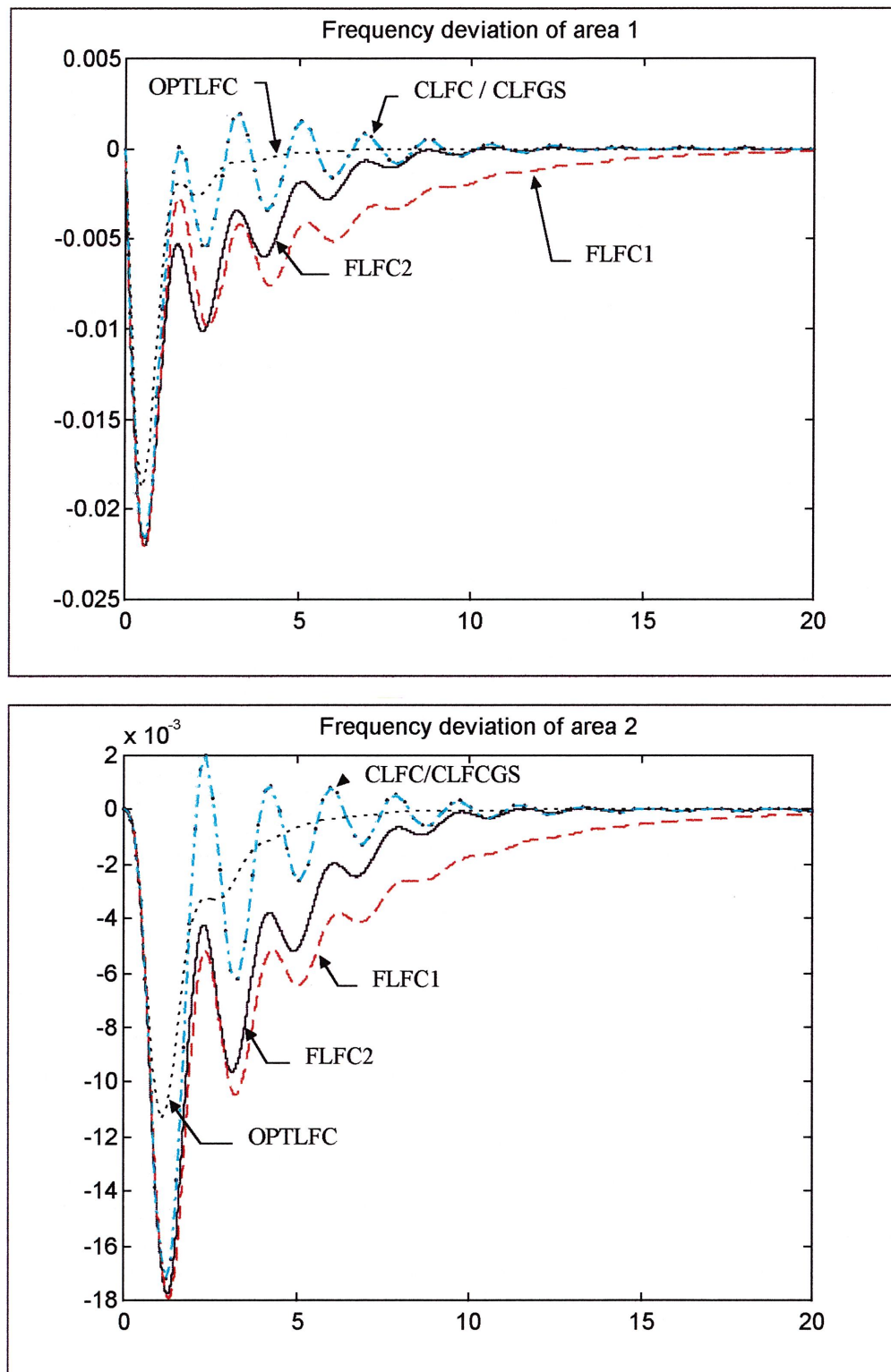


Fig. 4.21a Area 1 and 2 frequency deviation following 0.01 p.u. step load change in area 1 at nominal operating condition.

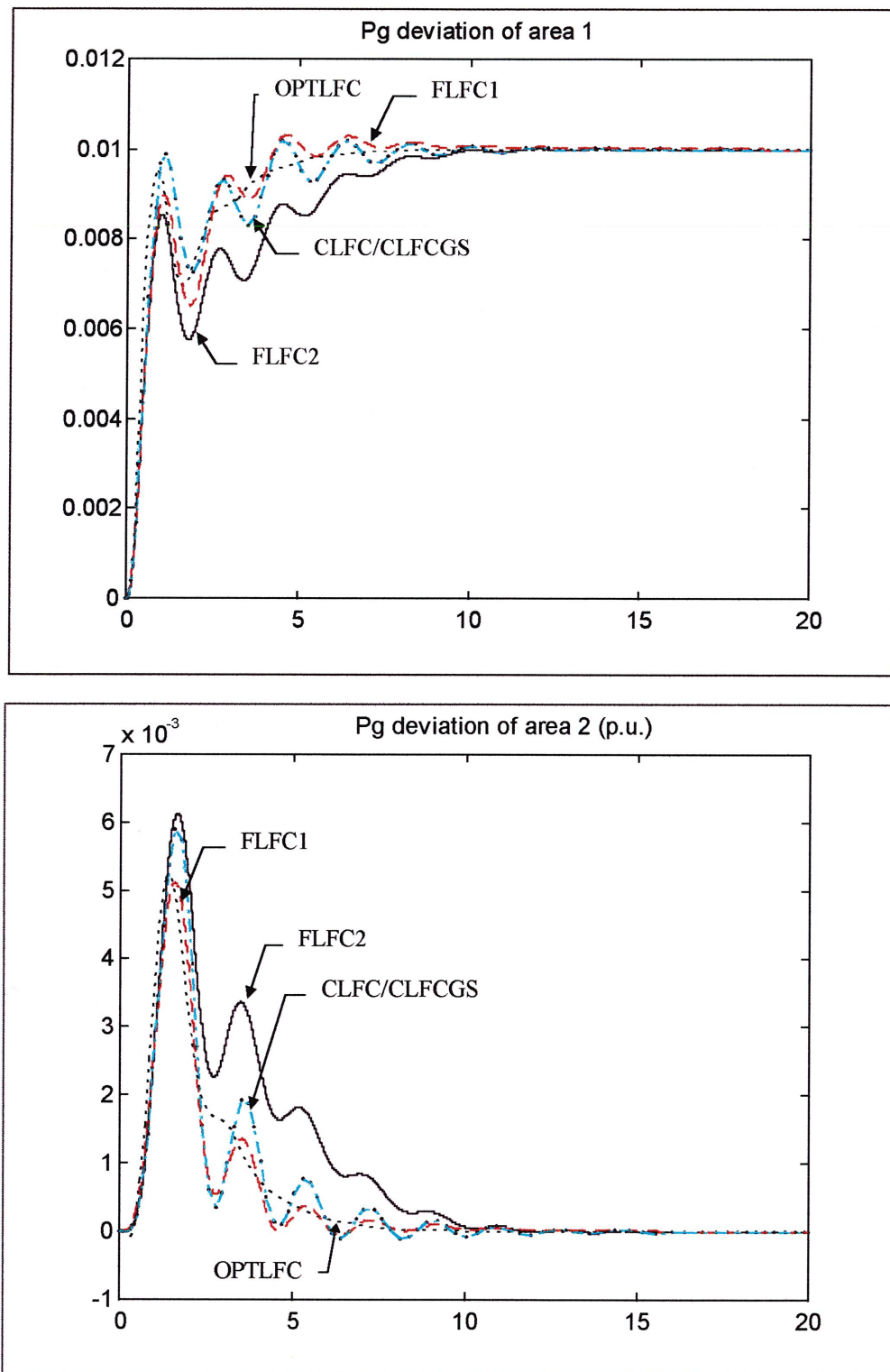


Fig. 4.21b Area 1 and 2 generation deviation following 0.01 p.u. step load change in area 1 at nominal operating condition.

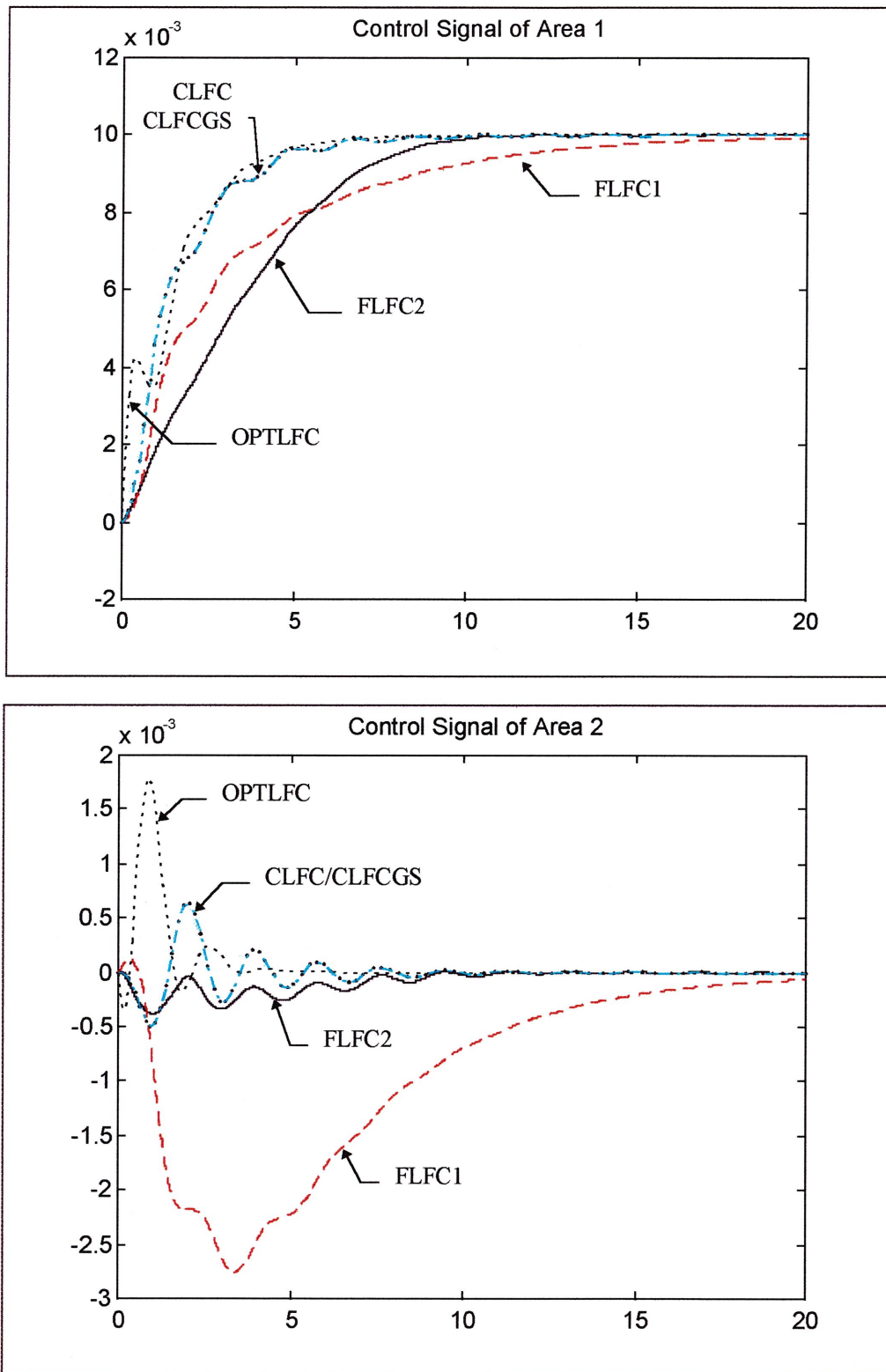


Fig. 4.21c Area 1 and 2 control signal following 0.01 p.u. step load change in area 1 at nominal operating condition.

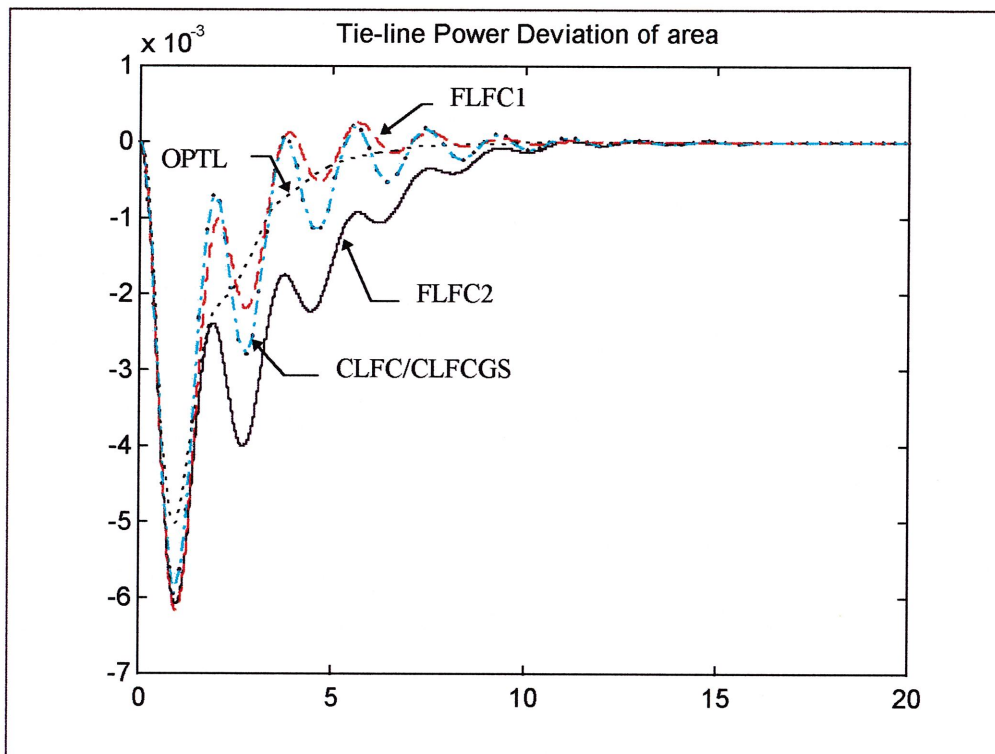


Fig. 4.21d Tie-line power flow deviation following 0.01 p.u. step load change in area 1 at nominal operating condition.

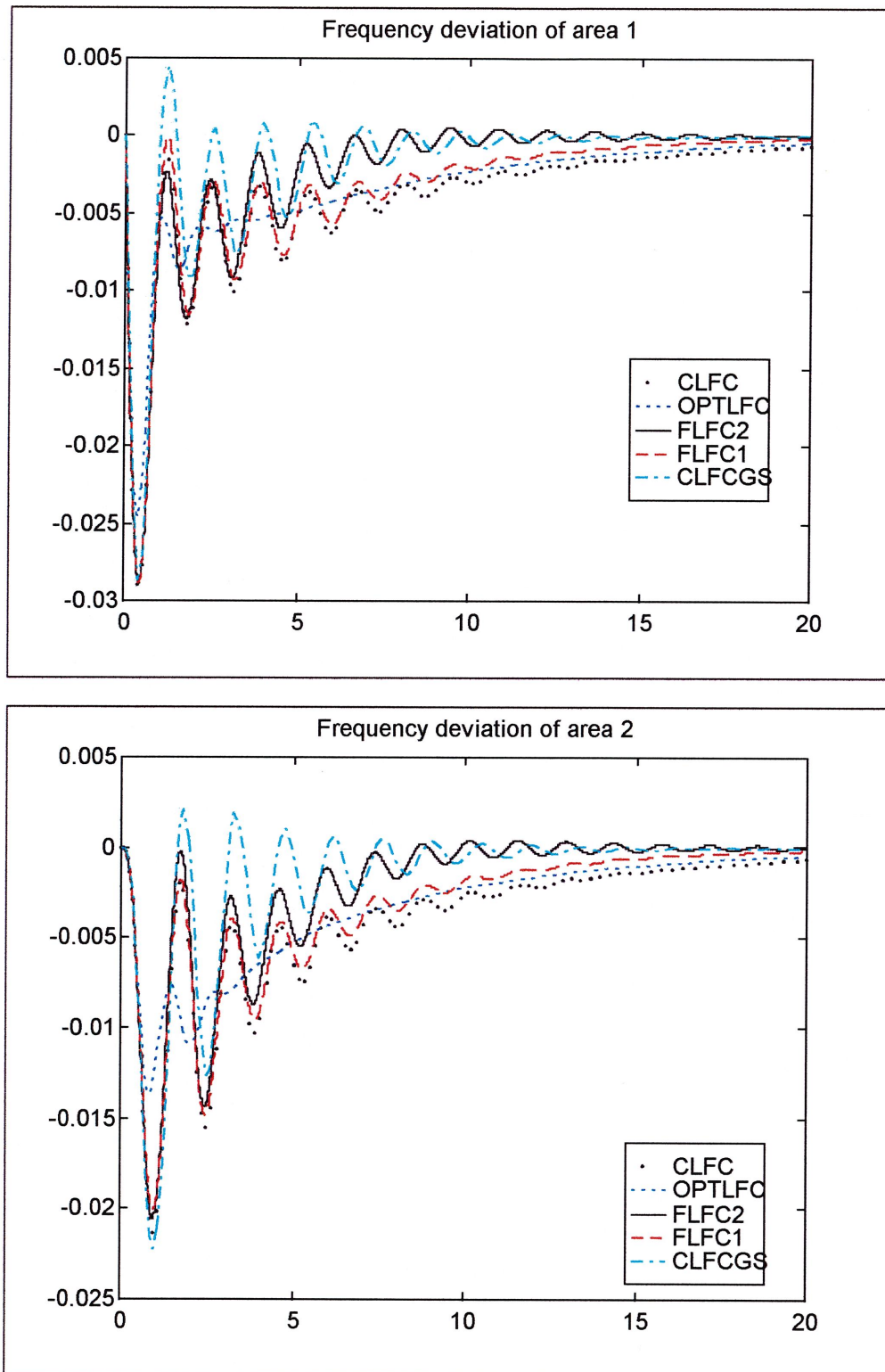


Fig. 4.22a Area 1 and 2 frequency deviation following 0.01 p.u. step load change in area 1 at off-nominal condition.

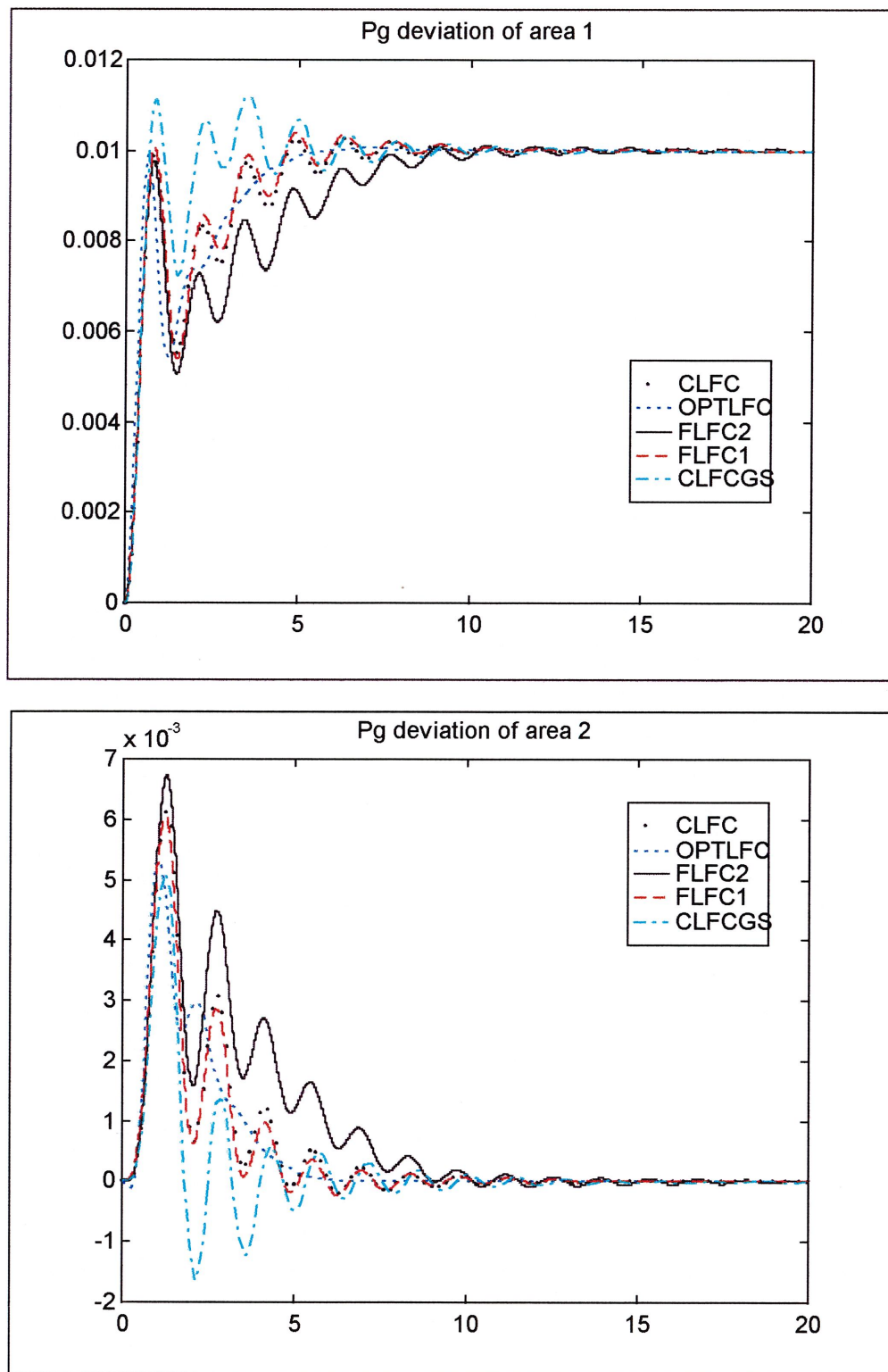


Fig. 4.22b Area 1 and 2 generation deviation following 0.01 p.u. step load change in area 1 at off-nominal operating condition.

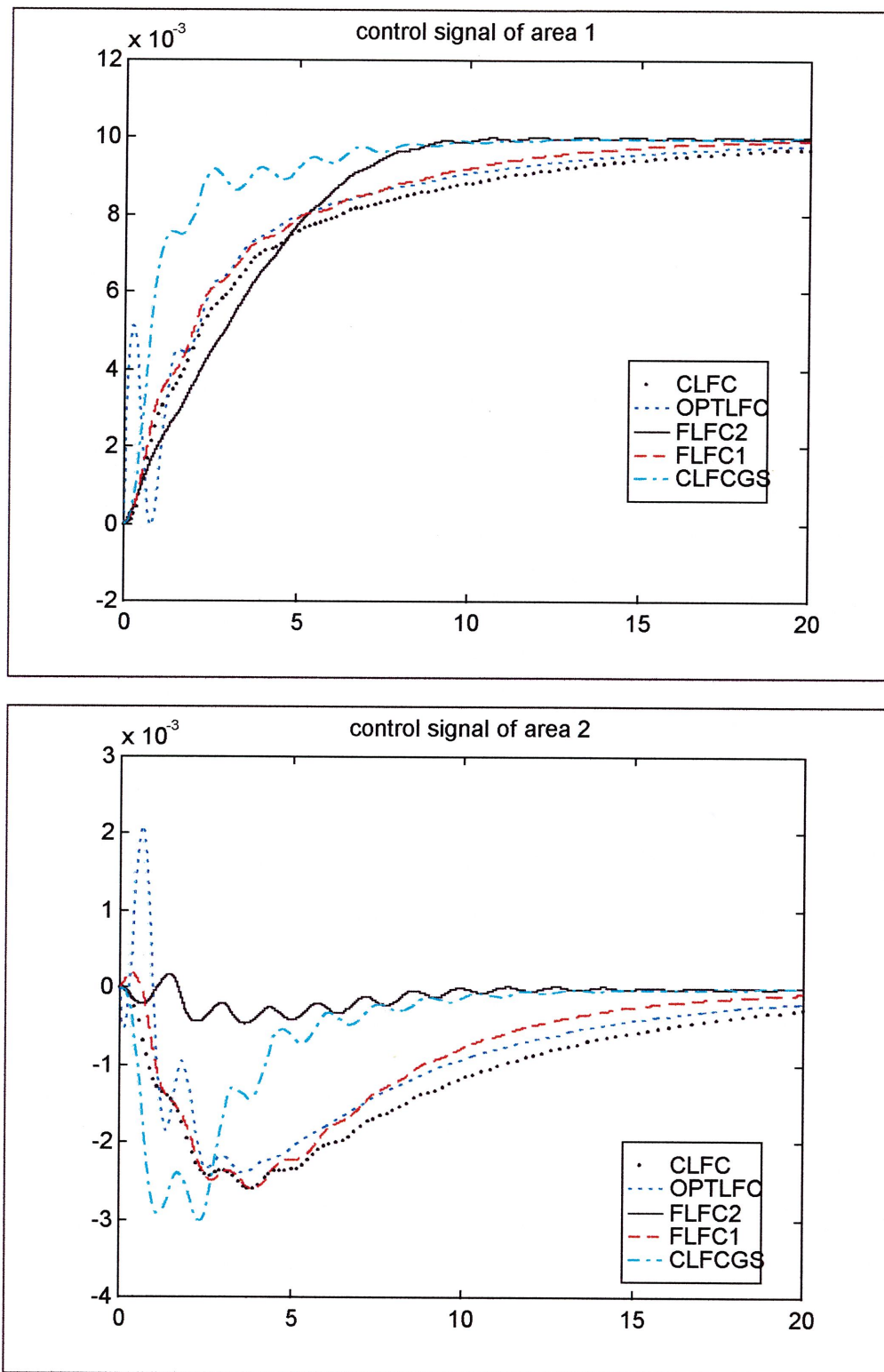


Fig. 4.22c Area 1 and 2 control signal following 0.01 p.u. step load change in area 1 at off-nominal operating condition.

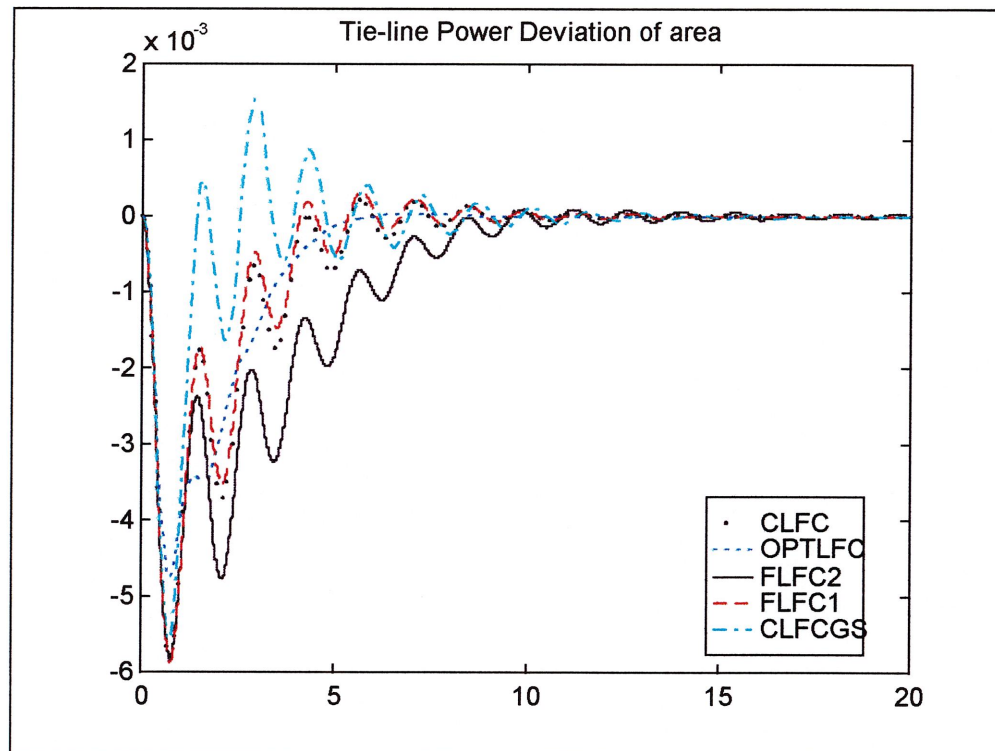


Fig. 4.22d Tie-line power flow deviation following 0.01 p.u. step load change in area 1 at off-nominal operating condition.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 SUMMARY AND CONCLUSIONS

Two applications of fuzzy logic control methodology in electrical power system control area are considered in this thesis. The application of fuzzy logic control for damping power system low frequency oscillations have been studied in the first part of this thesis. Different fuzzy logic based power system stabilizers (FLPSS) have been put under investigation with other well known power system stabilizers (PSS) such as the conventional lead compensator, optimal state regulator, suboptimal output regulator and rule-based stabilizer. A single machine infinite bus system is considered as the study system. To demonstrate the effectiveness of the fuzzy logic based PSS, the effect of system operating conditions as well as the effect of variation in machine inertia constant and transmission line reactance on system dynamics following a small disturbance in excitation reference voltage and input mechanical torque are considered for each stabilizer.

In the second part of this thesis, the application of fuzzy logic controllers for load frequency control has been investigated. In this part, two fuzzy logic load frequency controllers (FLFC) have been proposed. In addition, a conventional integral load frequency controller with fuzzy gain scheduling as well as an optimal state regulator with fuzzy gain scheduler have been also proposed. To demonstrate the

effectiveness of the proposed load frequency controllers, a comparison is made with the conventional integral LFC and the optimal state regulator.

The following conclusions are drawn from the two application of fuzzy logic controllers:

- (1) Though the optimal setting of the fuzzy controller parameters can be fixed for a specific operating condition, it is found from the simulation results in both studies, that the fuzzy control scheme is capable of enhancing the performance of the power system over a wide range of operating conditions and under different disturbances.
- (2) It is also found that the fuzzy logic is almost insensitive for system parameter variations as compared to the conventional controller, optimal, and suboptimal controllers.
- (3) The proposed load frequency controllers with fuzzy gain scheduling proved to be capable of enhancing the performance of the conventional integral and optimal controllers at off-nominal operating conditions.
- (4) The design of the fuzzy controller is model independent and does not require any real time model identification and has simple control algorithm.

5.2 CONTRIBUTIONS

In this thesis, the following points are believed to have a degree of originality:

- (1) A new fuzzy LFC based on only nine rules is proposed.
- (2) An optimal LFC with fuzzy gain scheduling concept is proposed.
- (3) An Integral type LFC with fuzzy gain scheduling concept is proposed.
- (4) A modification is made to the fuzzy Load-Frequency Controller (LFC) proposed by Indulkar et. al. [86] to overcome the non-zero steady-state error problem.

5.3 RECOMMENDATIONS FOR FUTURE WORK

- (1) Rigorous stability proof for the fuzzy controller still need further research, though some methods have been already published.
- (2) Further research is required in the area of merging between the fuzzy logic and other area of artificial intelligent (AI) such as artificial neural network (ANN), Genetic algorithm (GA) to further improve the fuzzy logic control scheme.
- (3) In the low-frequency oscillation problem, the application of the fuzzy PSS in multi-machine power system need further investigation taking into account the complexity of the multi-machine system wherein various modes of oscillations exist and the network topology (configuration) can vary largely during the electrical power system operation cycle.
- (4) The problem of Load-Frequency Control (LFC) can be further investigated by including the interaction between the AVR and Governor control loops. In addition, more constraints can be included in the study such as the generation rate constraints. Furthermore, non-identical multi-area system should be considered and the study of more than two area interconnected system can be investigated.

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APPENDIX A

A1. Parameters of the Single Machine Infinite Bus System [18]

All data are given in p.u. except for M and time constants.

A1.1 Generator:

$$\begin{array}{lll} M = 9.26 & T'_{do} = 7.76 & D = 0 \\ x_d = 0.73 & x'_d = 0.190 & x_q = 0.550 \end{array}$$

A1.2 Excitation:

$$K_A = 50 \quad T_A = 0.05 \quad E_{fdmax} = 7 \quad E_{fdmin} = -7$$

A1.3 Transmission Line and Local Load:

$$R = -0.034 \quad X = 0.99 \quad G = 0.249 \quad B = 0.262$$

A1.4 Operating Condition:

$$P_{e0} = 1.0 \quad Q_{e0} = 0.015 \quad v_{t0} = 1.05$$

A2. Constants K_1, K_2, K_3, K_4, K_5 :

$$\begin{bmatrix} K_1 \\ K_2 \end{bmatrix} = \begin{bmatrix} 0 \\ i_{q0} \end{bmatrix} + \begin{bmatrix} F_d & F_q \\ Y_d & Y_q \end{bmatrix} \begin{bmatrix} (x_q - x'_d)i_q \\ e'_{q0} + (x_q - x'_d)i_{d0} \end{bmatrix} \quad (A2.1)$$

$$K_3 = \frac{I}{[I + (x_d - x'_d)Y_d]} \quad (A2.2)$$

$$K_4 = (x_d - x'_d)F_d \quad (A2.3)$$

$$\begin{bmatrix} K_5 \\ K_6 \end{bmatrix} = \begin{bmatrix} 0 \\ v_{q0} / v_{t0} \end{bmatrix} + \begin{bmatrix} F_d & F_q \\ Y_d & Y_q \end{bmatrix} \begin{bmatrix} -x'_d v_{q0} / v_{t0} \\ -x_q v_{d0} / v_{t0} \end{bmatrix} \quad (\text{A2.4})$$

where

$$\begin{bmatrix} F_d \\ F_q \end{bmatrix} = \frac{v_0}{Z_e} \begin{bmatrix} -R_2 & X_1 \\ X_2 & R_1 \end{bmatrix} \begin{bmatrix} \cos \delta_0 \\ \sin \delta_0 \end{bmatrix} \quad (\text{A2.5})$$

$$Y_d \triangleq (C_1 X_1 - C_2 R_2) / Z_e \quad (\text{A2.6})$$

$$Y_q \triangleq (C_1 R_1 + C_2 X_2) / Z_e \quad (\text{A2.7})$$

$$\overline{v_0} = v_0 (\sin \delta + j \cos \delta) \quad (\text{A2.8})$$

$$\delta \triangleq \angle(e'_q, v_0) \quad (\text{A2.9})$$

$$C_1 \triangleq \text{real}(1 + ZY), \quad C_2 \triangleq \text{imag}(1 + ZY) \quad (\text{A2.10})$$

$$R_1 \triangleq R - C_2 x'_d, \quad X_1 \triangleq X + C_1 x_q \quad (\text{A2.11})$$

$$R_2 \triangleq R - C_2 x_q, \quad X_2 \triangleq X + C_1 x'_d \quad (\text{A2.12})$$

$$Z_e \triangleq R_1 R_2 + X_1 X_2 \quad (\text{A2.13})$$

R, X, Y, v_{t0}, v_0 are shown in Fig. 3.1.

APPENDIX B

B1: Nominal System Parameters for Two-Equal-Area System [68,76,85]

System frequency $f^o = 60\text{Hz}$

Total rated area capacity $P_r = 2000\text{ MW}$

Nominal Operating Load $P_d = 1000\text{ MW}$

Inertia Constant $H = 5.0\text{ s}$

Regulation $R = 2.40\text{ Hz/pu MW}$ (for 4% droop)

Load Frequency Characteristic Constant $D = 0.00833\text{ pu MW/Hz}$

Power system time constant $T_p \triangleq 2H/fD = 20\text{ s}$

Power system gain $K_p \triangleq 1/D = 120\text{ Hz/pu MW}$

Speed governor time constant $T_g = 0.08\text{ s}$

Turbine time constant $T_t = 0.3\text{ s}$

Frequency Bias $b = 0.425\text{ p.u. MW/Hz}$

Tie-line capacity $P_{tie\text{ max},12} = 200\text{ MW} = .1\text{ pu MW}$

Nominal tie-line power angle $\delta_1^o - \delta_2^o = 30^\circ$

Synchronising coefficient $T_{12} = 0.545\text{ pu}$

B2: The Optimal P-I Load Frequency Controller State and Control Weighting Matrices [77]:

The state weighting matrices (Q_a) for the combined system be defined as:

$$Q_a = \begin{bmatrix} b_1^2 & 0 & 0 & b_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_1 & 0 & 0 & (1 + a_{12}^2) & -a_{12}b_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -a_{12}b_2 & b_2^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (B2.1)$$

where $a_{12}=1$

and the control weighting matrix R be defined as:

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (B2.2)$$