Real-Coded Genetic Algorithm and Fuzzy Logic Approach for Real-Time Load-Tracking Performance of an Autonomous Power System

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Abstract. This paper focuses on the application of real-coded genetic algorithm (RGA) to determine the optimal controller parameters of an autonomous power system model for its load tracking performance analysis. To determine the real-time parameters of the studied model, Sugeno fuzzy logic (SFL) is used. RGA is applied to obtain the controller parameters for transient response analysis under various operating conditions and fuzzy logic is applied to develop the rule base of the SFL model. The developed fuzzy system gives the on-line controller parameters for different operating conditions. Time-domain simulation of the investigated power system model reveals that the proposed RGA-SFL yields on-line, off-nominal controller parameters, resulting in on-line terminal voltage response. To show the efficiency and effectiveness of RGA, binary coded genetic algorithm is taken for the sake of comparison.

Keywords: Automatic voltage regulator, load-tracking performance, optimization, real-coded genetic algorithm, Sugeno fuzzy logic.

1 Introduction

Independent power producers (IPPs) are participating in the power market to supply reliable power to the consumers [1]. The main requirement of the distributed generation (DG) is focused due to the restructuring of the electric power industry and the increase of electric power demand. So, in modern power system, the use of the DG becomes more important because of the stringent present-day energy crisis. Generally, a DG system consists of small-scale power generators that are located close to the load centre. The main advantages of the employment of the DG systems are that consumers can generate electric power with or without grid backup and the surplus power generation can be sold back to the grid under low load-demand conditions. For example, a hybrid fuel cell-diesel engine generator (DEG)

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system promises a lot of opportunities in remote areas which are far from the utility grid and DEGs may be employed to generate power for the connected loads [2].

The main function of the automatic voltage regulator (AVR) is to control the terminal voltage by adjusting the generator excitation under any load condition. Despite significant studies in the development of advanced control strategies, the classical proportional-integral-derivative (PID) controllers [3] remain the controllers of choice to control the AVR because of its simple structure and robustness to variations of the system parameters. Proper selection of the PID controller parameters is necessary for the satisfactory operation of the AVR.

Recently, evolutionary computation techniques such as genetic algorithm (GA) [4] and particle swarm optimization [5] have been applied to obtain the optimal PID controller parameters. Traditional, binary coded GA suffers from few drawbacks when applied to multi-dimensional and high-precision numerical problems [6]. The situation may be improved if GA is used with real number data, called as real-coded genetic algorithm (RGA) [7]. Sugeno fuzzy model for on-line tuning of the PID controller has been adopted in [5, 8].

Off-line conditions are sets of nominal system operating conditions, which is given in the SFL table and in real-time environment these input operating conditions vary dynamically and become off-nominal. This necessitates the use of very fast acting SFL to determine the off-nominal controller parameters for off-nominal input operating conditions occurring in real-time.

The objectives of this paper are (a) to determine the off-line, nominal controller parameters by employing either RGA or GA, (b) to explore the suitability of the SFL-based controller for on-line real-time environment, (c) to critically examine the performance of the proposed controller of the autonomous power system for practical implementation under any sort of input disturbances and (d) to establish the suitability of the RGA-SFL over the GA-SFL for the present application.

The rest of the paper is documented in the following headings. The next section describes the proposed autonomous power system model. In Section 3, the mathematical modeling of the present problem is formulated. A brief description of the RGA is given in Section 4. In Section 5, a short review of the SFL is done. Section 6 highlights on the input parameters of the studied autonomous power system model and those of the adopted algorithms. Simulation-based results of the present work are presented and discussed in Section 7. Finally, concluding remarks are focused in Section 8.

2 Autonomous Power System Model

An autonomous power system model of a typical DEG consisting of a speed governor and an AVR with a PID controller [5] is considered in the present work and is presented in Fig. 1. The upper half blocks of Fig. 1 represent the standard mechanical model of a DEG with a speed governor and the lower half blocks represent the electrical model of a DEG with an AVR [5]. Parameters of the speed governor are the droop R and a tunable integral controller gain K_{ii}. The objective of this integral controller is to eliminate the steady-state frequency error of the studied model.

The parameters H and D shown in Fig. 1 are p.u. inertia constant and the p.u. damping constant of the DEG, respectively.

Table 1 depicts the transfer function [9] and the parameter limits of the different components of the studied model.

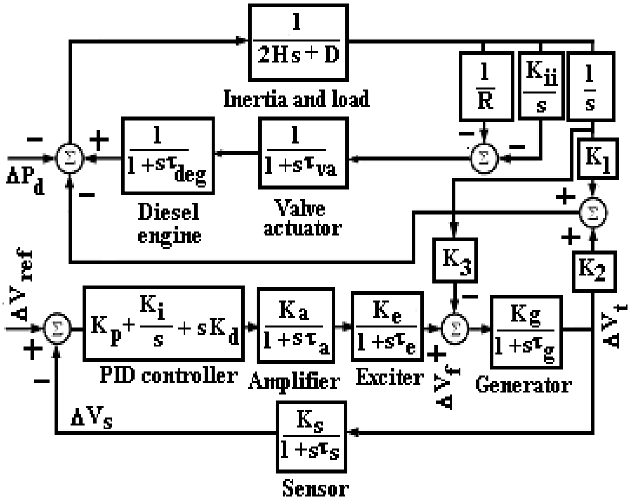

Fig. 1. Block diagram of the studied autonomous power system model

Table 1. Transfer functions and parameter limits of different components of the studied autonomous power system model

Component	Transfer function	Parameter limits
PID controller	$G_{PID}(s) = K_p + \frac{K_i}{s} + sK_d$	$0.0001 \le K_p,\ K_i,\ K_d \le 1.0$
I controller	$G_I(s) = \frac{K_{ii}}{s}$	$0.0001 \le K_{ii} \le 1.0$
Amplifier	$G_{amplifier}(s) = \frac{K_a}{1+s\tau_a}$	$10 \le K_a \le 40$; $0.02\ s \le \tau_a \le 1.0\ s$
Exciter	$G_{exciter}(s) = \frac{K_e}{1+s\tau_e}$	$1 \le K_e \le 10$; $0.4\ s \le \tau_e \le 1.0\ s$
Generator	$G_{generator}(s) = \frac{K_g}{1+s\tau_g}$	K_g depends on load (0.7-1.0); $1.0\ s \le \tau_g \le 2.0\ s$
Sensor	$G_{sensor}(s) = \frac{K_s}{1+s\tau_s}$	$0.001\ s \le \tau_s \le 0.06\ s$
DEG	$G_{\deg}(s) = \frac{1}{1+s\tau_{\deg}}$	$\tau_{\deg} = 2.31\ s$
Valve actuator (VA)	$G_{VA}(s) = \frac{1}{1+s\tau_{va}}$	$\tau_{va} = 0.82\ s$

3 Mathematical Problem Formulation

3.1 Eigenvalue Analysis

In the studied autonomous power system model the tunable parameters (K_p , K_i , K_d , and K_{ii}) are so tuned that some degree of relative stability and the damping of electromechanical modes of oscillations are obtained [10,11]. To satisfy these requirements, a multi-objective objective function is formulated and is presented in (1).

$$Min \quad J = 10 \times J_1 + 10 \times J_2 + J_3 + J_4 \tag{1}$$

The weighting factors involved in (1) are chosen to impart more weights to J_1 and J_2 , and thereby, making them mutually competitive with the other two components (like J_3 and J_4) during the process of optimization. The different components of (1) are stated below.

$J_1 = \sum_i (\sigma_0 - \sigma_i)^2$ if $\sigma_0 > \sigma_i$, σ_i is the real part of the *i*th eigenvalue. The relative stability is determined by $-\sigma_0$. The value of σ_0 is taken as -1.0 for the best relative stability and the optimal transient performance.

$J_2 = \sum_i (\xi_0 - \xi_i)^2$, if (β_i , imaginary part of the *i*th eigenvalue) > 0.0, ξ_i is the damping ratio of the *i*th eigenvalue and $\xi_i < \xi_0$. Minimization of this objective function will minimize the maximum overshoot.

$J_3 = \sum_i (\beta_i)^2$**,** if $\sigma_i \geq -\sigma_0$. High value of β_i to the right of the vertical line at $-\sigma_0$ is to be prevented. Zeroing of J_3 will increase the damping further.

$J_4 =$ an arbitrarily chosen very high fixed value (say, 10^6), which will indicate some σ_i values $\geq$ 0.0. This means unstable oscillation occurs for that particular set of parameters. This set of particular parameters will be rejected during the process of optimization.

It is to be noted here that by minimizing J , closed loop system poles are, consistently, pushed further left of $j\omega$ axis with reduction in imaginary part also.

Thus, enhancing the relative stability and increasing the damping ratio above ξ_0 .

3.2 Design of Misfitness Function

The prime requirements of the minimization of (1) are to obtain higher relative stability and to achieve better damping of the electromechanical modes of oscillations. These ensure minimal incremental change in terminal voltage (ΔV_t (p.u.)) response. This may be achieved when minimized overshoot (o_{sh}) , minimized undershoot (u_{sh}) , lesser settling time (t_{st}) , and lesser time derivative of incremental change in terminal voltage ($\frac{d}{dt}(\Delta V_t)$) of the small-signal/ transient response are achieved. To assess the performance of the eigenvalue analysis based minimization approach, modal analysis [10] is adopted. Based on the results of these, a misfitness function (MF) is designed in (2) [11].

$$MF = (o_{sh} \times 10^6)^2 + (u_{sh} \times 10^6)^2 + (t_{st})^2 + (\frac{d}{dt}(\Delta V_t) \times 10^6)^2 \tag{2}$$

These are determined by modal analysis subsequent to $\Delta\delta = 5^\circ$ = 0.0857 rad, state perturbation [10].

3.3 Constraints of the Problem

The constrained optimization problem for the tuning of parameters of the studied autonomous power system is subject to the minimum and maximum limits of the tunable parameters (K_p, K_i, K_d, K_{ii}) as given in (3).

$$\left.\begin{array}{ll} K_p^{\min} \le K_p \le K_p^{\max}, & K_i^{\min} \le K_i \le K_i^{\max} \\ K_d^{\min} \le K_d \le K_d^{\max}, & K_{ii}^{\min} \le K_{ii} \le K_{ii}^{\max} \end{array}\right\} \tag{3}$$

From the above discussions, the optimal values of the tunable parameters of the studied model are obtained by minimizing the J value (i.e. eigenvalue analysis) with the help of any of the optimizing techniques (RGA/GA). And, by adopting the modal analysis [10], the value of the MF is obtained.

4 Review of RGA and Its Application to Load-Tracking Problem

For effective genetic operation, the crossover and mutation operators which can deal directly with the floating point numbers are used in RGA. The different steps of RGA are [7] real coded initialization of each chromosome, selection operation based on computation of the fitness function and merit ordering, crossover and mutation operation, sorting of the fitness values in increasing order among the parents and the off-springs, selection of the better chromosomes as parents for the next generation, and updating of genetic cycle and fulfilling the stopping criterion.

5 Review of SFL for On-Line Tuning of Controller Parameters

The whole process of SFL can be categorized into three steps viz. fuzzification, Sugeno fuzzy inference, and Sugeno defuzzification. The details of the steps may be found in [5, 8].

6 Input Parameters

A comprehensive list of the parameter limits of the studied power system model are given in Table 1. For the simulation work, the other chosen values of the model are $K_a = 10$, $\tau_a = 0.1$ s, $K_e = 1.0$, $\tau_e = 0.4$ s, $K_r = 1.0$ $\tau_r = 0.05$ s, $\tau_{\deg} = 2.31$ s, $\tau_{va} = 0.82$ s, $K_1 = 1.5$, $K_2 = 0.2$, $K_3 = 1.5$, $H = 1.9$, $D = 0.8$, $R = 0.074$. The value of K_g is load dependent [9]. Number of parameters to be optimized is four. The minimum and the maximum limits of the tunable parameters are presented in Table I. For GA [5, 8], number of bits = (number of parameters) × 8 (for binary coded GA, as considered in the present work), population size = 60, number of iterations = 100, runtime = 30, crossover rate = 80%. and mutation probability = 0.001 are chosen. For RGA [7, 12], population size = 60, number of iterations = 100, runtime = 30, crossover rate = 80%., mutation probability = 0.001, crossover = single point crossover, mutation = Gaussian mutation, selection = Roulette wheel and selection probability = 1/3.

The software has been written in MATLAB-7.3 language and executed on a 3.0-GHz Pentium IV personal computer with 512-MB RAM.

7 Simulation Results and Discussions

For the present work, K_g is varied from 0.7 to 1.0 in steps of 0.1 and τ_g is varied from 1.0 to 2.0 in steps of 0.2. Thus, total 24 different sets of nominal input conditions are obtained. The algorithms employed for the present work are RGA, and GA. The results of interest including modal analysis based small-signal response characteristics are bold faced in the respective tables. For time-domain plots of the ΔV_t (p.u.), input step perturbation of 1% is applied either in reference voltage (ΔV_{ref}) or in load demand (ΔP_d). The major observations are documented below.

7.1 Eigenvalue-Based System Performance and Misfitness Function Analysis

Table 2 includes 8 different selected sets of input conditions and establishes optimization performance of RGA-based approach is better than GA-based approach. The modal analysis-based small-signal response profiles of the incremental changes of terminal voltages of studied model are also presented in Table II. It shows, RGA-based technique yields optimal controller gains and offers lesser value of the *MF*.

Table 2. Sugeno fuzzy rule base table, optimized controller gains, optimum *J* values and modal analysis based transient response profile of incremental change in terminal voltage with varying K_g and τ_g

K_g, τ_g	Algorithm	Optimal controller gains				J	Modal analysis-based transient response profile			
		K_p	K_i	K_d	K_{ii}		u_{sh} ($\times 10^4$)	o_{sh} ($\times 10^4$)	t_{st} (s)	MF ($\times 10^9$)
0.7,	GA	0.0946	0.0834	0.0109	0.1000	35.7153	-3.3255	8.7213	20.000	9.1119
1.0	RGA	0.1000	0.0845	0.0145	0.1000	**26.2980**	-0.0695	8.7227	18.811	**7.9629**
0.7,	GA	0.0644	0.0525	0.0050	0.1000	29.1682	-0.0101	8.7227	17.949	7.9308
1.2	RGA	0.1000	0.1000	0.0050	0.1000	**28.7676**	-0.1870	8.7227	8.438	**7.7833**
0.8,	GA	0.0849	0.0765	0.0082	0.1000	38.5021	-3.4694	8.7213	20.000	9.2097
1.0	RGA	0.1000	0.0726	0.0315	0.1000	**27.1475**	-0.0112	8.7213	14.275	**7.8099**
0.8,	GA	0.0889	0.0644	0.0138	0.1000	34.5489	-2.1180	8.7227	20.000	8.4572
1.2	RGA	0.1000	0.0797	0.0078	0.1000	**27.0290**	-0.0104	8.7227	12.539	**8.1658**
0.9,	GA	0.0895	0.0813	0.0080	0.1000	35.5397	-3.5925	8.7213	20.000	9.2967
1.0	RGA	0.1000	0.1000	0.0063	0.1000	**26.8785**	-0.0144	8.7213	7.152	**7.8572**
0.9,	GA	0.0998	0.0801	0.0080	0.1000	39.1675	-3.6027	8.7227	20.000	9.3066
1.2	RGA	0.1000	0.0620	0.0311	0.1000	**29.8006**	-0.0109	8.7227	12.450	**7.8636**
0.9,	GA	0.1000	0.0487	0.0050	0.0995	38.6098	-3.6532	8.7256	20.000	9.3483
2.0	RGA	0.1000	0.0905	0.0050	0.1000	**35.7949**	-0.8358	8.7256	17.120	**7.9766**
1.0,	GA	0.0737	0.0684	0.0050	0.1000	28.8732	-0.0093	8.7213	7.254	7.6587
1.0	RGA	0.1000	0.1000	0.0050	0.1000	**25.8896**	-0.0044	8.7213	5.572	**7.6571**

7.2 Analysis of the Transient Response of Change in Terminal Voltage

Fig. 2 is pertaining to the comparative GA- and RGA-based time-domain transient response profiles of ΔV_t (p.u.) with 1% simultaneous step change in reference voltage and load demand for nominal set of input parameters. This figure portrays that RGA-based approach yields optimal ΔV_t (p.u.) response profile. The proposed RGA-based optimal controller gains settle the ΔV_t (p.u.) response quickly. Thus, the RGA-based controller gains perform better than the GA-based controller gains.

For on-line, off-nominal input sets of parameters, the SFL model is utilized to get the on-line, optimal controller gains and these controller gains also yield the optimal incremental change in terminal voltage response profile (Fig. 3). From Fig. 3 it is observed that RGA-SFL model yields optimal incremental change in terminal voltage response.

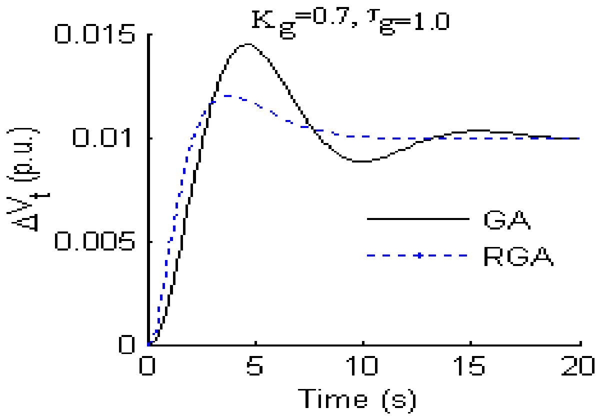

Fig. 2. Comparative GA-, and RGA-based time-domain transient responses of the incremental change in terminal voltage (p.u.) with 1% step change in reference voltage and load demand for nominal set of input parameters

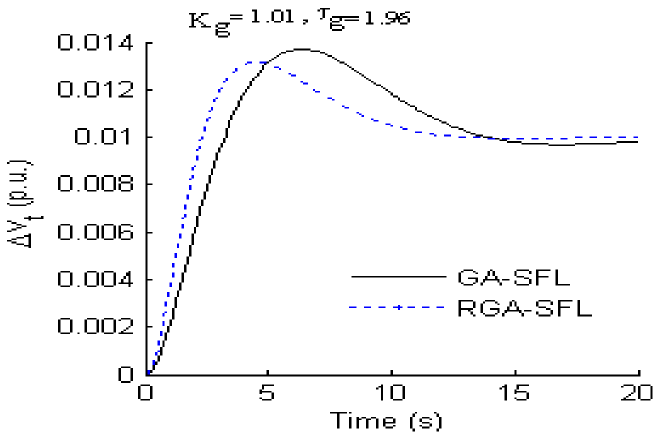

Fig. 3. Comparative GA-SFL-, and RGA-SFL-based time domain transient responses of the incremental change in terminal voltage (p.u.) with 1% step change in reference voltage and load demand for off-nominal set of input parameters

7.3 Convergence Profile

Fig. 4 portrays the comparative convergence profiles *J* value for the algorithms like GA and RGA and it indicates that RGA-based meta-heuristic offers faster convergence profile and lesser value of *J* than GA counterpart.

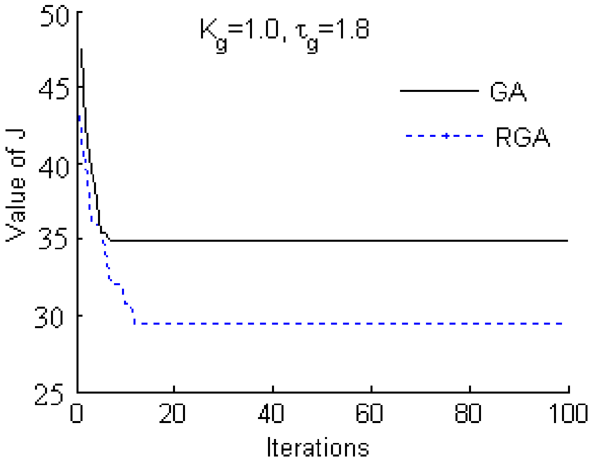

Fig. 4. Comparative GA-and RGA-based convergence profiles of *J*

7.4 SFL-Based Response

Table 3 illustrates the SFL-based off-nominal, on-line optimal gains, *J* values and the corresponding modal analysis based small-signal response profile of the incremental change in terminal voltage for on-line, off-nominal input set of parameters.

Table 3. Sugeno fuzzy based off-nominal, on-line optimal gains, *J* values and transient response profile of incremental change in terminal voltage

K_g, τ_g	Algorithm-SFL	Optimal controller gains				J	Modal analysis-based transient response profile			
		K_p	K_i	K_d	K_{ii}		u_{sh} ($\times 10^4$)	o_{sh} ($\times 10^4$)	t_{st} (s)	MF ($\times 10^9$)
0.72, 1.42	GA-SFL	0.0798	0.0525	0.0050	0.1000	36.3182	-3.3692	8.7239	20.000	9.1457
	RGA-SFL	0.1000	0.0647	0.0117	0.1000	**29.9933**	-0.0165	8.7239	20.000	**8.0106**
0.87, 1.89	GA-SFL	0.0881	0.0516	0.0050	0.1000	40.3497	-3.2957	8.7254	20.000	9.0994
	RGA-SFL	0.1000	0.0475	0.0050	0.1000	**35.2068**	-0.0098	8.7254	13.654	**8.7997**
0.95, 1.67	GA-SFL	0.0948	0.0555	0.0050	0.1000	37.6234	-3.6710	8.7248	20.000	9.3598
	RGA-SFL	0.0525	0.0525	0.0207	0.1000	**34.9699**	-0.0110	8.7248	16.743	**7.8925**
1.01, 1.96	GA-SFL	0.0762	0.0315	0.0050	0.1000	38.4689	-3.7318	8.7255	20.000	9.4062
	RGA-SFL	0.1000	0.0525	0.0050	0.0240	**31.0984**	-0.0142	8.7255	18.917	**7.9714**

7.5 Performance Evaluation under different Disturbances

Time-domain transient responses under step disturbances (either positive or negative or zero) in reference voltage and/or in load demand for the studied power systems model are displayed in Fig. 5 for $K_g = 0.7$ and $\tau_g = 1.0$. This figure is achieved under certain increment/decrement/no change in reference voltage and/or loading/unloading as laid down in the different sketches of Fig. 5(a)-(f). From the different sketches (a–f) of this figure, it is noticed that the controller gains yielded by adopting the RGA exhibits better transient response of the incremental change in terminal voltage of the studied power systems model as compared to the GA-based approach. With the RGA-based optimal parameters and along with the faster action of the controlling mechanism of the automatic generation control loop, the proposed autonomous power systems model restores the system nominal performance quickly under different modes of investigated input perturbations.

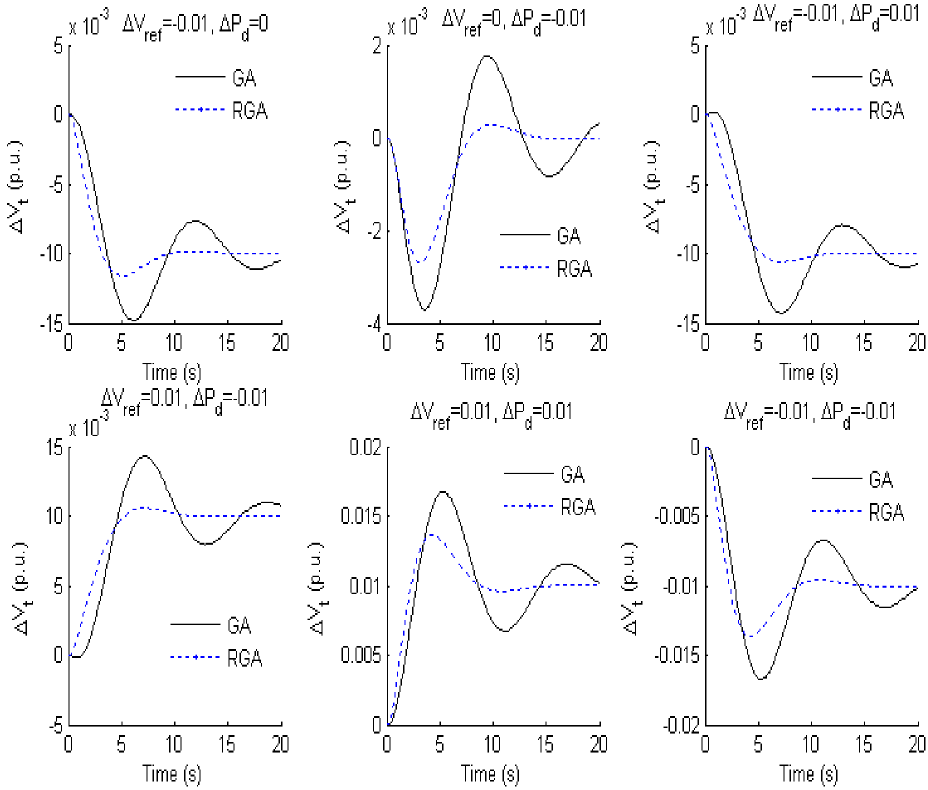

Fig. 5. Comparative GA- and RGA-based transient performance study for the studied model under different perturbations for nominal set of input parameters

7.6 Analysis of the Transient Response of Change in Frequency

Fig. 6 is pertaining to the comparative GA-, evolutionary programming (EP) [13] and RGA-based time-domain transient response profiles of Δf (p.u.) with 1% simultaneous step change in reference voltage and load demand for nominal set of input parameters. This figure portrays that RGA-based approach yields optimal Δf (p.u.) response profile. The proposed RGA-based optimal controller gains settle the Δf (p.u.) response quickly. Thus, the RGA-based controller gains perform better than either GA-based or EP-based controller gains.

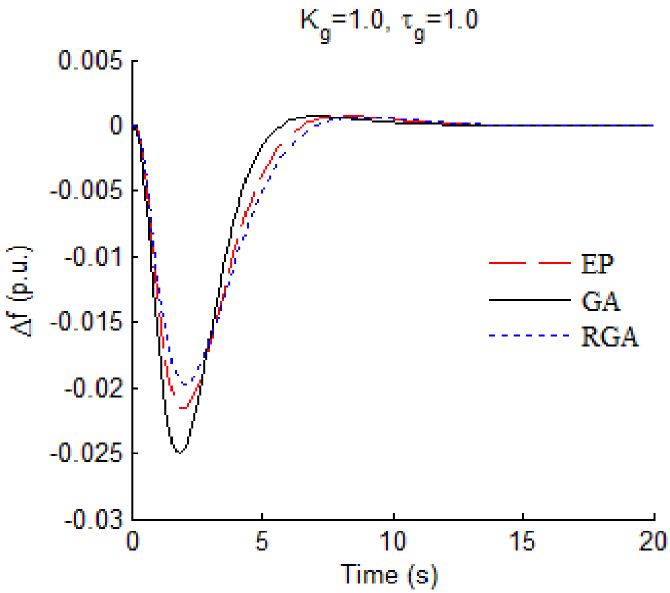

Fig. 6. Comparative GA-, and RGA-based time-domain transient responses of the incremental change in frequency (p.u.) with 1% step change in reference voltage and load demand for nominal set of input parameters

7.7 AVR without PID-controller

Fig. 7 presents the step response of the incremental change in terminal voltage of the studied power systems model without inclusion of the PID-controller. It is observed from this figure that the studied system is not capable to settle the terminal voltage to the desired value within a specified time. This necessitates the requirement of proper tuning of the controller gains.

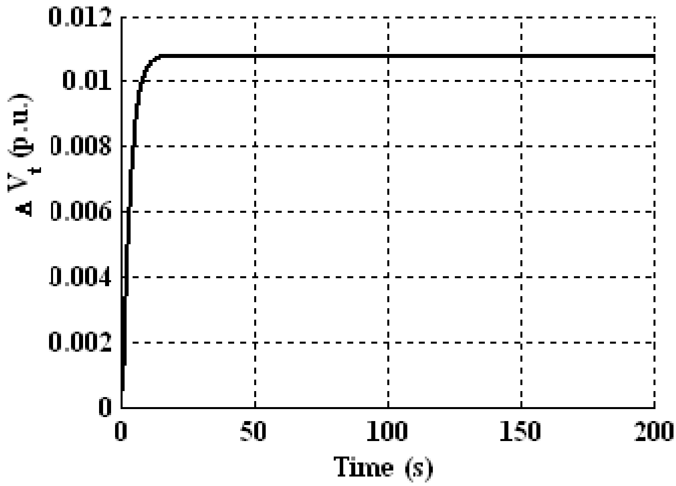

Fig. 7. Step response of incremental change in terminal voltage of the studied autonomous power systems without PID controller

8 Conclusion

In this paper, RGA is used to optimize the different tunable parameters of load-tracking performance of an autonomous power system model. For on-line, off-nominal system parameters SFL is applied in the present work to get on-line output terminal voltage response. The on-line computational burden of SFL is noticeably low. Consequently, on-line optimized transient response of incremental change in output terminal voltage is obtained. A time-domain simulation of the studied model is carried out under different sorts of input perturbations for practical application and exhibits a dynamic performance with truly optimized different controller gains. It is also presented that the DEG plays a significant role on maintaining the terminal voltage variations along with the optimized controller gains of the studied model. The potential benefit yielded by the RGA is compared to that yielded by GA for this specific application arena of power systems.

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