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ORIGINAL PAPER

Application of the hybrid genetic particle swarm algorithm to design the linear quadratic regulator controller for the accelerator power supply

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Abstract

Purpose The purpose of this paper is to study a new method to improve the performance of the magnet power supply in the experimental ring of HIRFL-CSR.

Methods A hybrid genetic particle swarm optimization algorithm is introduced, and the algorithm is applied to the optimal design of the LQR controller of pulse width modulated power supply. The fitness function of hybrid genetic particle swarm optimization is a multi-objective function, which combined the current and voltage, so that the dynamic performance of the closed-loop system can be better. The hybrid genetic particle swarm algorithm is applied to determine LQR controlling matrices Q and R.

Results The simulation results show that adoption of this method leads to good transient responses, and the computational time is shorter than in the traditional trial and error methods.

Conclusions The results presented in this paper show that the proposed method is robust, efficient and feasible, and the dynamic and static performance of the accelerator PWM power supply has been considerably improved.

Keywords Particle swarm optimization · Genetic algorithm · Accelerator power supply · Linear quadratic regulator optimal controller · Weighting matrix

Introduction

An accelerator is used to charge particles to obtain a high-energy level through an electric field. The current accelerators are mainly divided into two types: cyclotron and linear accelerators. The main constructions include the magnet, power supply, vacuum, LLRF control system, injection and extract [1]. Among these devices or systems, the power supply is very important, the power supply generates the magnetic field by providing current to the magnet; the electric field is generally provided by the power source equipment. Simple structure, low cost and easy operation are the advantages of pulse width modulation power supply, which can also avoid the pollution of huge impact and harmonics to other systems. Therefore, the research on the application of pulse width modulation power supply in accelerator is of great significance. To obtain a high dynamic performance and low ripple performance for the accelerator power, there are many ways to control the accelerator power. Several controllers are widely used for the accelerator power, such as PI and state feedback techniques, including single closed-loop control, sliding mode control, repetitive control, double closed-loop control and so on [2, 3]. With regard to the magnetic power supply of HIRFL-CSR, PWM state space equation matrices have been provided [4]. A LQR (linear quadratic regulator) controller based on GA(genetic algorithm) is designed, and a model-prediction control method of the power supply for particle accelerators has been developed [5]. In [6], the LQR controller was designed, and the PSO (particle swarm optimization) is successfully applied to the weight matrix optimization of LQR controller. However,

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all these methods are very limited and cannot improve the dynamic performance of pulse energy.

A hybrid genetic particle swarm algorithm is introduced and applied to determine the optimal value of LQR controller in PWM magnetic power supply of HIRFL-CSR. The fitness function of the hybrid genetic particle swarm optimization algorithm is a multi-objective function that combines current and voltage, which can make the dynamic performance of the closed-loop system better. Thus, a new method to optimize the system is proposed, which has the advantages of the shortest response time and the highest accuracy.

This paper is organized as follows: the mathematical model of the PWM power supply is described in "Mathematical model of the power supply" section. In "The design of the LQR controller" and "The hybrid genetic particle swarm algorithm" sections, the design of the LQR controller and the hybrid genetic particle swarm algorithm are explained, respectively. The design of the LQR controller based on the hybrid genetic particle swarm algorithm is presented in "Design of the LQR controller based on PSO-GA" section. In the last two sections, the simulation comparison results and discussions are presented, and the main conclusions of our work are stated.

Mathematical model of the power supply

The heavy ion accelerator magnet power is mainly a single-phase power supply, and its power load is the magnet. Therefore, this research primarily involves the mathematical model of a single-phase PWM inverter. As shown in Fig. 1, the model of the PWM magnet power supply in HIRFL-CSR is depicted.

Figure 1 shows that the voltage of the load is denoted by V_o, the filter capacitors are denoted by C_1 and C_2, the filter inductors are denoted by L_1, and the corresponding resistances are denoted by R_1 and R_2, respectively, and R_3 and L_3 are the magnet coil loads. The activation function of the insulated gate bipolar transistor (IGBT) (T_1, T_2, T_3, and T_4) is regulated by the controller. $V_1 = E$, when T_1 and T_4 are connected, and T_2 and T_3 are connected $V_1 = -E$. The mathematical model that describes this process is:

$$\begin{cases} V_1 - V_O = R_1 i_{L1} + L_1 \frac{di_{L1}}{dt} \\ i_{L1} = C_1 \frac{dV_O}{dt} + i_{L3} + C_2 \frac{dV_{C2}}{dt} \\ V_O = i_3 R_3 + L_3 \frac{di_3}{dt} \\ V_O = V_{C2} + R_2 C_2 \frac{dV_{C2}}{dt} \end{cases} \tag{1}$$

The PWM state–space matrices are written as follows:

$$\begin{pmatrix} \dot{i}_{L1} \\ \dot{i}_{L3} \\ \dot{V}_{C2} \\ \dot{V}_O \end{pmatrix} = \begin{pmatrix} -\frac{R_1}{L_1} & 0 & 0 & -\frac{1}{L_1} \\ 0 & -\frac{R_3}{L_3} & 0 & \frac{1}{L_3} \\ 0 & 0 & -\frac{1}{R_2 C_2} & \frac{1}{R_2 C_2} \\ \frac{1}{C_1} & -\frac{1}{C_1} & \frac{1}{R_2 C_1} & -\frac{1}{R_2 C_1} \end{pmatrix} \begin{pmatrix} i_{L1} \\ i_{L3} \\ V_{C2} \\ V_O \end{pmatrix} + \begin{pmatrix} \frac{1}{L_1} \\ 0 \\ 0 \\ 0 \end{pmatrix} V_1 \tag{2}$$

$$Y = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} i_{L1} \\ i_{L3} \\ V_{C2} \\ V_O \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \end{pmatrix} V_2 \tag{3}$$

The state vector is given by:

$$X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} i_{L1} \\ i_{L3} \\ V_{C2} \\ V_O \end{pmatrix} \tag{4}$$

The control vector is expressed as:

$$Y = \begin{pmatrix} i_{L3} \\ V_O \end{pmatrix} \tag{5}$$

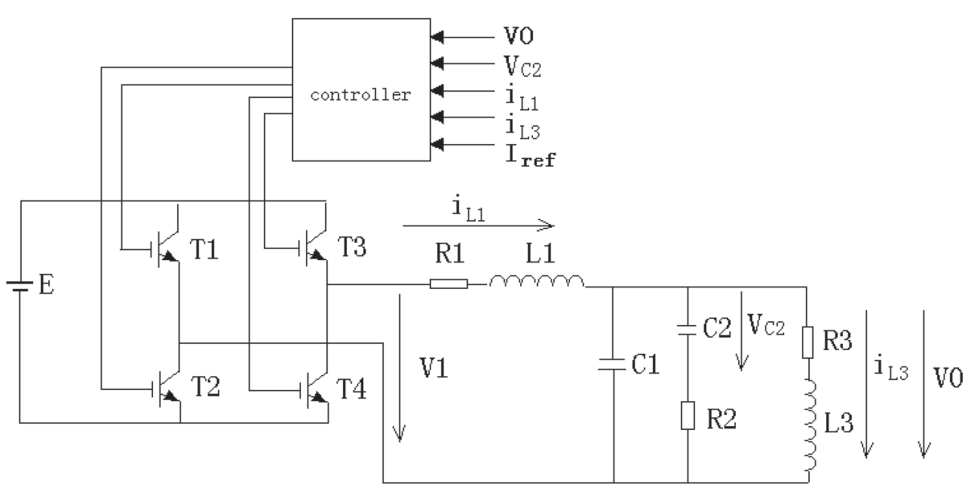

Fig. 1 PWM model of the HIRFL-CSR

where

$$V_2 = E\frac{t_1 - t_2}{t_1 + t_2} \tag{6}$$

t_1 is the on time in one period when T_1 and T_4 are conducted, and t_2 is the on time when T_2 and T_3 are turned on.

The design of the LQR controller

The response of the system can be improved by adopting LQR control method. In the past 50 years, LQR design has been widely studied [7, 8]. Therefore, the linear optimal control theory has been well developed. LQR control is based on the selection of the two matrices Q and R, these matrices ensure that better closed-loop performance can be obtained. The object of the LQR controller is a linear system of the state space. The objective function is the integral of control variables and the quadratic function of the state. For a system can be expressed by state equation, the following applies:

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases} \tag{7}$$

In order to obtain the best LQR controller, the state feedback gain $K(u = Kx)$ is used to minimize the given performance index:

$$J' = \frac{1}{2}\int_0^\infty (x(t)^T Qx(t) + u(t)^T Ru(t))dt \tag{8}$$

with the state vector $x = (x_1, x_2, \ldots, x_n)$, the control input $u = (u_1, u_2, \ldots, u_n)$. The expressions of the matrices Q and R are as follows: Q (an $n \times n$ matric) is a positive semi-definite matrix, and R (an $m \times m$ matric) is a positive definite matrix. The pair (A, B) must be controllable.

To determine K, solving the algebraic Riccati equation (ARE) can obtained the value of P:

$$-PA - A^T P + PBR^{-1}B^T P - Q = 0 \tag{9}$$

The input of optimal control is obtained:

$$u = Kx = -R^{-1}B^T P \tag{10}$$

The system becomes:

$$\begin{cases} \dot{x} = Ax + BKx \\ y = Cx \end{cases} \tag{11}$$

The LQR design can be regarded as the minimization of performance index J, the J can be viewed as an energy function, so that minimizing it keeps the small total energy of the closed-loop system. The state vector $x(t)$ and control input $u(t)$ are weighted in J. In addition, if performance index J is minimized, then it is certainly finite, and since it is an infinitive integral of $x(t)$, this implies that $x(t)$ goes to zero as t approaches infinity. This guarantees the stability of the closed-loop system.

The Q is the weight matrix of the performance index function to the state vector. The larger the element, the more important the variable is in the performance function. The R is the weight matrix of the control input, the larger the element, the greater the control constraint. The main method for determining Q and R is to use the trial and error procedure, which need to take a lot of time [9]. Harvey proposed a method based on eigenvalues and eigenvectors [10], but its accuracy is not high. In this paper, the quadratic optimization method is applied to design LQR controller, and a PSO-GA hybrid algorithm is propose to determine Q and R.

The hybrid genetic particle swarm algorithm

In this section, the LQR control methods using the hybrid genetic particle swarm algorithm are described.

A. Particle swarm optimization

In 1995 Kennedy and Eberhart proposed the PSO algorithm [11]. A standard PSO algorithm is presented by Shi in 1998 [12]. PSO is inspired by a group of birds or fish in sociological behavior. The PSO can be expressed as follows: there are N particles in a D-dimensional space, the position of particle ith is a D-dimensional vector, and it can be expressed as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ for $i = 1, 2, \ldots, N$, the position of each particle is a potential solution.

The fitting value is calculated by substituting X_i in the objective function, the pros and cons of the solution are then measured by the fitness value. The flight speed of particle ith is a D-dimensional vector, described as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The optimal location search by particle ith is $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$, and the optimal location search by the particle swarm is $P_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$. We can use the following equations to adjust the particle velocity and position:

$$V_{id}^{k+1} = wV_{id}^k + c_1 rand_1^k(P_{gd}^k - X_{id}^k) + c_2 rand_2^k(P_{gd}^k - X_{id}^k) \tag{12}$$

$$X_{id}^{k+1} = X_{id}^k + V_{gd}^{k+1} \tag{13}$$

where d is the dimension $(d = 1, 2, \ldots, D)$, i is the number of particles $(i = 1, 2, \ldots, N)$, c_1 and c_2 are nonnegative constant learning factors, and $rand_1^k$ and $rand_2^k$ are two pseudorandom numbers with a uniform distribution in the interval of

[0, 1] that are independent of each other. The upper limit of the speed is $|V_{id}| \leq Vmax_{id}$.

Particle swarm optimization is a random search algorithm based on group cooperation developed by simulating the foraging behavior of birds. It is generally considered to be a type of swarm intelligence (SI). PSO is initialized as a group of random particles (random solution), and then the optimal solution is found through iteration. In the solution space, searching follows the optimal particles simply. The advantage of the algorithm is that it can be easily implemented against an intelligence background. Therefore, the algorithm is suitable for scientific research and engineering applications [13–16].

The PSO algorithm is a global optimization algorithm. It is mainly used for optimizing complex nonlinear functions and can also be adopted to solve combinatorial optimization problems. In the optimization process, as the particle swarm nears the optimal particle, its speed is decreased. Therefore, the particle swarm exhibits a strong homoplasy, and it easily converges to the local minimum point.

B. Genetic algorithm

In 1975, Holland proposed the Genetic algorithm. The GA is a evolutionary technique based on the genetics and selection mechanics, and it combines the artificial phenomenon of survival of the fittest with genetic operators [17]. It has successful application in self-adaptive control systems, image processing, neural networks, machine learning, etc. [18–21].

The GA can be regarded as an search process, in which a population of solutions evolves over a sequence of generations. In GA, the population is called a set of solutions, and a chromosome represented a solution. In most cases, chromosomes are expressed according to strings. The size of population is saved in each generation. For each generation, the fitness of each chromosome is evaluated by a defined fitness function, then the chromosomes of the next generation are selected probabilistically based on their fitness value. Some selected chromosomes mate randomly and produce offspring. When producing offspring, the selected solutions then undergo recombination through the crossover and mutation operators. Because chromosomes with high fitness values are more likely to selected, the average fitness values of new-generation chromosomes may be higher than those of previous generations. Until the end condition is satisfied, the process of evolution is repeated [22].

GA is robust because it does not limit the search method in the hypothetical search space. Compared with the traditional improved technology, GA is more likely to get the global optimal solution of a given problem, because it evaluates many research points at the same time. In addition, only simple performance indicators are considered in genetic algorithms, which do not require or use derivative information. The GA process is performed through the following iterative steps.

1) Selection operation: Through the method of spinning a roulette wheel, two pairs of chromosomes from the previous population are selected to undergo genetic operations for reproduction.
2) Crossover operation: The crossover operation mainly exchanges information from the two chromosomes. Through selecting two chromosomes of the present population, the fitness of the produced chromosomes can be improved.
3) Mutation operation: The genetic representations of the chromosomes are altered according to the rule of certain probabilistic. The GA continues to generate a new population until it reaches the desired point.

C. The hybrid genetic particle swarm algorithm

In order to improve the global search ability, this paper combines particle swarm optimization with genetic algorithm [23–26]. A hybrid optimization algorithm based on particle swarm optimization and genetic algorithm is proposed [27], which first preserves the optimal M particles by evolving a certain number of generations and removes pop_size-M particles. Then based on the position values of these M particles, pop_size individuals are selected and copied, and GA operators such as the crossover and mutation operators are computed. Finally, the position values of the M particles preserved by PSO are merged with the pop_size-M particles obtained by the GA evolution to form a new particle population for the next generation of evolutionary computations. The matching search process is depicted as follows:

Step 1 Initialize the relevant parameters: the number of particle groups pop_size, the number of particles retained after evolution via PSO M, the PSO weighting factors c_1 and c_2, the GA crossover and mutation probabilities pc and pm, respectively, the maximum particle velocity V_max, the PSO evolution algebraic parameter k_ max and the hybrid algebraic parameter max_gen;

Step 2 In the feasible domain range generate the initial pop_size particles and calculate the objective function value;

Step 3 Let gen = 1;

Step 4 If gen ≤ max_gen, go to step 5; otherwise, step 11 will be taken;

Step 5 Update the particle position and velocity using PSO;

Step 6 Sort the pop_size particles according to the target function value and select the smallest number of M particles;

Step 7 Copy to generate pop_size-M GA particles by the position values of the retained M particles;

Step 8 Perform crossover and mutation operations on the pop_size-M particles;

Step 9 Merge the M particles reserved through PSO and the pop_size-M particles obtained by the GA to form a new particle population for the next generation;

Step 10 Let gen = gen + 1, and go to step 4;

Step 11 Outputs the optimal objective function value and the optimal solution (position).

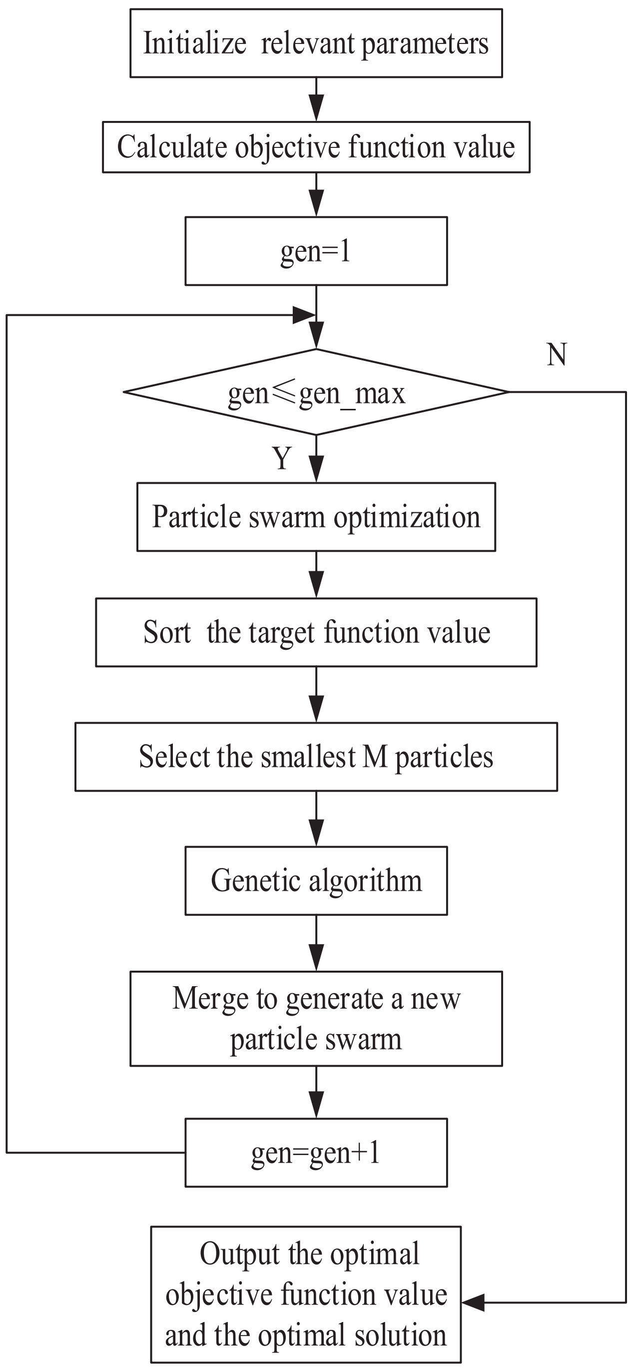

Fig. 2 PSO-GA hybrid algorithm process chart

The detailed process is shown in Fig. 2.

Design of the LQR controller based on PSO-GA

Applying state feedback to the optimization algorithm is a favorable control technique. As previously mentioned, the difficulty of LQR design is to select the matrices Q and R, which is usually obtained after many attempts by the design engineers. Even with the designer's knowledge and efforts, there is no guarantee that the controller is the best LQR controller. Several techniques are used to select the Q and R of the LQR controller[28]–30. In this case, we take the PSO-GA algorithm to select matrices Q and R. The LQR controller based on the PSO-GA algorithm structure diagram is shown in Fig. 3.

The LQR controller is a closed-loop controller, and the weight matrices Q and R are optimized by the hybrid genetic particle swarm algorithm. In this case, Q is a diagonal matrix and has a dimension 4×4 ($Q = \text{diag}\ (q_{11}, q_{22}, q_{33}, q_{44})$). R is a 1×1 matrix($R = r_l$). In order to obtain the values of two matrices elements, the closed-loop system's step response under LQR control is calculated in each iteration. The optimal values are tested with the fitness function defined based on the parameters of the step response [31]:

$$J = K \times (1 - \exp(-1)) \times (M_p + M_{p1}) + (\exp(-1) \times (t_s - t_r)) \quad (14)$$

where t_r is the rise time of the output current, t_s is the settling time of the output current, M_p is the overshoot of the output current, M_{p1} is the overshoot of the output voltage, and K is a coefficient. In the case under study, $K = 1$. The fitness function is a multi-objective comprehensive value in which the dynamic characteristics of output voltage and output current are considered.

In this way, the time-consuming stage of selecting Q and R can be performed very accurately, and the system can be optimized to the expected closed-loop specifications automatically. Finally, the closed-loop system has the less oscillation, less overshoot, and a short settling time.

The simulation results

To validate the previously mentioned method, a entire system model is created in MATLAB environment. To evaluate the optimized LQR controller designed with the hybrid genetic particle swarm algorithm, analyze the characteristic value of step response of closed-loop system. In Fig. 4, the comparison of current step response is obtained by particle swarm optimization-genetic

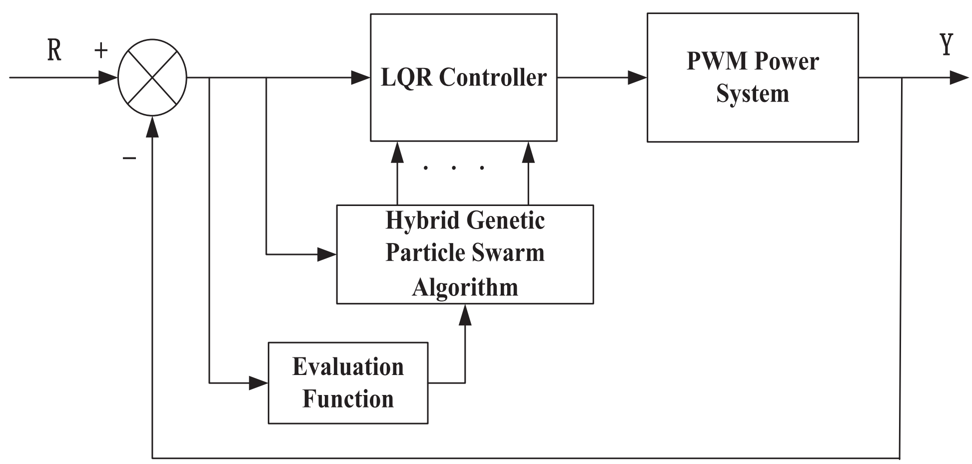

Fig. 3 Structure diagram of the LQR control system based on PSO-GA

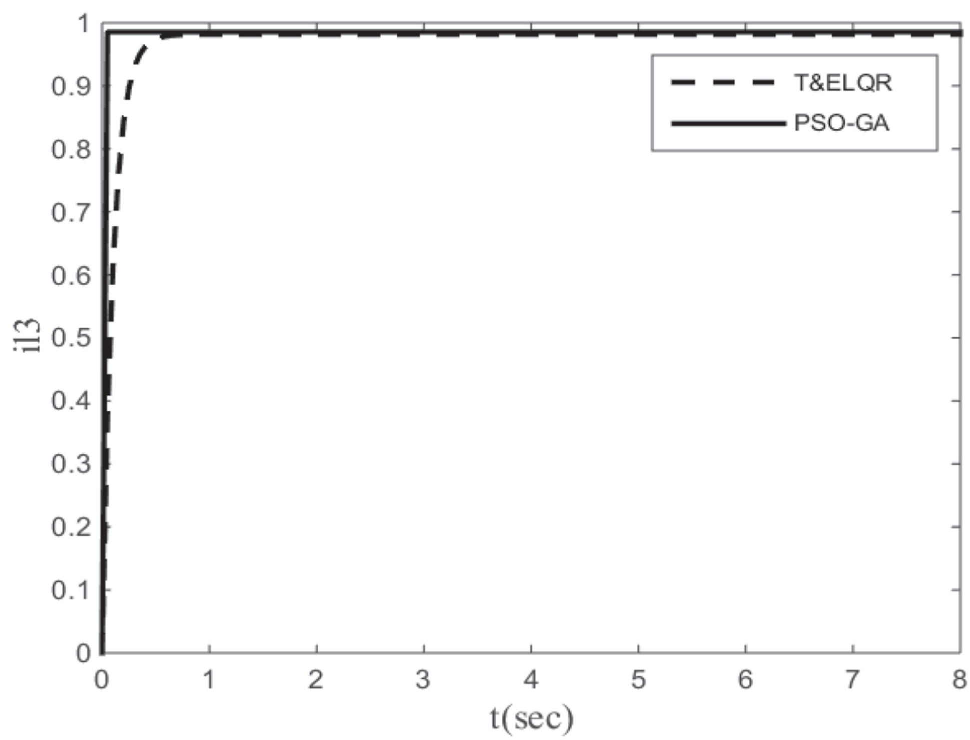

Fig. 4 Comparison of the current step responses between the two controllers

algorithm and trial and error method. Figure 5 shows a comparison of voltage step responses. The curve of the global optimal fitness value, which has been achieved by the PSO-GA, is shown in Fig. 6. The precision degree is evaluated based on the values of the step response in Table 1.

As the results show, after applying the method described in this paper, the voltage overshoot and current rise time are smaller than other methods, and the control effect is better. Therefore, the obtained simulation results demonstrate that using PSO-GA to optimize the weighed matrix Q and R of the LQR controller has the advantage of a better dynamic performance.

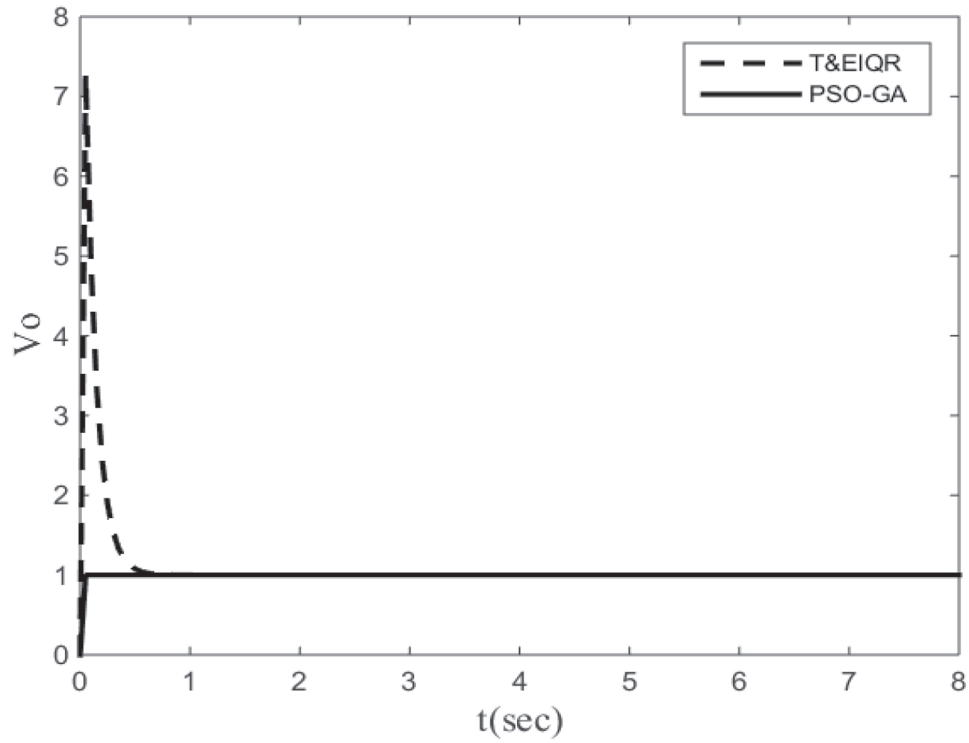

Fig. 5 Comparison of the voltage step responses between the two controllers

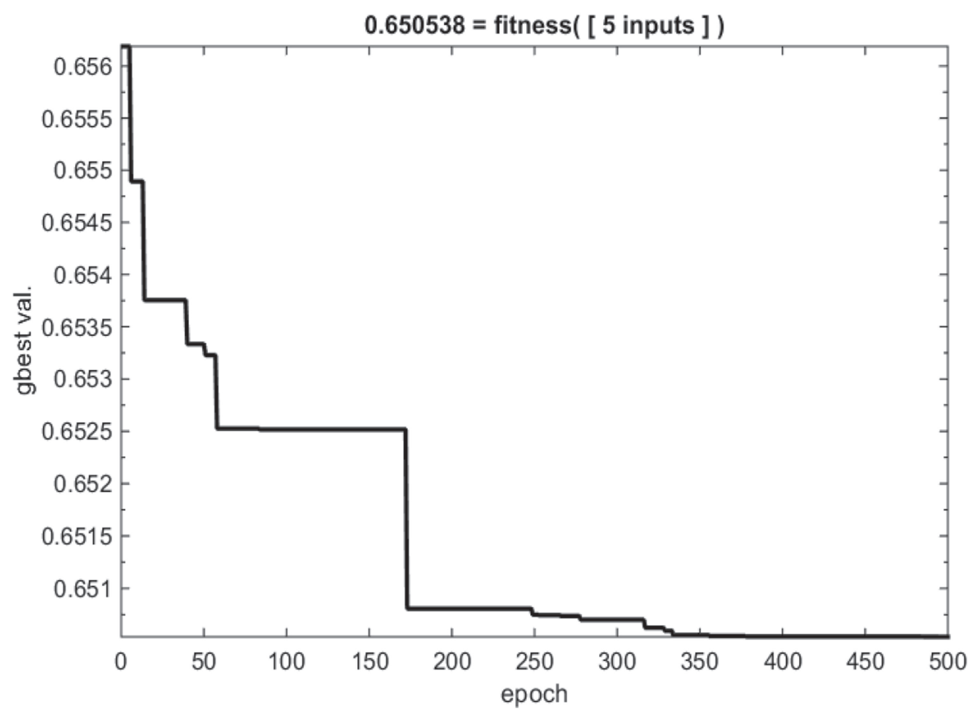

Fig. 6 Curve of the global optimal fitness value based on PSO-GA

Conclusions

In order to improve the performance of the magnet power supply for accelerator, LQR controller is designed in this paper. The weighed matrix of the LQR controller has been optimized by a hybrid genetic particle swarm optimization algorithm, which avoids the drawbacks of the artificial selection of matrices Q and R when designing the optimal LQR controller. The simulation results show that adoption of these techniques leads to good transient responses, and the computational time is shorter than the

Table 1 Comparison results for the various control strategies

	M_{P1} (%)	t_r (s)
Open loop	12	2.37
LQR1	286.39	0.51
LQR-GA [4]	33	1.61
LQR-PSO [6]	0.9	0.14
LQR-PSO-GA	0.7	0.11

traditional trial and error methods. It is also evident that the LQR controller based on PSO-GA attains satisfactory control results. The proposed method is robust, efficient and feasible, and the dynamic and static performance of the accelerator PWM power supply have been considerably improved.

Appendix

System parameters:

$L_1 = 0.3$ mH
$L_2 = 91.4$ mH
$C_1 = 10$ μF
$C_2 = 47$ μF
$R_1 = 0.01$ Ω
$R_2 = 0.0796$ Ω
$R_3 = 1$ Ω

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