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# Synchronous Generator Excitation System Optimization Control Based on Multi-agent Genetic Algorithm

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**Abstract:** Excitation control system of synchronous generator is a strong nonlinearity, multi-variable, strong couple and time-varying control system. It is very difficult for traditional Proportional Integral Derivative (PID) to get good control performance. A new excitation control strategy based on PID controller and Cerebellar Model Articulation Controller (CMAC) is proposed in this study. To solve the problem of PID and CMAC compound controller multi-parameter setting, an Improved Multi-agent Genetic Algorithm (IMAGA) is presented. The PID parameters Kp, Ki, Kd and CMAC parameters η, α are regarded as a agent. Each agent continuously improves its fitness value through competition and cooperation between the other agents according to the objective function of Integral of Time-weighted Absolute value of the Error (ITAE). This algorithm adopts multi-agent coordinate optimization to realize the five parameters of Kp, Ki, Kd, η, αonline tuning. The simulations results show that the compound control scheme based on multi-agent genetic algorithm can improve the precision of excitation control, the speed of responding and has better dynamic and steady-state characteristics.

**Key words:** Multi-agent genetic algorithm, CMAC controller, excitation controller, PID controller, synchronous generator

## INTRODUCTION

Excitation control system of synchronous generator is a strong nonlinearity, multi-variable, strong couple and time-varying control system. The Proportional Integral Differential (PID) control strategy has been widely applied to the excitation control for synchronous generator (Wang *et al*., 2007). With the development of power industry, it is hard to build the accurate mathematical model for complex excitation control system. Therefore, the traditional PID control strategy based on accurate mathematical model is difficult to obtain satisfactory control effect for complex power system (Cheng *et al*., 2007). In recent years, some scholars have launched many new excitation control schemes and parameter optimization strategies for synchronous generator, such as fuzzy control (Jie *et al*., 2011), Particle Swarm Optimization (PSO) (He *et al*., 2010), Genetic Algorithm (GA) (Zhou *et al*., 1997; Li, 2002). These researches have made gratifying progress in the excitation control for synchronous generator. But fuzzy control effect depends largely on membership function and fuzzy rules; Genetic algorithm or particle swarm optimization is easy to get local optimum and falls into premature convergence.

The neural network technology has made great progress in the control field in recent years, especially Cerebellum Model Articulation Controller (CMAC) (Li, 2005). The PID and CMAC compound controller is more suitable for nonlinear real-time power system control. But it is a pity that multiple control parameters are difficult to tune because of coupling among the control parameters. Improper selection of parameters will lead to the deterioration of system performance, even instability. The literature (Li *et al*., 2002) demonstrated that fixed gain PD controller can only achieve locally finite stability when the system exist CMAC estimation bias or random disturbance. The literature (Liu, 2003) optimized the parameters of PID controller with genetic algorithm. The literature (Lin and Mei, 2005) proposed a new scheme that CMAC learning rate was optimized by adaptive genetic algorithm. The above literatures obtained some results; meanwhile they did not consider control parameters coordination and optimization between PID and CMAC. The study (Cheng and Liu, 2011) has achieved very good results, because it adopts genetic algorithm to realize multi-parameter coordination optimization, such as PID parameters Kp, Ki, Kd and CMAC parameters η, α. But it is still likely to fall into premature phenomenon.

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Considering the strong nonlinear and time-varying of generator excitation system, a compound excitation controller is proposed based on PID and CMAC. In order to solve the problem of multi-parameter tuning, a new kind of multi-parameter self-tuning scheme based on Multi-agent Genetic Algorithm (MAGA) (Zhong *et al*., 2004) is proposed which PID parameters Kp, Ki, Kd and CMAC parameters $\eta$, $\alpha$ are regarded as a agent. According to the objective function of Integral of Time-weighted Absolute value of the Error (ITAE), each agent continuously improved its fitness value through competition and cooperation with adjacent other agents, so the optimal parameters can be obtained quickly.

This study is organized as follows. Excitation system model for synchronous generator is constructed in next section. Then the new PID and CMAC compound excitation controller is designed based on improved multi-agent genetic algorithm optimization. Then simulation experimental results are proposed to illustrate the effectiveness of the proposed control system. Finally, conclusions are drawn in this study.

## EXCITATION SYSTEMN MODEL

**Synchronous generator model:** Typical excitation control system generally consists of synchronous generator, voltage measurement and excitation power unit. Synchronous generator has the characteristics of nonlinear, time-varying and complex system. Without considering the magnetic saturation condition, the generator can be described as one order inertial element:

$$G_G(s) = \frac{K_G}{1+T_{d0}s} \tag{1}$$

where $K_G$ is the amplification factor of the generator; $T_{d0}$ is time constant; S is complex variables.

**Voltage measuring unit model:** The voltage measuring unit is used to detect the output voltage of the synchronous generator. The measuring voltage is send to excitation controller which realizes the control for excitation power unit. Among them, the rectifier filter circuit is a slight delay, using first-order approximation to describe the transfer function. So the voltage measuring unit can be expressed as:

$$G_M(s) = \frac{K_C}{1+T_R s} \tag{2}$$

where $K_C$ is the input and output ratio of voltage sensor; $T_R$ is the filter circuit time constant, general value between 0-0.07s.

**Excitation power unit model:** The main function of power unit is to magnify the excitation control signal, in order to control the appropriate power, namely power conversion function. The unit can be regarded as a first-order process; its transfer function is expressed as:

$$G_A(s) = \frac{K_A}{1+T_A s}$$

where, voltage proportional coefficient $K_A$ for power amplification unit; $T_A$ is the time constant of the amplifying unit.

## AN IMPROVED MULTI-AGENT GENETIC ALGORITHM

**One-dimensional multi-agent structure:** The literature (Zhong *et al*., 2004) introduced lattice-like multi-agent structure into GA (MAGA). Each agent resides in the grid points in lattice-like structure environment and it only competes and cooperates with its five neighbors. The relative experimental results show that multi-agent genetic algorithm can obtain better optimization results than some other popular GAs. However, compared with the one-dimensional multi-agent structure (Zeng *et al*., 2008), the conventional MAGA has the large amount of calculation and not suitable for complex system real-time control, such as excitation system control. In a one-dimensional environment, the agent only competes and cooperates with around two neighbors which generates a new agent instead of the current agent by a certain rule (Zeng *et al*., 2008). The structure of one-dimensional multi-agent is shown in Fig. 1.

In this study, each agent represents an individual L(1,i) and occupies a fixed grid point in the evolutionary population; all agents locate in a 1×popsize scaled cycle chain. Each agent only has local perception, so it can only interact with its two neighborhood agents. Neighbors of the agent L(1, I) in position (1, I) are expressed as Neb(1, i) = {L(1, i1), L(1, i2)}. Where i represents 1, 2, 3…,popsize and the positions as shown below:

$$i1 = \begin{cases} i-1 & i \neq 1 \\ \text{popsize} & i=1 \end{cases}$$

$$i2 = \begin{cases} i+1 & i \neq \text{popsiae} \\ 1 & i=\text{popsiae} \end{cases} \tag{4}$$

**An improved multi-agent genetic algorithm:** The conventional Multi-agent Genetic Algorithm (MAGA) combines the advantages of distribution artificial intelligence based on agent calculations and traditional genetic algorithm. Each agent represents a candidate

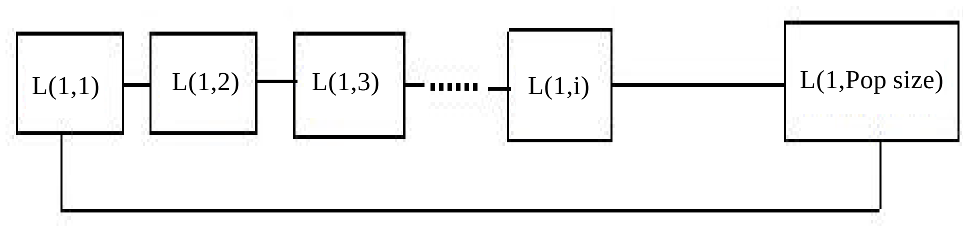


Fig. 1: One-dimensional Muti-agent Structure

solution to the parameter optimization for excitation system of synchronous generator which increases its fitness value by competing and cooperating with its two neighbors. The algorithm involves the operators as following.

- **Competitive operator:** The agent Y(I, j) = ($y_1$, $y_2$, $y_3$,…,$y_n$) only competes with its two neighbors. Suppose that an agent Max (i, j) = ($m_1$, $m_2$,…, $m_n$) is the maximum fitness values or energy in its two neighborhoods. If the fitness value of agent Y(I, j) is greater than agent Max(i, j), the agent Y(I, j) continues surviving, otherwise it will be died and be replaced by a new agent New (i, j). The generation of the new agent New (i, j) = ($e_1$, $e_2$, $e_3$,…,$e_n$) is determined by the following Eq. 5:

$$e_k = \begin{cases} \underline{x_k} & (max_k + U(-1,1)\times(max_k - y_k)) < \underline{x_k} \\ \overline{x_k} & (max_k + U(-1,1)\times(max_k - y_k)) > \overline{x_k} \\ max_k + U(-1,1)\times(max_k - y_k) & \text{else} \end{cases} \tag{5}$$

By the heuristic competitive strategy, the new agent reserves some useful information both the agent Y(I, j) and agent Max (i, j).

- **Cooperation operator:** Each agent will cooperate with its next neighbor agents to improve its energy. It is random selection crossover point in the two parent agents, then carrying out arithmetic crossover in crossover point. Suppose that agent A= ($a_1$, $a_2$, $a_3$,…, $a_n$) and agent B= ($b_1$, $b_2$, $b_3$,…, $b_n$) are crossover in the k-point which will produce two offspring as the following:

$$\begin{cases} \text{agent} \quad A' = (a_1, a_2, a_3, \ldots, a_k', b_{k+1} \ldots, b_n) \\ \text{agent} \quad B' = (b_1, b_2, b_3, \ldots, b_k', a_{k+1} \ldots, a_n) \end{cases}$$

where, $a_k' = a_k + \beta(b_k - a_k)$, $b_k' = v_k + \beta(u_k - v_k)$, $u_k$ and $v_k$ are the domain of $b_k$, β is a random value within [0, 1].

If the energy of agent A' is greater than the energy of agent A, then the cooperation of them is successful, the agent A is replaced by agent A', else the original agent A is retained.

**Mutation operator:** Each agent implements adaptive mutation with the probability of $P_m$. The mutation type used here is Gaussian mutation. The new agent New(1, j) = ($e_1$, $e_2$, $e_3$.,…,$e_n$) is determined by Eq. 7:

$$e_k = \begin{cases} l_k & U(0,1) \le P_m \\ l_k + G(0, 1/t) & \text{else} \end{cases}$$

where, k = 1, 2,…, n t is the evolution algebra, G(0, i/t) is Gaussian random number generator. According to the literature (Zeng *et al*., 2008), the suitable Pm is advised to be set as 1/t.

**Elitist strategy:** Each agent must be involved in the competitive selection, crossover cooperation and mutation operation. After every evolution, the highest fitness value agent L $Best^t$ in current generation will be compared with once the best agent $Best^{t-1}$ in the all past generations. Save the biggest fitness value individual of the two agents and use it to replace the smallest fitness value one in current generation. With elitism strategy, the new agent can inherit the good solution from the former generation. This strategy can make the best solution within ith generation better than or equals to the best solution in the former (i-1)th generation and also ensure the convergence of the algorithm.

## ADAPTIVE EXCITATION CONTTOLLER BASED ON IMAGA

**Design of adaptive excitation controller:** The traditional compound controller is difficult to deal with distributed, time-varying nonlinear excitation system control for synchronous generator. It also lacks effective multi-parameter self-tuning method due to the parameter mutual coupling among the PID and CMAC controller. A

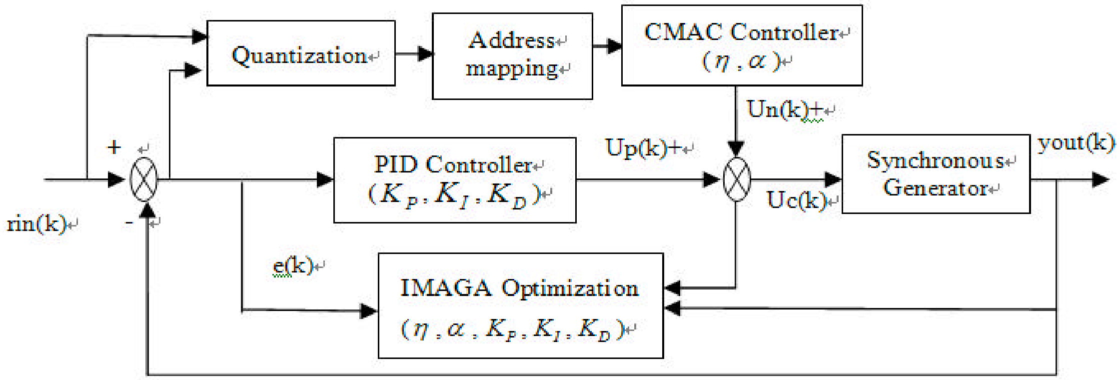


Fig. 2: Composite structure of adaptive CMAC controller based on improved GA optimization

new multi-optimization PID and CMAC compound excitation controller based on Improved Multi-agent Genetic Algorithm (IMAGA) is proposed in this study and its control structure is as shown in Fig. 2.

As you can see from the Fig. 2, the improved CMAC and PID compound controller uses the system error e(k)=rin(k)-yout(k) as weights training signal. The inverse dynamic model of the excitation control system is to be realized for CMAC which including the conventional PID controller and CMAC controller. The improved structure effectively overcomes the study conflict of the conventional PID and CMAC controller which lead to system instability. In addition, in order to implement real time excitation control, one-dimensional multi-agent genetic algorithm is used to optimizing the five parameters for new compound controller. The new controller work is divided into two stages of control and study.

In control stage, the given output rin(k) is quantified as one-dimensional input address, through which finds the corresponding C unit in the CMAC memory. The output Un(k) of CMAC controller is equal to the sum of the C unit weights. Un(k) is defined as Eq. 8:

$$U_n(k) = \sum_{j=1}^{C} \omega_j(k) a_j(k) \tag{8}$$

where, C is the number of associative units.

The total output of the new compound controller is the sum of the CMAC output and PID output which are optimized by IMAGA.

$$U_c(k) = U_n(k) + U_p(k) \tag{9}$$

In learning stage, weights of CMAC network are corrected by the system error. The weight adjustment equation is as follows:

$$w(k) = w(k-1) + \eta \frac{e(k)}{c} + \alpha_r (w(k-1) - w(k-2)) \tag{10}$$

where, η is the learning rate, e(k) is tracking error of the system. The optimization cost function J is defined as the Eq. 11:

$$J = \int_0^\infty (t|e(t)|)dt \tag{11}$$

where, e(t) is the system tracking voltage error.

**Adaptive excitation control algorithm steps:** Assume $P^t$ represents the agent chain in the tth generation. $P^{t+1/3}$, $P^{t+2/3}$ are the mid-result between $P^t$ and $P^{t+1}$. $Best^t$ is the best agent among $P^0$, $P^1$,..., $P^t$; $LBest^t$ is the best agent in $P^t$. Flow chart is as Fig. 3.

**Step 1:** The [min, max] range of five optimized parameters is to be determined based on general experience. The decimal code for each of actual parameter is defined as Eq. 12:

$$K = \min + (\max - \min) \times rand \tag{12}$$

where, rand∈(0,1) is a random number, the individual agent is ($K_p$ $K_I$ $K_D$ η α),other parameters such as iteration times, population size are to be set in the same time

**Step 2:** It randomly generates popsize agents in the range of the given to form $P^0$

**Step 3:** Each agent of $P^t$ competes with its two neighbors to form the population $P^{t+2/3}$

**Step 4:** If U(0,1)<$P_c$, each agent in $P^{t+2/4}$ performs hybrid crossover between the neighborhoods agents, obtaining $P^{t+2/3}$

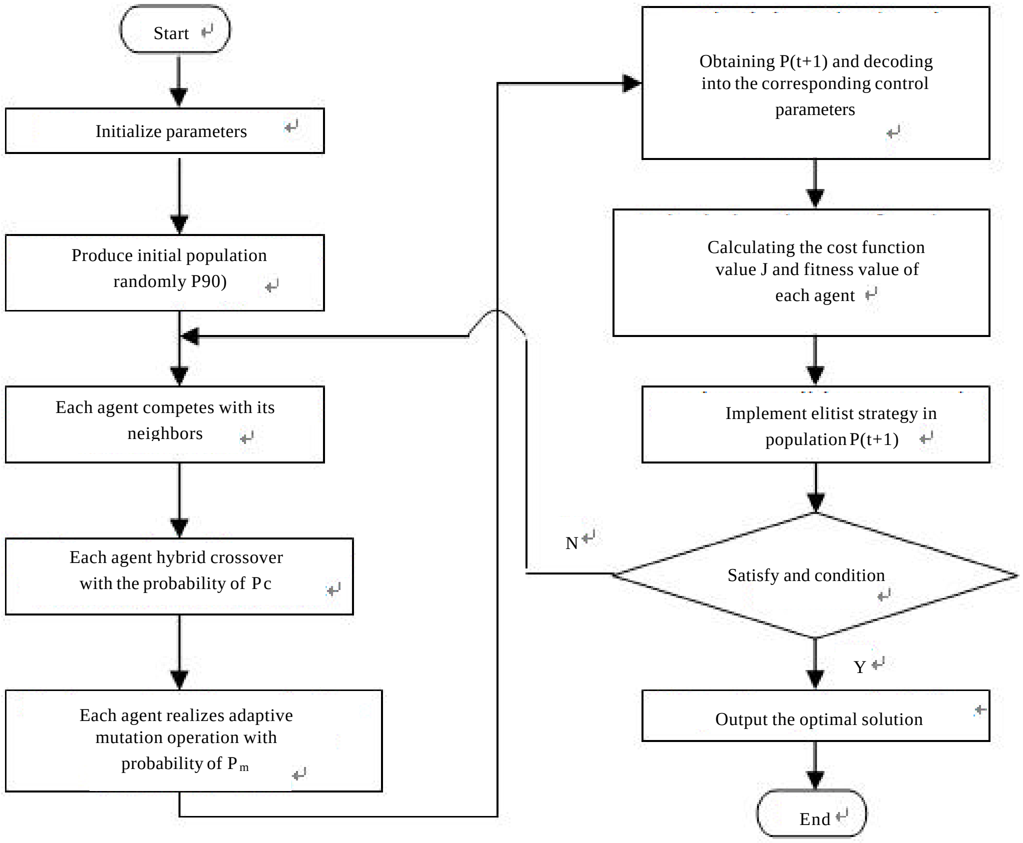


Fig. 3: Excitation control parameters optimization flow chart

**Step 5:** If U(0,1) $<P_c$, each agent in $P^{t+1/4}$ performs mutation operation, obtaining $P^{t+1}$

**Step 6:** Each individual agent is decoded into the corresponding control parameters. According to the Eq. 11, the value J of the cost function is calculated for each of individual agent by the results of simulation experiment

**Step 7:** Elitist strategy is implemented in $P^{t+1}$. Find $Lbest_{t+1}$ and compare with $Best^t$

**Step 8:** If the termination criteria are reached, output $Best^t$. Otherwise, return to Step 3

## MATLAB SIMULATION ANALYSIS

In this section, the simulation analysis of the PID and CMAC controller based on one-dimensional multi-agent genetic algorithm optimization (MASPIDCMAC) is conducted for excitation control of synchronous generator. The three experiments of no-load step response for excitation control, -10% step response and model parameters mutation is applied to verify the effectiveness of the proposed excitation control strategy. In simulation, the control model parameters are set: Sampling time T = 0.001s, $K_G$ = 1, $T_G$ = 6, $K_M$ = 1, $T_M$ = 0.02, $K_E$ = 1, $T_E$ = 0.3. The PID controller parameters are same as the literature (Jie *et al*., 2011), i.e. Kp = 199.325, Kd = 10.128, Ki = 29.638, $\eta$ = 0.02, $\alpha$ = 0.04. The range of adaptive parameters is $K_p \in [50, 250]$, $K_i \in [0,10]$, $K_d \in [0,30]$, $\eta$ = [0.0, 0.05], $\alpha \in [0.0, 0.05]$, respectively. The object function is as above. In order to compare the performance of the proposed excitation control scheme, the excitation control results of GAPID and GAPIDCMAC algorithm simulation are given under the same conditions.

**Simulation of 100% voltage step response:** The 100% step response experiments of three excitation control schemes for synchronous generator are carried out in accordance with the above parameters. The simulation time is 3 sec. The input-output simulation curves of GAPID, GAPIDCMAC and MASPIDCMAC are respectively shown in Fig. 4 and 5 (the red curve represents the results of the proposed scheme, the green one is the results of the GAPID controller, the black one is the results of the GAPIDCMAC and the dotted one is

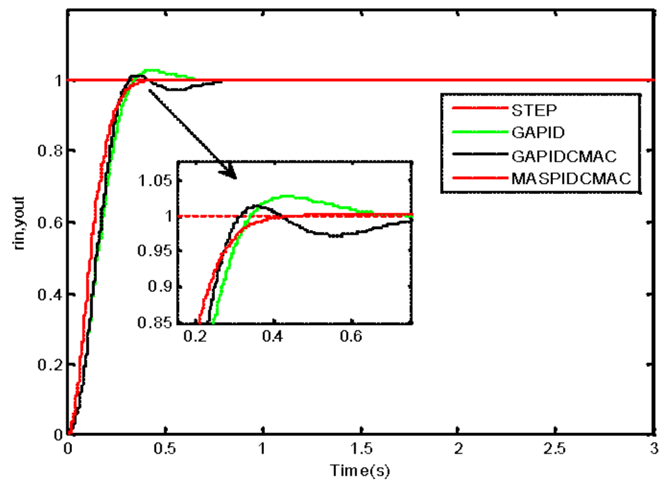


Fig. 4: Excitation simulation for step response

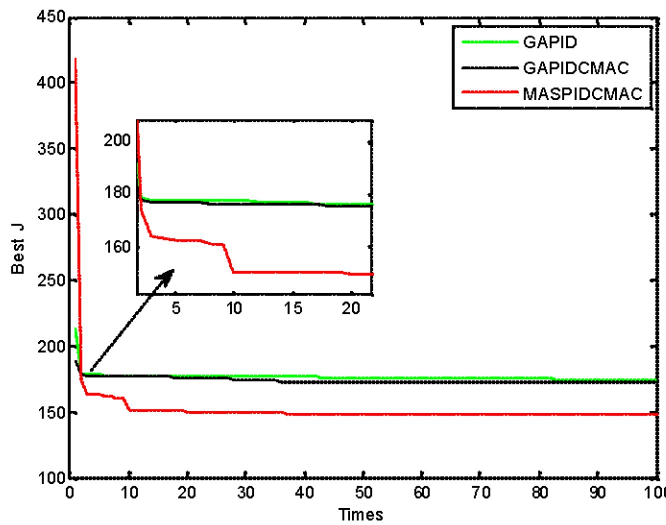


Fig. 5: Excitation simulation step response

Table 1: Comparison of the step response results of three excitation controllers under 50 times mean values

| Mean value of 50 times | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Controller | Kp | Ki | Kd | $\eta$ | $\alpha$ | ITAE | M% | Tr/s |
| GAPID | 247.8740 | 6.3486 | 25.9879 | 0.0054 | 0.0069 | 168.4818 | 2.69 | 0.271 |
| GAPIDCMAC | 244.0115 | 1.4374 | 29.7878 | 0.0087 | 0.0048 | 166.2989 | 1. 27 | 0.255 |
| MASPIDCMAC | 243.0138 | 0 | 32.0892 | 0.0100 | 0.0035 | 152.4805 | 0.07 | 0.236 |

the given step signal). The 100% step response performances of three excitation control scheme for synchronous generator are shown as in Table 1. According to Table 1, the integral of time-weighted absolute value of the error (ITAE) and the overshoot (M%) of the GAPIDCMAC controller are the smallest and it's rise time is the shortest.

As you can see from Fig. 4 and 5, the proposed scheme has the faster learning speed and higher accuracy under the same experimental conditions than the conventional GAPID controller and GAPIDCMAC controller. The control effect of the MASPIDCMAC controller is better than the other two strategies and the rise time is shortened obviously, almost no overshoot.

**Simulation of -10% voltage disturbance:** In order to verify anti-interference capability of the proposed excitation control scheme, the given voltage signal is

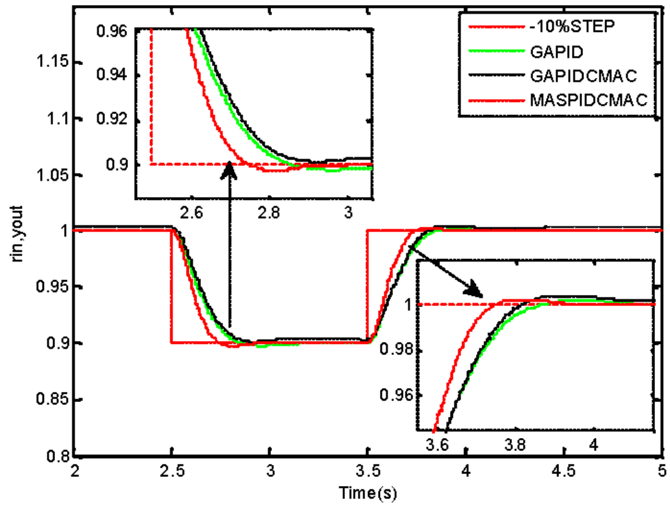


Fig. 6: Output voltages under the external disturbance

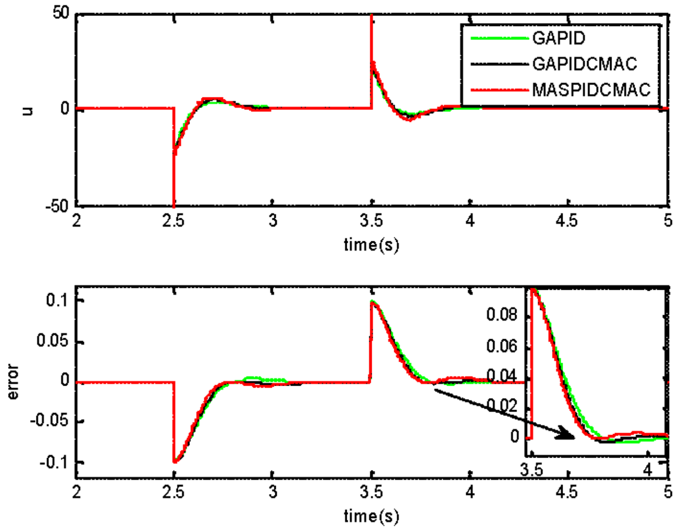


Fig. 7: Output voltages under the external disturbance

reduced to 90% of steady-state voltage value when the simulation is running in between 2.5 and 3.5 sec. The total simulation time is 5 sec. The excitation control effects of GAPID, GAPIDCMAC and MASPIDCMAC are respectively shown in Fig. 6 and Fig. 7 (the red simulation curve represents the results of the proposed scheme, the green one is the results of the GAPID controller, the black one is the results of the GAPIDCMAC controller and the dotted one is the voltage given signal).

As can be seen from the Fig.7, by the learning of CMAC and the parameters optimization by MAGA, the output voltage under the proposed control strategy can fast tracking the given signal. Compared with the other two control strategies, the output voltage of synchronous generator smoothly return to rated voltage rapidly after the external disturbance disappeared at 3.5 sec. It also can be seen from the Fig. 6, the voltage adjustment time of the MASPIDCMAC is the shortest about 0.12 sec after the external disturbance disappeared. From the Fig. 7, we can see the tracking error under the proposed excitation control strategy is the smallest in the three excitation control scheme. Comparative analysis indicates that the MASPIDCMAC controller has stronger anti-disturbance ability.

**Robustness simulation analysis:** In order to investigate the robustness of the proposed new PID and CMAC compound excitation control strategy, the parameters of

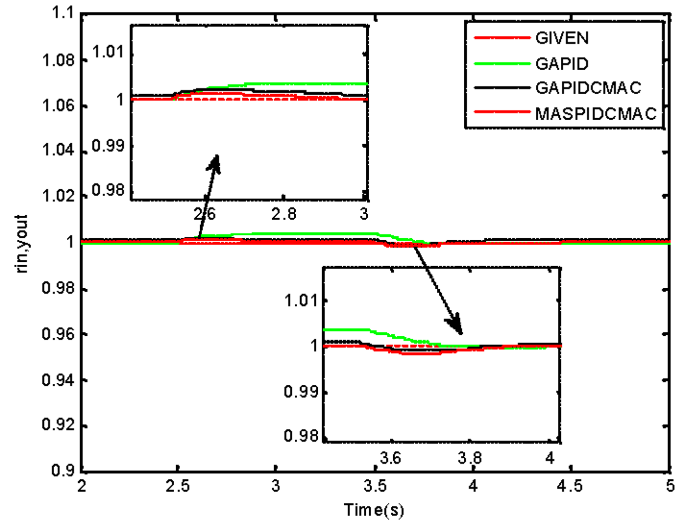


Fig. 8: Output voltages under the model uncertain

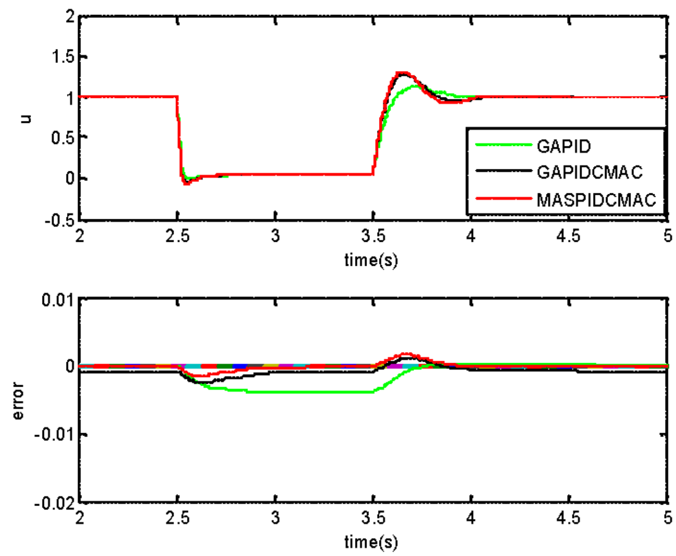


Fig. 9: Output control signal under the model uncertain

synchronous generator model change suddenly when the system is running in between 2.5s and 3.5s. The parameters change as follow: $K_G = 20$, $T_G = 25$, $T_M = 0.008$. The corresponding simulation results are shown in Fig.8 and Fig. 9 (the red simulation curve represents the results of the proposed scheme, the green one is the results of the GAPID controller, the black one is the results of the GAPIDCMAC controller and the dotted one is the voltage given signal).

From the Fig. 8 simulation plot, it shows that the traditional GAPID controller is sensitive to the control object parameter change. It can not properly track the given signal. As you can see from the Fig. 9, on the contrary, the proposed excitation control strategy not only has more rapid the response speed but also has higher control precision through on-line parameters adjustment by MAS genetic algorithm. In Fig. 9, the output error of the proposed strategy is always maintained in a small range comparing with the conventional GAPID and the GAPIDCMAC control. The new MASPIDCMAC controller has better robustness and faster learning speed.

## CONCLUSION

A new PID and CMAC compound excitation controller for synchronous generator based on one-dimensional multi-agent genetic algorithm (MASPIDCMAC) was proposed in this study which having an effective multi-parameter optimization control strategy. This scheme combines all advantages of multi-agent genetic algorithm, CMAC neural network and PID controller. From the experimental results, the new compound excitation controller for synchronous generator has the smaller voltage error, shorter adjusting time, smaller overshoot comparing with the conventional CMAC compound excitation controller and PID excitation controller. Meanwhile, the proposed method overcomes the problem that the control parameters are difficult to tune because of mutual coupling in conventional PID and CMAC compound controller. It is possible that the PID and CMAC controller based on multi-agent genetic algorithm can be easily implemented finally.

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