FUZZY RULE TABLE OPTIMIZATION OF POWER SYSTEM STABILIZER USING GENETIC ALGORITHM

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Abstract: *This paper investigated the rule table optimization of fuzzy power system stabilizer (FPSS) benefiting from rule basis of related previous studies. In the previous studies, fuzzy rules for Power System Stabilizer (PSS) were obtained by trial and error according to the experience of experts. There were a few rule tables occurred in that way in the literature. In this subject field, five rule tables with a few differences among them were taken. Genetic algorithm (GA) was employed as an optimization method, and single machine infinite bus (SMIB) model was used for simulation system. This work proposed to contribute optimization performance of FPSS adding these rule tables to the initial population of GA. Thus GAs reached an optimum solution more quickly. Simulation studies and the integral of absolute error (IAE) performance results for four loading conditions were shown. The effectiveness of the proposed approach was discussed by comparing it with the five rule tables.*

Keywords: *Power system stabilizer, optimization, fuzzy control, rule table, genetic algorithm*.

1. Introduction

Power systems are complex non-linear systems and often exhibit low frequency electro-mechanical oscillations due to insufficient damping caused by adverse operating conditions. PSSs are widely used to suppress these oscillations and enhance the overall stability of power systems [1]. Several methods are used in the design of PSSs. Various tuning methods of conventional power system stabilizer (CPSS) and FPSS applications have been mentioned in the literature [2-3].

A number of PSSs was applied in the simulation model of the power system and their stabilizing effects were investigated. The action of conventional PSS (CPSS) is to extend angular stability limits of a power system by providing supplemental damping to the rotor oscillations through generator excitation [4]. To accomplish this same action, FPSS, a fuzzy logic based controller, uses fuzzy design parameters such as scaling factors, membership functions, and a rule table. FPSSs generally use speed deviation and its derivative as input signals.

Fuzzy control techniques have been applied to PSSs since 1990. Two feedback signals, speed deviation, and its derivatives are widely used as inputs to the FPSS system. In the literature, a few rule bases obtained from FPSS design have come to the fore of the studies using these input variables. Although they have the same logic base, there are just a few differences among them. Five examples of rule tables in the literature can be given to fulfill PSS function as 1st [4], 2nd [5], 3rd [6], 4th [7], and finally as 5th [8].

In order to increase controller performance, it may be necessary to optimize its parameters. In the same way, the fuzzy controller contains a number of sets of parameters. These are fuzzy membership functions [9], scaling factors [6] and a fuzzy rule table [8]. Different methods were used to optimize these parameters. Tabu search [8] and GAs [1],[10-13] are among them.

GA is defined as a global optimization technique based on the mechanics of natural selection and survival of the fittest [14]. They can be described as being global search methods. They are optimization algorithms which do not require information about derivatives and have been successfully applied to PSS design [15-17].

The modification of the rule base was chosen as the main focus in this paper where the improved performance was done via GA. Five of the rule tables that used previous FPSS applications were chosen. These tables were put in randomized to generate an initial population of candidate solutions in the optimization process of GA. Thus, it enabled the process to begin from these rule tables formed via expert vision. It provided both increasing success and rapidity of GA to find an optimum solution.

The objective function of the GA was evaluated via the simulation of a Matlab / Simulink model of a single machine infinite bus (SMIB) system. In other words, the simulation result gave the objective function result. The proposed result was compared with the results of the rule table chosen from previous FPSS studiesand CPSS tuned for the system. Granting to the simulation effects and the quantitative criteria of measuring operations, the proposed approach provided a good damping over a spacious range of loading conditions.

Received on: 25.05.2017
Accepted on: 20.07.2017

2. Power System Stabilizer for a Single Machine system

A linearized model of Heffron-Phillips was used in a Matlab/Simulink environment as a simulation model (Figure 1). The model, SMIB, is comprised of a synchronous generator with a terminal voltage “ ” connected to an infinite bus with a voltage “ ” through a lossless transmission line having external reactance “ ”. The dynamic behavior of SMIB system was modeled by [18-19].

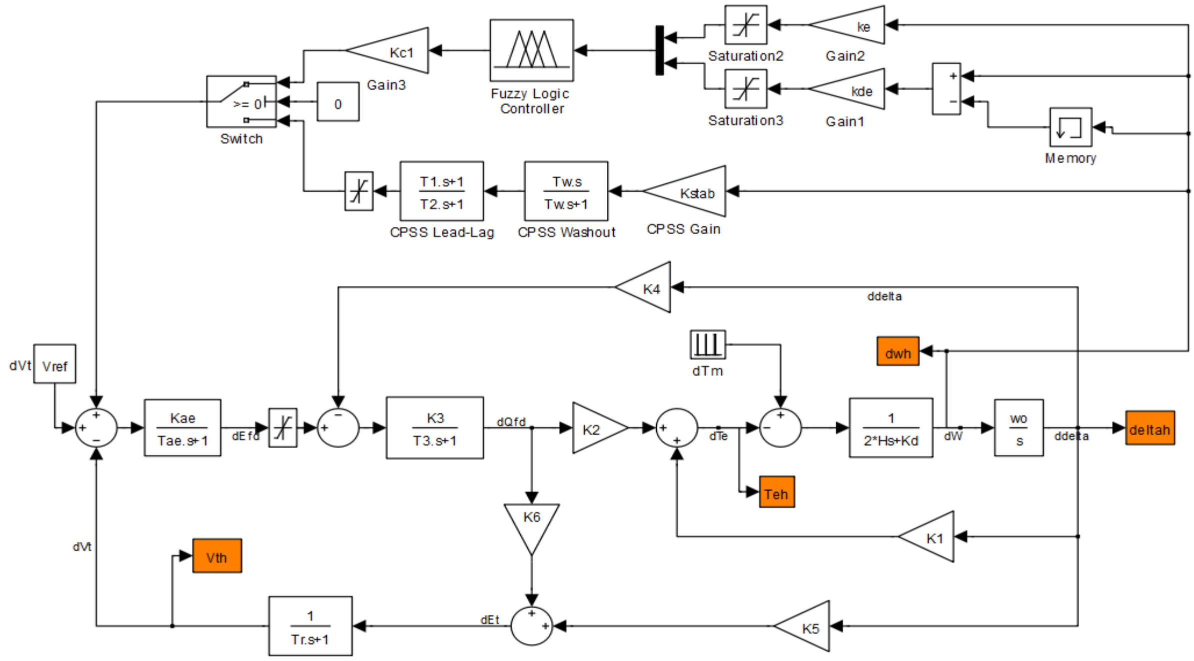

Figure 1. SMIB system with CPSS or FPSS

The model used in this study was third-order and included an exciter modeled as a first order transfer function. The exciter part tries to equalize the terminal voltage value "v_t" to the reference voltage "v_{ref}". In order to fulfill this task, it uses a controllable excitation voltage "E_{fd}". "v_{ref}" and mechanical torque "T_m" can be used as disturbance inputs of the system. It is important that reference values of the model should be normally zero because the model is based on differences. Thus, reference inputs can be applied as a disturbance.

In this study, a Heffron-Phillips model was equipped with a simplified exciter and CPSS. CPSS can be assumed as adopted for this system, because simulation data belonging to both the model and CPSS were taken from [20]. Simulations were implemented using Matlab/Simulink. Deviations of output voltage and power angel were used as performance evaluation of the system. In order to observe dynamic behavior of the system, a disturbance signal was applied to voltage and mechanical torque inputs. In order to obtain quantities of the variations belonging to system dynamics, IAE is used (1). The smaller IAE values imply a better performance [21]. IAE computing is started after the system has stabilized, to obtain more accurate results.

$$IAE(x) = \int |x| \cdot dt \tag{1}$$

Light, moderate, heavy and reactive loading conditions of the CPSS system expressed as six K coefficients are shown in Table 1 [20]. The reactive loading condition uses three times increased external reactance "X_e". The performance of the system can be evaluated under these loading conditions.

Table 1. Four loading conditions applied for power plant

	Light	Moderate	Heavy	Reactive
P (p.u.)	0,6	1,5	1,8	1,0
Q (p.u.)	0,0361	0,2303	0,3352	0,3333
X	Xe	Xe	Xe	3*Xe
K1	1,4336	1,6117	1,5911	0,7430
K2	1,5855	1,8883	1,8987	1,0776
K3	0,2889	0,2889	0,2889	0,4180
K4	2,0294	2,4170	2,4303	1,3794
K5	0,0194	-0,1524	-0,1717	-0,1739
K6	0,2628	0,1898	0,1866	0,4561

In order to compare with CPSS, a Mamdani type FPSS block from [22] was applied. It was tuned for the same system and claimed that the FPSS has a superior performance than CPSS (Fig. 1). But in [22] CPSS were taken from [23].

Speed deviation "$\Delta\omega$" and acceleration "$p\Delta\omega$" of the generator were chosen as input signals of the FPSS, and product of two sigmoid curves was chosen as the membership functions. The membership function of the speed deviation is shown in Figure 2. Limits of the second input and output "Δu_{PSS}" were taken as ±0.003 and ±0.2 respectively. The size of these membership function boundaries was estimated looking the size of the input and output signals in CPSS simulation.

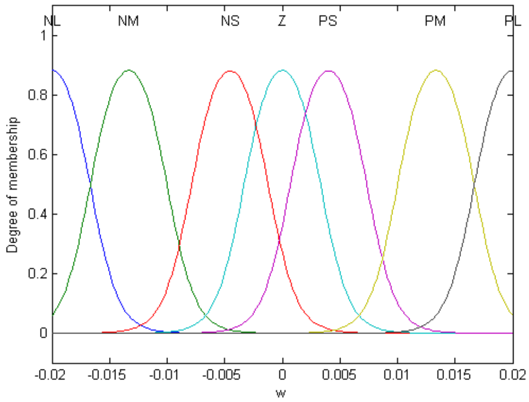

Figure 1. Membership function of first input [22]

Because middle values of input variables were more intensive, these functions were lumped in the middle value. Beside these function limits, scaling factors were tuned using trial and error method to improve a performance of the FPSS. These coefficients for speed deviation, its derivative and output of controller were taken as 1, 0.8 and 5 respectively. Moreover, min and max operators were used for implication and aggregation methods which are also used as AND/OR methods for the fuzzification part, respectively. The bisector method is chosen for the defuzzification. Finally, rule table with seven linguistic variables and 49 rules for the FPSS are given in Table 2 and named as a rule1.

Table 2. Fuzzy rule table for PSS "rule1" [4]

Δω	pΔω						
	NL	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NL	NM	NM	NS	Z
NM	NL	NM	NM	NM	NS	Z	PS
NS	NL	NM	NS	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PS	PM	PL
PM	NS	Z	PS	PM	PM	PM	PL
PL	Z	PS	PM	PM	PL	PL	PL

3. Previously Designed Rule Tables for PSS

The rule table of a fuzzy logic based controller is often determined by trial and error method in order to achieve better control performance [5]. In addition to rule1, four more rule tables were chosen from previous studies related FPSS applications and named as rule2 to rule5. All of them were tuned via trial and error and their differences from the rule1 were signed as dark background (Tables 3 - 6). In order to obtain superior performance, optimization of the FPSS parameters is necessary.

Table 3. Fuzzy rule table for PSS "rule2" [5]

Δω	pΔω						
	NL	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NL	NM	NM	NS	Z
NM	NL	NL	NM	NM	NS	Z	PS
NS	NL	NM	NS	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PS	PM	PL
PM	NS	Z	PS	PM	PM	PL	PL
PL	Z	PS	PM	PM	PL	PL	PL

Table 4. Fuzzy rule table for PSS "rule3" [6]

Δω	pΔω						
	NL	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NL	NM	NM	NS	Z
NM	NL	NL	NM	NM	NS	Z	PS
NS	NL	NM	NM	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PM	PM	PL
PM	NS	Z	PS	PM	PM	PL	PL
PL	Z	PS	PM	PM	PL	PL	PL

Table 5. Fuzzy rule table for PSS "rule4" [7]

Δω	pΔω						
	NL	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NL	NL	NM	NS	Z
NM	NL	NL	NM	NM	NS	Z	PS
NS	NL	NM	NS	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PS	PM	PL
PM	NS	Z	PS	PM	PM	PL	PL
PL	Z	PS	PM	PL	PL	PL	PL

Table 6. Fuzzy rule table for PSS "rule5" [8]

Δω	pΔω						
	NL	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NL	NL	NM	NS	Z
NM	NL	NL	NM	NM	NS	Z	PS
NS	NL	NM	NM	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PM	PM	PL
PM	NS	Z	PS	PM	PM	PL	PL
PL	Z	PS	PM	PL	PL	PL	PL

4. Genetic Algorithm and Optimization of Rule Bases

The fundamentals of a GA are determining initial population, writing objective functions and applying genetic operations. In the GA method, the population of strings evolve iteratively by generating new individuals and taking the place of their parents.

As a first step, the individuals of the initial population are identified as chromosome structures in GA. The individuals in this study refer to the rule tables. Thus an initial population matrix is created as [49 x population size]. The population size refers to both the number of chromosomes and individuals in GA. In Matlab Fuzzy Logic programming terminology, each chromosome vector is formed as numbers from 1 to 7. Here 1 indicates NL and 7 indicate PL and these numbers are a consequent part of each rule in the rule matrix (2).

fis.rule(i).consequent = rule_number (2)

Because each rule table includes 49 rules, the length of chromosome would be 49. Due to the similarity of some rule tables according to pre-simulation results, rule1, 2 and 4 are selected as group1, rule 3 and 5 are selected as group2. In order to increase the control performance of FPSS, only one rule table from each group (rule1 and rule3) is used in the initial population of GA. Other individuals in the population are randomly created.

The objective function is determined in accordance with the aim of the optimization process. Moreover, it defines how well an optimized result is. The objective function is also called as a fitness function. The functioning of each individual of the population is measured according to its 'fitness' values. Within this study, a function formed simulation file is used to calculate fitness values of chromosomes in the population. FPSS simulation system has four observed parameters which show the performance of the control system. These are deviations of the output voltage, speed, angle and electromechanical torque. Average values of these variations are used as fitness values of each individual. These are evaluated by IAE criteria (3) and supposed to be minimized by GA.

$$fitness = \frac{1}{IAE\left(observed\ \ parameter\right)} \tag{3}$$

With the fitness values the GA generates a new and improved population from the old one using genetic operations. Most commonly used operations are the following: selection, crossover, and mutation. Selection is an operation whereby an old string is copied into a 'mating pool' according to its fitness. More highly fitted strings receive a higher number of copies in the next generation. Crossover exchanges genetic material from two parent chromosomes, allowing their beneficial genes to be combined in their offspring. Mutation is an operation which is able to create a new genetic material in the population, changing some chromosomes according to a probabilistic law [24]. The methods of GA operators are @selectionstochunif, @crossoverscattered and @mutationadaptfeasible for selection, crossover, and mutation respectively as Matlab/gatool functions. Since usage of these rule tables speeds up the optimization process, GA stops due to reaching StallGenLimit data. Due to the elite count, the best chromosome is excluded by a mutation process. GA parameters used for optimization process are summarized in Table 7.

Table 7. The parameters of the GA

Population size	20
Chromosome Size	49
Elite Count	1
CrossoverFraction	0.75
MigrationInterval	5
MigrationFraction	0.2
Generations	100
StallGenLimit	20 - 30

Limit values of the homogenously dispersed trim functions used for membership functions for control inputs and outputs in GA application realized by Matlab /gatool (Table 8). Here the limit value of the control output was slightly changed in order to make fine tuning over performance results.

Table 8. Limit values of membership functions

Input/Output	Limit values of MFs
speed deviation	±0.02
derivation of speed deviation	±0.003
control output	±0.6

In order to find the best optimization procedure, six cases were used with four aims. That is, 24 optimization studies were held, totally. And four parameters were observed for each studies. While the aim is the minimization of the speed deviation swing, observed parameters can be variation of the swings of power angle, output voltage, speed deviation and electromagnetic torque. The cases include 20 or 30 GA generations, with determined population randomly or randomly and added five individuals and with centroid or bisector rule for defuzzification (Table 9). Where, the population with initials contains previous five rule tables as individuals of the initial population. Due to its difficulty, SMIB system was run in reactive loading condition during the all optimization studies. The performance results of the studies has been grouped by aim of the optimization (Figures 3-6). The performance is calculated according to the IAE performance evaluation criteria for four observed parameters. These are variations of the swings of power angle, output voltage, speed deviation and electromagnetic torque. Because SMIB system runs with error difference principle, these are named as $\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e$ here.

The studies of optimizations with the Case 1, 2 and 3 generally give good results. That is, the optimizations with initial population are superior then others with random populations. Also, speed deviation aimed optimization looks generally successful. As a performance value, power angle swing seems the most difficult to optimize. Other than these, it can be said that case 6 is successful except electromagnetic torque swing optimization.

Table 9. Case studies used for each aim

	Opt. aim	Pop. Type	Gen.	Defuzz. rule
Case I	$\min\{\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e\}$	with 5 init.	20	Centroid
Case II	$\min\{\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e\}$	with 5 init.	30	Centroid
Case III	$\min\{\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e\}$	with 5 init.	30	Bisector
Case IV	$\min\{\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e\}$	rand.	20	Centroid
Case V	$\min\{\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e\}$	rand.	30	Centroid
Case VI	$\min\{\Delta V_t, \Delta\delta, \Delta\omega, \Delta T_e\}$	rand.	30	Bisector

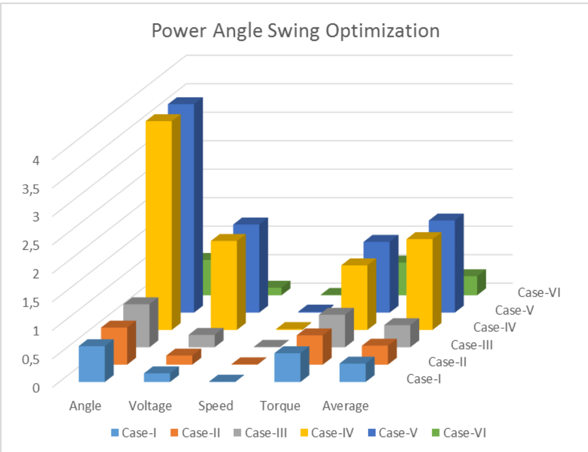

Figure 1. Six optimization studies with four results and their average using minimization of the aim of power angle swing minimization

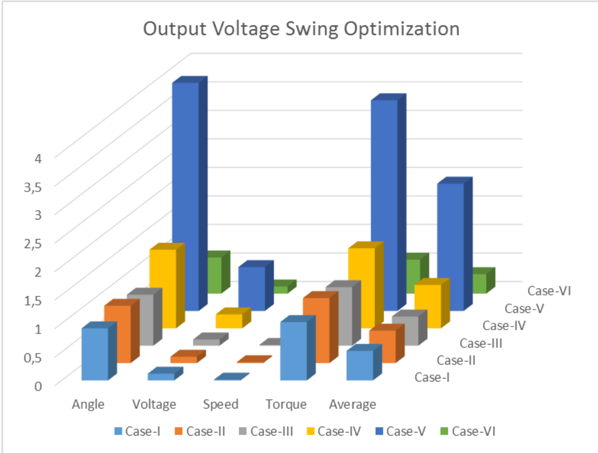

Figure 2. Six optimization studies with four results and their average using the aim of output voltage swing minimization

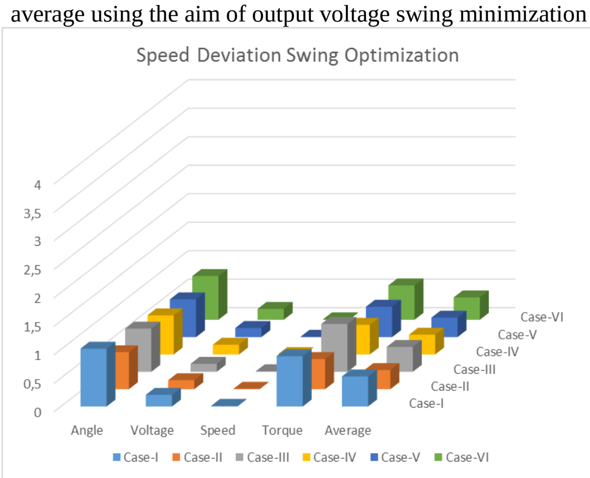

Figure 3. Six optimization studies with four results and their average using the aim of speed deviation swing minimization

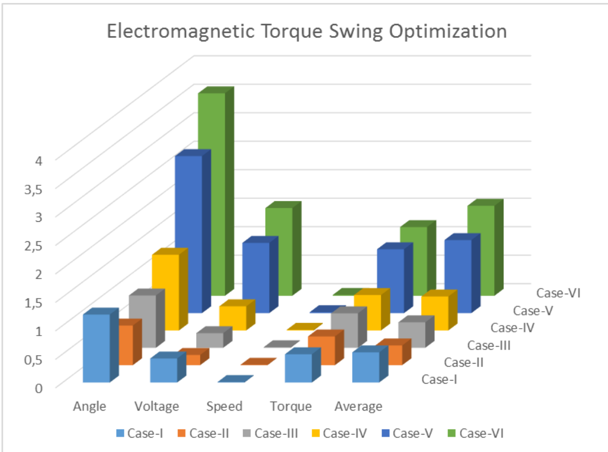

Figure 4. Six optimization studies with four results and their average using the aim of speed deviation swing minimization

5. Simulation Results

Due to its best average value, power angle swing minimization aimed with the Case 1 has been chosen for the proposed rule table representation among the optimization studies in Figures 3-6. Optimized rule table and surface representation have been shown in Table 10 and Figure 7.

Table 10. The proposed rule table

	pΔω						
	NL	**NM**	**NS**	**ZP**	**PS**	**PM**	**PL**
NL	NM	NM	NL	Z	PL	NS	Z
NM	NS	NM	NL	NS	NS	Z	PL
NS	NL	NM	NM	NS	PM	PS	PM
Z	NM	NM	NS	Z	PS	PM	NM
PS	PM	PS	NM	PS	PL	PM	PL
PM	NS	Z	PM	NS	Z	PM	PL
PL	Z	Z	PM	PM	PM	PL	PM

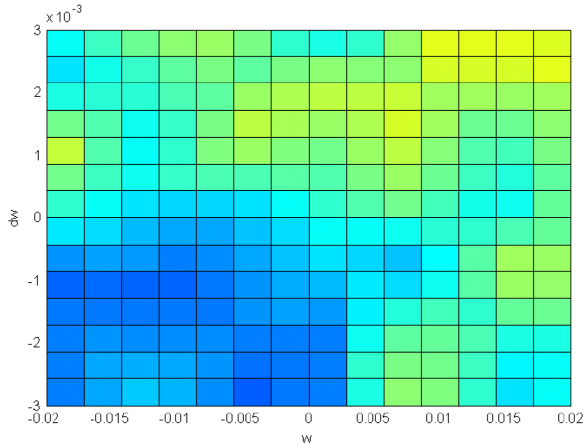

Figure 5. Surface map of the proposed rule table

Performance results of the proposed rule table in terms of four loading conditions are visualized in Figure 8. Reactive loading which is used during the optimization looks the worst case.

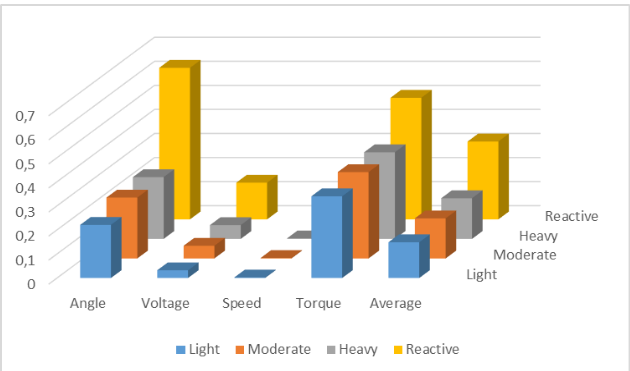

Figure 6. Performance of the proposed rule table in terms of loading conditions

In order to visualize the superiority of the proposed rule table, comparison studies were held (Figures 9-12). Where, stability curves of the observed parameters versus time are shown comparing the adopted CPSS in [20] and the two groups of FPSS mentioned in chapter IV with proposed rule table. In addition, a disturbance is applied to the mechanical torque input in the SMIB system between 2-2.5 seconds with an amplitude of 0.5 p.u. for all the case studies. Although the existence of overshoot, the output voltage has reached steady-state more quickly with the optimized FPSS rule table. Damping of the CPSS curves needs longer time.

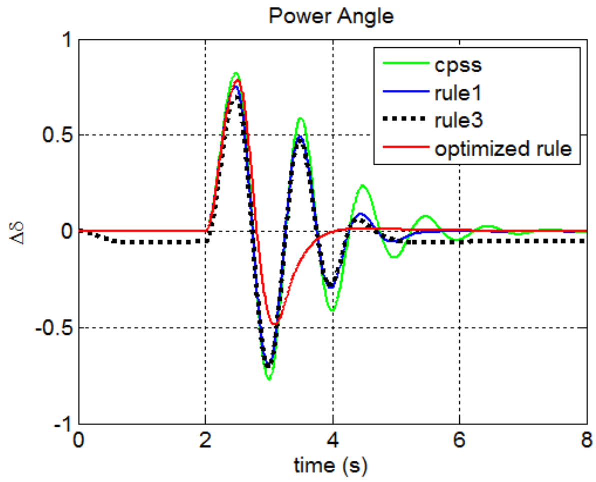

Figure 7. Comparison of proposed rule table in terms of power angel variation performance

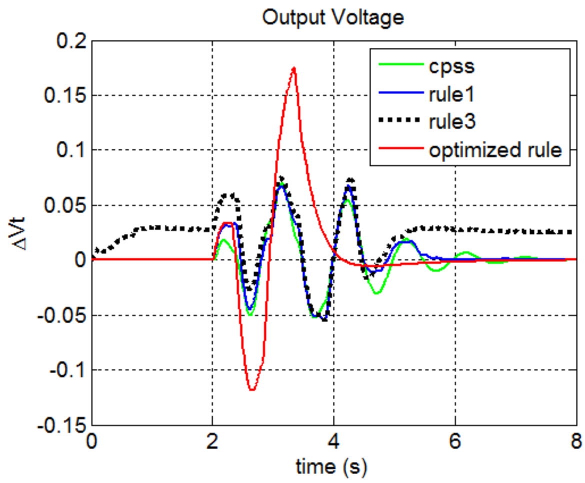

Figure 8. Comparison of proposed rule table in terms of output voltage variation performance

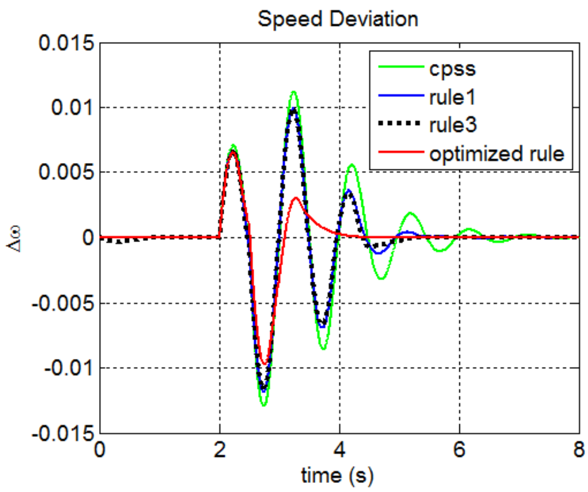

Figure 9. Comparison of proposed rule table in terms of speed deviation variation performance

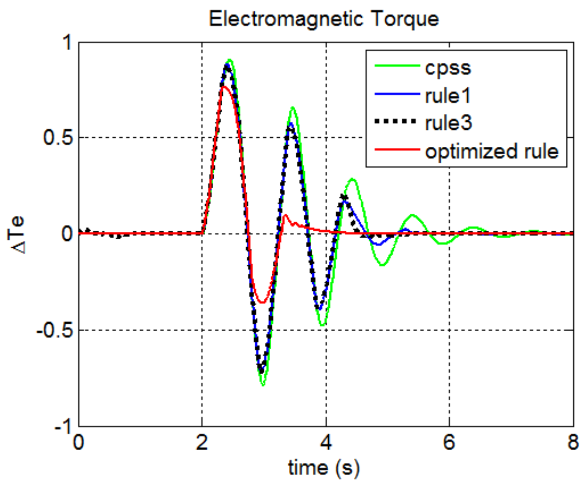

Figure 10. Comparison of proposed rule table in terms of electromagnetic torque variation performance

6. Conclusion

In this paper, rule table optimization is investigated in order to increase the performance of the PSS which is designed for the SMIB system performance. Adding to consequent parts of the rule tables which are previously designed for the SMIB system to the initial population of GA, optimization performances are speeded-up. Thus, optimizing the five previous rule table, a new improved fuzzy PSS rule table was proposed.

Four aims with six case have been used during the investigation and four output parameters have been observed. Thus 24 optimization studies have been held. As a result minimizing power angle swing aimed optimization with centroid rule and 20 GA generations have been chosen as best.

According to the comparison studies, superiority of the proposed rule table has been shown.
It was shown that the proposed table has been successful for all loading conditions, as well.

In addition, since bisector method caused little oscillations after the curves settle, use of centroid method is more appropriate during optimization process.

As a result, it was shown that the superior controller can be derived using existing fuzzy rule tables.

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