Optimization Of Controller Parametersfornon-Linear Power Systems Using Different Optimization Techniques

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Abstract

The problem of designing controllers for non-linear power system is considered here. In case of fault in the power system, power angle and the terminal voltage are the parameters which are to be monitored. The non-linear controller is designed using Direct Feedback Linearization (DFL) technique. The simulation has been carried out taking different values of initial power angles and results were obtained for power angle and terminal voltage. Due to the limitations of fuzzy logic controller, genetic algorithm and particle swarm optimization are taken as optimization techniques for optimizing controller parameters. The consequent parameters of fuzzy logic controller can be optimized with genetic algorithm. The shape of the output characteristic can be smoothened by means of optimization technique. The paper presents the results on power angle and terminal voltage for non-linear power systems. The emphasis is on establishing a controller for transient and fault condition occurring in power system.

Keywords: *Automatic Voltage Regulator (AVR), Power System Stabilizer (PSS), Direct feedback linearization (DFL), Fuzzy Logic Controller (FLC), Genetic Algorithm (GA)*

1. Introduction

For engineering system large ranges of operations cannot be avoided, and the non-linearities and uncertainties involved in the system models as well as the disturbances present in the environment cause the extreme complexity of the global problem. System stability is the most important issue for power systems; if stability is lost, network collapse may occur with devastating economical losses and power grid damages. Considerable attention has been given in the literature to excitation control system design and its performance characteristic in enhancing power system stability. Transient stability and the voltage regulation are of major concern in large disturbance dynamic performance assessment of power system. The basic function of excitation system is to supply and automatically adjust the field current of the synchronous generator to regulate terminal voltage. The power system stabilizer provides the supplementary signal through the excitation AVR loop which dampens the power oscillations. The common feature of AVR/PSS controller is that they are typically based on model established by approximate linearization of non-linear equation of a power system at certain operating point. This kind of controller suffers performance degeneracy when operating condition change due to highly non-linear inherent characteristic of power system. [1],[2]. To assess the performance of the excitation system in enhancing stability, the design criterion must take into account operation under realistic power system disturbances and hence the non-linearities of the plant must be included [3]. The DFL approach arose from practical concerns, related to power system nonlinearity [3],[4] and was subsequently developed to deal with a number of power system control issues.

2. Dynamical model of power system

We focus our attention on single machine infinite bus power system. Since a SMIB system qualitatively exhibit important aspects of the behavior of a multi-machine system and is relatively simple to study. It is extremely useful in describing the general concept of power system stabilizer, the influence of various factors upon stability and alternative controller concepts. In power system dynamics, the most important component is the synchronous generator with its associated excitation control. Although the actual dynamic response of a synchronous generator in a practical power system when a fault occurs is very complicated including many non-linearities such as the magnetic saturation, the classical third order dynamic generator model is commonly used for designing the excitation controller.

The single machine infinite bus model for power system is shown in fig.1. The classical third order dynamical model of a SMIB power system can be written below:

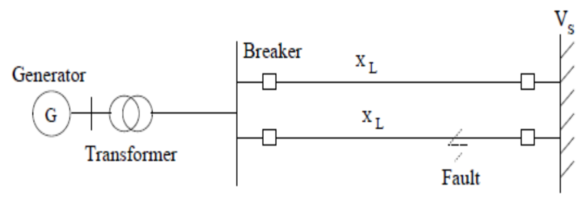

Figure 1. Schematic model of SMIB system

Mechanical equation:

$$\Delta\dot{\delta}(t) = \omega(t) \quad (1)$$

$$\dot{\omega}(t) = \frac{-D}{H}\omega(t) - \frac{\omega_0}{H}\Delta P_e(t) \quad (2)$$

Generator Electrical Dynamics:

$$E\dot{q}(t) = \frac{1}{T_{do}}(E_f(t) - E_q(t)) \quad (3)$$

Electrical Equations:

$$E_q(t) = \frac{x_{ds}}{x_{ds'}}E_q'(t) - \frac{x_d - x_d'}{x'_{ds}}V_s cos\delta(t) \quad (4)$$

$$E_f(t) = K_c\, u_f(t) \quad (5)$$

$$P_e(t) = \frac{V_s E_q(t)}{x_{ds}} sin\delta(t) \quad (6)$$

$$I_q(t) = \frac{V_s}{x_{ds}} sin\delta(t) = \frac{P_e(t)}{x_{ad} I_f(t)} \quad (7)$$

$$Q_e(t) = \frac{V_s}{x_{ds}} E_q(t) cos\delta(t) - \frac{V_s^2}{x_{ds}} \quad (8)$$

$$E_q(t) = x_{ad}\, I_f(t) \quad (9)$$

$$V(t) = \frac{1}{x_{ds}}\{x_s^2 E_q^2(t) + V_s^2 x_d^2 + 2x_s x_d x_{ds} P_e(t) cot\delta(t)\}^{1/2} \quad (10)$$

The model (1) to (3) is linearized using direct feedback linearization (DFL) technique.[5]

The linearized model is

$$\Delta\dot{\delta}(t) = \omega(t) \quad (11)$$

$$\dot{\omega}(t) = \frac{-D}{H}\omega(t) - \frac{\omega_0}{H}\Delta P_e(t) \quad (12)$$

$$\Delta\dot{P_e}(t) = -\frac{1}{T_{do}'}\Delta P_e(t) + \frac{1}{T_{do}'} v_f(t) \quad (13)$$

$v_f(t)$ is the new input defined as:

$$v_f(t) = I_q(t)\left[K_c\, u_f(t) + T_{do}(x_d - x_d')\frac{V_s}{x_{ds}} sin\delta(t)\omega(t)\right] + T_{do}'\left[Q_e(t) + \frac{V_s^2}{x_{ds}}\right]\omega(t) - P_m$$

After linearization, we can employ linear control theory, such as LQ-optimal control theory, to design a feedback law given as

$$v_f(t) = f(\delta(t), \omega(t), P_e(t))$$

To give the desired stability and performance properties, $v_f(t)$ and $P_e(t)$ are the control inputs.

The fault considered in this paper is a symmetrical three-phase fault, permanent type.

The fault sequence is described as:

Stage 1: the system is in a pre-fault steady-state

Stage 2: a fault occurs at t=0.1 sec

Stage 3: the fault is removed by opening the breakers of the faulted line at t=0.25 sec

Stage 4: the system is in a post-fault state.

3.Controller design technique

The problem of PSS parameter tuning is a complex exercise. In recent years, several approaches based on optimal control, adaptive control, variable structure control and intelligent control have been applied to PSS design problem.

Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead-lag controller design.[6] The gain setting of these stabilizers are determined based on the linearized model of the power system around a nominal operating point. Since power system are highly non-linear and the operating conditions can vary over a wide range, conventional power systems performance is degraded when the operating point changes from one to another because of fixed parameters of the stabilizers. Also conventional techniques are time consuming as they are iterative and require complex computation procedures and show convergence.

Recently metaheuristic optimization technique like GA, Tabu Search, simulated annealing, Bacteria foraging, PSO[7-9] have been applied for PSS parameter optimization. In this paper PSO algorithm has been implemented to calculate the optimum value of PSS parameters. PSO is a population based stochastic optimization technique inspired by social behaviour of bird flocking or fish schooling [9]. PSO shares many similarities with GA like initialization of population of random solution and search for the optimal solution by updating generations.

A. *Fuzzy logic controller*

Fuzzy logic control is a method based on fuzzy set theory, in which the fuzzy logic variables can be of any value between 0 and 1 instead of just true or false. When the variables are selected, the decision will be made through specific fuzzy logic function.Although FLC have been successfully applied in many complex industrial processes, they experience a deficiency in knowledge acquisition and rely to a great extent on empirical and heuristic knowledge which in many cases can't be obtained easily. There is no generalized method for the formulation of fuzzy control strategies, and design relies on repeatedly modification of control rules to obtain satisfactory performance.

FLC controls have been demonstrating their feasibility in the field use. Expert's knowledge can be incorporated into fuzzy rules. Design of FLC is generally to determine:
Input and output variables.
Parameters of MF's
Fuzzy rules, to improve performance of FLC
Parameter tunings are needed

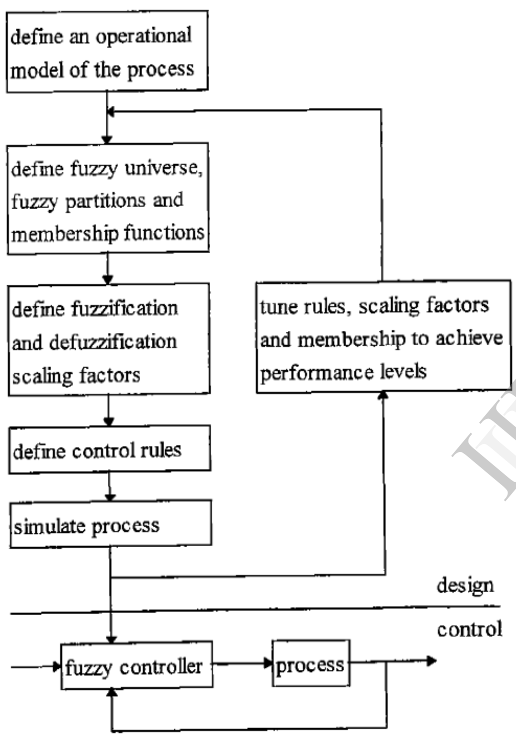

Figure 2. Fuzzy design methodology

Table 1: Rule base with five membership function

$\Delta\omega$ / $\Delta\dot{\omega}$	NB	NS	ZO	PS	PB
NB	NB	NB	NB	NS	ZO
NS	NB	NS	NS	ZO	NS
ZO	NB	NS	ZO	PS	PB
PS	NS	ZO	PS	PS	PB
PB	ZO	PS	PB	PB	PB

Figure 2 shows the block diagram for implementation of fuzzy logic controller. Figure 3 shows the rule base for a 5×5 membership function. Where $\Delta\omega$ and $\Delta\dot{\omega}$ are the inputs to the fuzzy logic controller.

4. Optimization tools for tuning controller parameter

Genetic algorithm (GA)is a method for solving both constrained and unconstrained optimization problems that is based on natural selection. The GA repeatedly modifies a population of individual solution. At each step, the GA selects individuals at random from the current population to parents and uses them to produce the children for the next generation. Over successive generations, the population evolved toward an optimal solution. The optimization methods like GA and Particle swarm optimization (PSO) can be incorporated in a fuzzy system to improve the results when the number of variables is incremented.

A. GA-Based Optimal Tuning

Genetic algorithm is an efficient optimization approach in complex control systems with many tuning parameters. In fuzzy logic controller, many parameters influence the behaviour of it. They are shape of the membership function, consequent parameters, scaling factors etc. the conventional optimization techniques are usually not efficient enough for stabilizing the system. The parameters of FLC can be optimized with Genetic algorithm. Genetic algorithm (GA) is an optimization method based on the mechanics of natural selection and natural genetics. Its fundamental principle is the fittest member of population has the highest probability for survival.The most familiar conventional optimization techniques fall under two categories viz. calculus based method and enumerative schemes. Though well developed, these techniques possess significant drawbacks. Calculus based optimization generally relies on continuity assumptions and existence of derivatives. Enumerative techniques rely on special convergence properties and auxiliary function evaluation. The genetic algorithm, on the other hand, works only with objective function information in a search for an optimal parameter set. The GA can be distinguished from other optimization methods by following four characteristics.

- The GA works on coding of the parameters set rather than the actual parameters.
- The GA searches for optimal points using a population of possible solution points, not a single point.
- The GA uses only objective function information. No other auxiliary information (e.g. derivatives, etc.) is required.

- The GA uses probability transition rules, and not the deterministic rules.

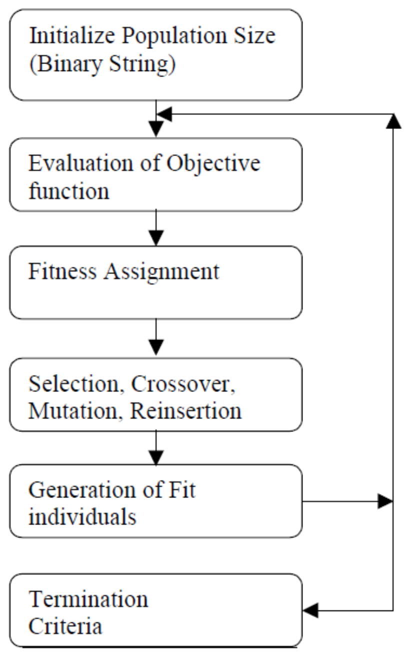

Figure 3. Flow chart for Genetic Algorithm

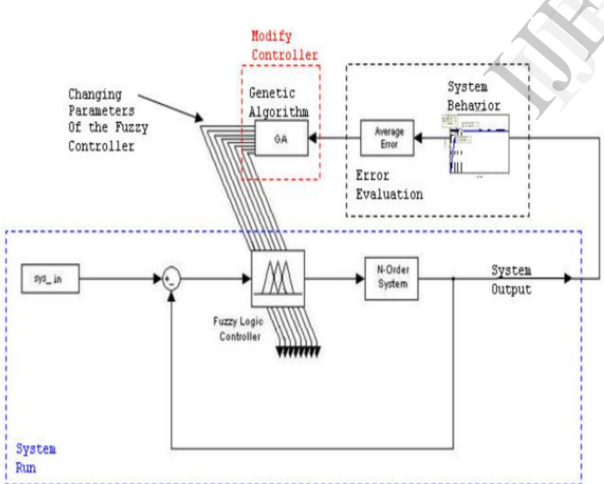

Figure 4.Schematic diagram of the controller design and GAtuning process

Above figure3. shows the flow chart for Genetic Algorithm.The genetic operation can be implemented to determine almost all of the parameters in fuzzy controllers. Figure 4 shows the schematic diagram for controller design for implementing GA based tuning.

B. Particle swarm optimization

The particle swarm optimization (PSO) is a new evolutionary computation technique and has been introduced in various application fields in recent years. [10] PSO is a meta-heuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classical optimization methods such as gradient descent and quasi-newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc. PSO is originally attributed to Kennedy, Eberhart and Shi [11] [12] and was first intended for simulatingsocial behaviour,[13] as a stylized representation of the movement of organisms in a bird flock or fish school. The convergence of the PSO algorithm toward the global optimal solution is guided by the objective function. This method for optimization can be used for optimizing the controller parameters of power system. PSO algorithm can perform well in the nonlinear PID control system design.

5. Simulation Results

In this section, through simulation results in different cases the power angle and terminal voltage responses has been shown. Figure5 and 6 shows the power angle and voltage responses for initial power angle of 72 degree and mechanical input power of 0.9 p.u.

The controllers employed in the simulations are:

DFL-LQ controller

$$v_{f1} = 19.3\partial + 6.43w - 47.6\Delta Pe + Pmo$$

Voltage controller

$$v_{f2} = -47.03\Delta Vt + 6.93w - 28.6\Delta Pe + Pmo$$

We observe that using only DFL-LQ optimal controller or a DFL voltage regulator, one cannot achieve both good transient response and good post-fault performance. To overcome this problem a typical switching scheme is selected, the switching time should be reasonably chosen within the post-transient period,

which requires that the fault sequence must be known as a prior. Further the exact switching time has to be determined by trial in simulation. The simulation results for co-ordinated controllers are shown in figure 8 and 9.

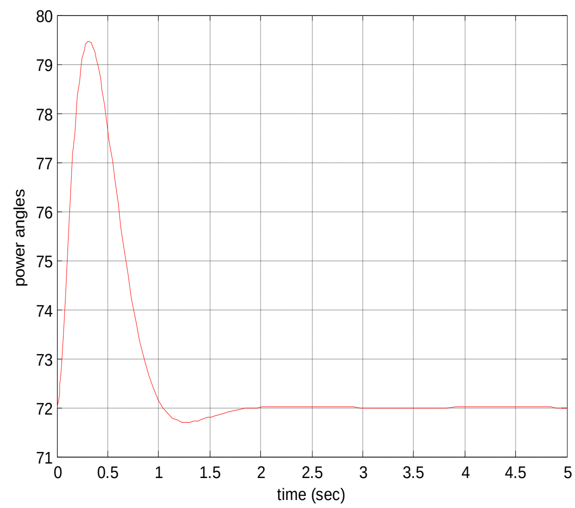

Figure5: Power angle response for initial angle 72 and Mechanical power, Pm0=0.9

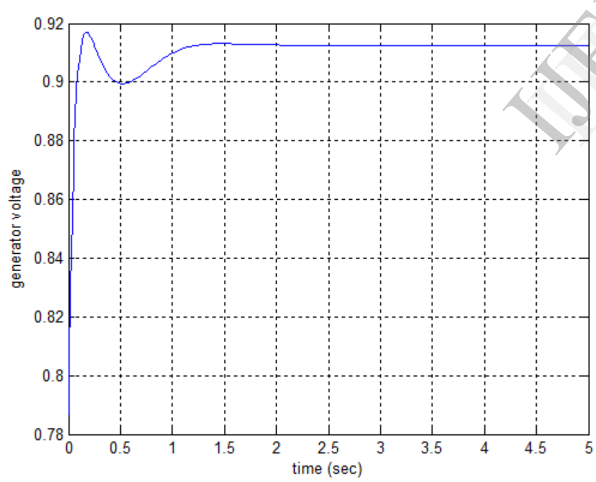

Figure6: Terminal voltage for initial angle 72 and Mechanical power, Pm0=0.9

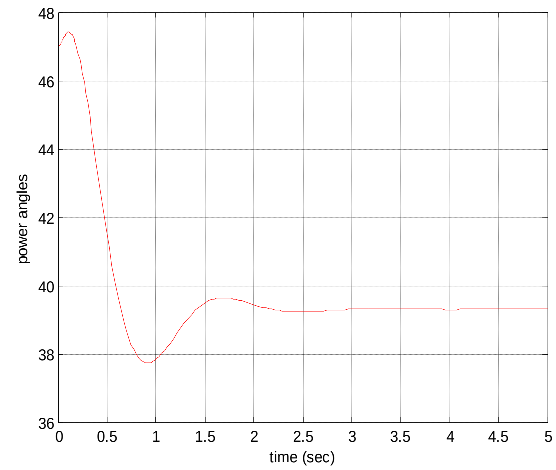

Figure 7: Power angle response for Excitation controller

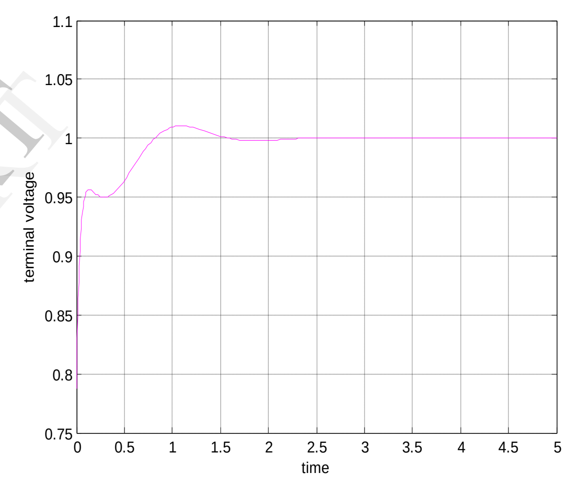

Figure 8: Voltage response for Excitation controller

6. Conclusion

New variable structure excitation and coordinated controllers for a power system have been proposed in this paper to achieve both transient stability enhancement and good post-fault performance of the generator terminal voltage$V_t(t)$. These are proposed as alternative to the usual AVR/PSS combination in generator control. Design procedure has been developed for the controllers. The new controllers have been tested through simulation in different cases and the controllers have been compared against each other. The simulation results show that both transient stability enhancement and good post-fault performance of the generator terminal voltage $V_t(t)$ can be achieved. They are independent of the operating point of the system. They are simple and effective. The coordinated controller can maintain transient stability of the system even when a large sudden fault occurs close to the generator terminal.

The further work to be done is to design optimized power system controller using the optimization techniques discussed in the paper.

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APPENDIX

The parameters of SMIB power system are as follows:
$Xd = 1.863$, $xd' = 0.257$, $x_T = 0.127$
$Tdo' = 6.9$, $x_L = 0.4853$, $H = 4$, $D = 5$,
$Kc = 1$, $xad = 1.712$, $w_0 = 314.159$
The physical limit of excitation voltage is taken as
$-3 \leq Kcuf \leq 6$
The operating point of the power system used in simulation is:
$\delta 0 = 72$, $Pm0 = 0.9$ p.u, $Vt0 = 1.0$ p.u.

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