Boost Converter Optimal Control Based on MFAC and FPSOA under Model Mismatch

Zhanjun Huang[1], Zhanshan Wang[1], Cui Lei[2], Shijie Yan[1], Huaguang Zhang[1],
1. School of Information Science and Engineering, Northeastern University, Shenyang, 110004
E-mail:zj_huang@sina.com
E-mail: wangzhanshan@ise.neu.edu.cn
2. Nanjing Research Institute on Simulation Technique, Nanjing, 210000
E-mail:cuileineu@163.com

Abstract: An optimal control of boost converter based on model-free adaptive controller (MFAC) and fuzzy particle swarm optimization algorithm (FPSOA) is proposed to realize a better response performance and robustness under model mismatch and the parameter time variation. The data-based MFAC is investigated to design the boost converter, which avoids the precise modeling and greatly reduces the influence of model mismatch. Additionally, the FPSOA is used for online optimization of the controller parameters to improve the response performance and robustness. Comparing with the traditional optimal control methods of boost converter, the proposed method avoids the contradiction of establishing accurate model and complex systems design. It inhibits the influences of the parameter time variation and model mismatch, and has a better dynamic and static performance. Finally, the test is implemented on a semi-physical simulation platform for power electronic control systems. The comparison of MFAC and classic state feedback exact linearization control in various model mismatch situations are used to show the effectiveness of the obtained results.

Key Words: Model-free adaptive, Fuzzy particle swarm optimization algorithm, Boost converter, Optimization

1 INTRODUCTION

DC/DC converter is a widely used power electronic switching circuit. As a typical DC/DC converter, boost converter is essentially a strongly nonlinear, multi-mode(DCM and CCM), time-varying dynamic system and has a period doubling, bifurcation, chaos phenomenon[1]. Nonlinear control combined with the advantages of PI regulator for switching converter system can be used to improve the dynamic and steady-state characteristics of the system [2]-[3]. In [16], based on boost converter nonlinear model, control object-based rather than based on nonlinear control method, feedback exact linearization control method based on differential geometry theory state is developed in some papers. In order to obtain a better dynamic quality, nonlinear control based on backstopping is developed in [17]. Compared with state feedback precise linearization control, it simplifies the control algorithm and improves the control performance of the system.

Although the study of the above control method has yielded some results, it makes the analysis of the whole control object parameter more complex because of the special position of boost DC-DC converter topology inductance. The presence of model mismatch and the parameter Time-Variation are not given full consideration in the control method based on control object model, and the control method has strong robustness only when the system parameters change in a certain range. In practical applications, when the inductive device changes in a wide range due to aging, output voltage ripple is large and even leads to system instability. At this time, the state feedback exact linearization control method is often unable to play a good role in the control, and even cannot control the boost converter. The main contributions of this paper are summarized as follows:

- The controller of the boost converter based on data-driven model-free adaptive control is investigated in this paper to reduce the dependence of existing boost converter controller on the control object model. This method reduces the influence of model mismatch and the parameter Time-Variation for the boost converter. It also avoids the contradiction of establishing accurate model and complex systems design.
- The advanced fuzzy particle swarm optimization algorithm is used to optimize the controller parameters online, then obtains global optimal solution and optimizes results. Comparing the conventional experience of trial and error debugging controller parameters, it is more accurate and convenient to obtain the optimal combination of parameters for the boost controller. Thus, the boost converter achieves a better response performance and robustness under model mismatch.
- The influence of the change of the controlled object model is considered. When the inductor and load resistor of boost converter mismatch respectively, the model-free adaptive control and status feedback precise linearization are compared to study the practical effect.

2 THE BASIS THEORY OF MODEL-FREE ADAPTIVE CONTROLLER

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Model-free adaptive control is an entirely new theory and technology in the field of automatic control. According to many papers, the parameter estimation algorithm and control law algorithms can come up with a MFAC control method. It does not rely on a parameter mathematical model of the controlled system, the control method are summarized as follows:

Estimation algorithm $\phi(k)$:

$$\hat{\varphi}(k)=\hat{\varphi}(k-1)+\frac{\eta\Delta u(k-1)}{\mu+\Delta u(k-1)^2} *(\Delta y(k)-\hat{\varphi}(k-1)\Delta u(k-1)) \tag{1}$$

$$\text{If } \left.\begin{cases}|\hat{\varphi}(k)|\le\varepsilon \\ or\,|\Delta u(k-1)|\le\varepsilon\end{cases}\right\}, \text{then } \hat{\phi}(k)=\hat{\phi}(1) \tag{2}$$

Control law algorithm $u(k)$:

$$u(k)=u(k-1)+\frac{\rho\hat{\phi}(k)}{\lambda+\left|\hat{\phi}(k)\right|^2}(y_r(k+1)-y(k)) \tag{3}$$

The ρ and η in algorithms are step-size constants, the weighting factor λ 、 μ are parameters of the system. ε is a sufficiently number (0.00001), $\hat{\phi}(k)=\hat{\phi}(1)$ is the initial value of $\phi(k)$. The specific derivation can refer to reference [4].The basic algorithm of model-free control law is composed of online interaction of the pan-model identification algorithm and basic control algorithm. When the value of $\hat{\Phi}(k)$ is recognized, control law can be applied to the system to perform feedback control, the control result will get a new set of observation data. Add this new set of data to the existing data, identify $\hat{\Phi}(k+1)$, and then go on like this.

3 THE DESIGN OF FUZZY PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization algorithm is a computational intelligence based on swarm intelligence optimization algorithm. Because of its simple concept, easy operation, good robust, particle swarm algorithm has cut a striking in engineering optimization [6]-[9].

The inertia weight, fixed inertia weight and a linear value of particle swarm optimization algorithm[10]-[12]are simple for most nonlinear problems, clearly is weak and difficult to use, which may result in poor optimization results. Therefore, in order to improve the algorithm's superiority, Shi and Eberhart introduced a particle swarm algorithm [13]-[14] by the improved fuzzy changing inertia weight system dynamic.

3.1 Select Optimization Objective Function

To the control system described in this paper, the objective function is selected to make the deviation of the optimized control system to zero, and make the system has a faster response and smaller overshoot. Therefore, the objective function is often used ITAE (Integral of time multiplied by absolute error)

$$J_{ITAE}=\int_0^{\infty}t\left|e(t)\right|dt \tag{4}$$

|e(t)| is system error absolute value.

3.2 Standard Particle Swarm Optimization

The standard particle swarm optimization steps are as follows:

Step 1: The initialization of Particle Swarm. Analysis the problem optimized. Equal reasonable probability distribution function is used to generate a group of (series) particles reasonably, and then the speed and position of each particle are assigned randomly. And the maximum generation or minimum is set as objective function value.

Step 2: Measure the fitness of each particle according to the objective function. In the processing optimization problem in this paper, the objective function is minimized.

Step 3: Get individual optimal value pbest by comparing. Compare each particle’s contemporary fitness with the previous particles pbest. If the contemporary fitness p_f is better than the previous pbest, then the pbest will be updated by the contemporary fitness p_f ,the position of the particle is also updated.

Step 4: Derive group optimal value gbest by comparing. Elect the best contemporary groups in each best contemporary particle above, and then compare the fitness with previous gbest. If the best contemporary group is better than precious gbest, then the contemporary optimal particle properties is updated by the gbest.

Step 5: Update the velocity and position of each particle. Update the particle's velocity and position according to the following formula (5) and (6):

$$v_i^{k+1}=w\cdot v_i^k+c_1\cdot rand_1\cdot(x_i^p-x_i^k) +c_2\cdot rand_2\cdot(x_i^g-x_i^k) \tag{5}$$

$$x_i^{k+1}=x_i^k+v_i^{k+1} \tag{6}$$

In the above formula, w is weighting factor, $i=1,2,\ldots,M$ is each particle in the particle population. $k=1,2,\ldots,k_{\max}$ is generation the particles are in. v_i^k represents the speed of particle i at generation k , x_i^k represents the position of particle i at generation k . x_i^p represents the best location of particle i , x_i^g represents the best location of all the groups. c_1 and c_2 are acceleration constant, and characterize individual and social cognition, learning ability respectively. Normally, to ensure good effect of the algorithm, take $c_1=c_2=2$. $rand_1$ and $rand_2$ are random number in $[0,1]$. From the above formula (5) (6), evolution particle state is profiled by previous experience and the random process.

Step 6: Algorithm update cycle. When it does not meet the termination conditions, repeat steps 2. When the termination condition is satisfied, exit the algorithm, and get the optimal solution. Termination condition is often the maximum generation or optimal objective function value.

3.3 The Fuzzification of Inertia Weight

The fuzzy system has two input variables, respectively, are the population optimum performance indicators (CBPE) and the current inertia weight (weight). The system has an output variable, namely inertia weight variable w_change. The standardized CBPE form is as follows:

$$NCBPE = \frac{CBPE - CBPE_{\min}}{CBPE_{\max} - CBPE_{\min}} \qquad (7)$$

In formula (7), $CBPE_{\min}$ is the minimum estimated value. $CBPE_{\max}$ is non-optimal solution, represents the $CBPE$ is greater than or equal to a non-feasible solution. The value $CBPE_{\min}$ is 0. By a large number of experimental studies, when $CBPE_{\max} = 1$, the optimizer can have good result.

There are three fuzzy statuses in all fuzzy variables: low, medium, and high state. Corresponding membership function are $f_{left\_Triangle}$, $f_{Triangle}$, $f_{right\_Triangle}$.

$$f_{left\_Triangle}(x) = \begin{cases} 1 & if \quad x < x_1 \\ \dfrac{x_2 - x}{x_2 - x_1} & if \quad x_1 \le x \le x_2 \\ 0 & if \quad x \ge x_2 \end{cases} \qquad (8)$$

$$f_{Triangle}(x) = \begin{cases} 0 & if \quad x < x_1 \\ 2\dfrac{x - x_1}{x_2 - x_1} & if \quad x_1 \le x \le \dfrac{x_2 + x_1}{2} \\ 2\dfrac{x_2 - x}{x_2 - x_1} & if \quad \dfrac{x_2 + x_1}{2} \le x \le x_2 \\ 0 & if \quad x \ge x_2 \end{cases} \qquad (9)$$

$$f_{right\_Triangle}(x) = \begin{cases} 0 & if \quad x < x_1 \\ \dfrac{x - x_1}{x_2 - x_1} & if \quad x_1 \le x \le x_2 \\ 1 & if \quad x \ge x_2 \end{cases} \qquad (10)$$

x_1 and x_2 determines the shape and position of the function.

Table1.Variables and Variable Scope

Functions	Range of variables
$f_{Triangle}$	(0.05,0.4)
$f_{right\_Triangle}$	(0.3,1)
$f_{left\_Triangle}$	(0.2,0.6)
$f_{Triangle}$	(0.4,0.9)
$f_{right\_Triangle}$	(0.6,1.1)
$f_{left\_Triangle}$	(-0.12,-0.02)
$f_{Triangle}$	(-0.04,0.04)
$f_{right\_Triangle}$	(0.0,0.05)

Table2. Fuzzy Rules

If	Then
Var1=1 and Var2=2	Var3=1
Var1=1 and Var2=3	Var3=1
Var1=2 and Var2=1	Var3=3
Var1=2 and Var2=2	Var3=2
Var1=2 and Var2=3	Var3=1
Var1=3 and Var2=1	Var3=3
Var1=3 and Var2=2	Var3=2
Var1=3 and Var2=3	Var3=1

In summary, the flow chart of optimizing the parameters of the controller by using fuzzy particle swarm optimization algorithm is shown in Fig. 1.

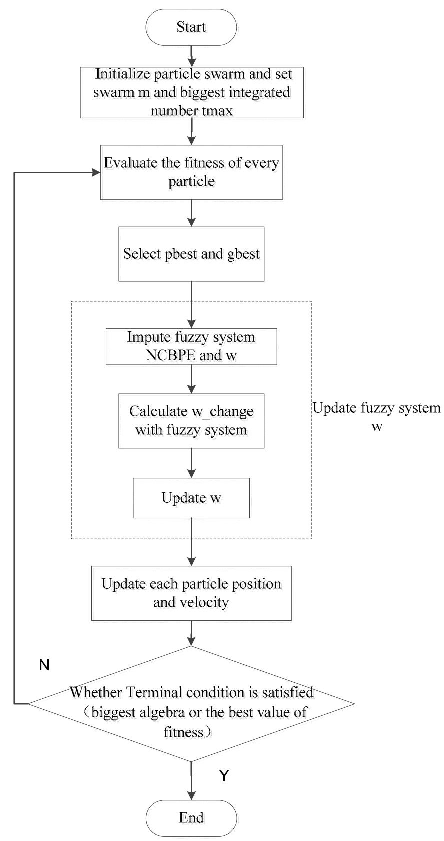


Fig.1.The flow chart of fuzzy adaptive particle swarm algorithm to optimize the controller parameters.

4 SEMI PHYSICAL SIMULATION ANALYSIS AND RESEARCH

4.1 The Process to Design An Optimized Controller

In this paper, it is implemented by the power electronic control system semi-physical simulation platform [15]. Select and produce the actual Boost converter circuit, build a model-free adaptive controller in the MATLAB.

Parameters of the actual boost converter are selected as follow. Input voltage $U_{in} = 5V$, desired output voltage

$U_{ref} = 12V$, load $R_L = 100\Omega$, switching frequency $f_s = 10kHz$, input inductor $L = 0.5mH$, output capacitor $C = 470\mu F$, which are shown in Fig. 2.

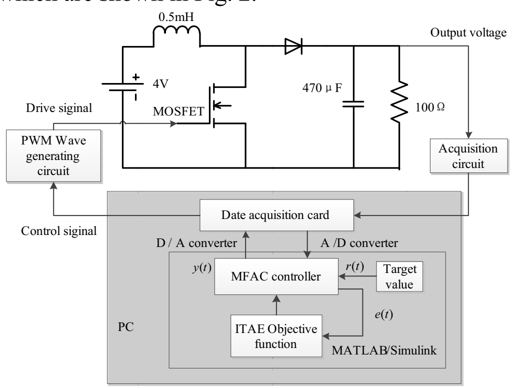


Fig. 2. Structure of parameter optimization.

The optimization processes are as follows: FAPSO produces particle swarm, the particles in the particle swarm are assigned to MFAC controller parameters ρ and λ in turn. Then run the control system, achieve corresponding performance index of the set's parameters. The performance indicators pass to FAPSO as the fitness value of the particle, and determine whether they can exit the algorithm.

4.2 The Optimization of MFAC Controller Parameters

According to the parameters trial and error experience in reference, set the MFAC controller parameters: estimation algorithm $\hat{\varphi}(1) = 0.1$,step sequence $\eta_k = 1$,weighting coefficient $\mu = 0.1$. MFAC controller's step sequence ρ_k and weighting coefficient λ have greatest impact on the control effect. First set the MFAC controller $T = 0.00001s$, $\rho_k = 0.0001$, $\lambda = 0.001$. According to fuzzy particle swarm optimization algorithm, set the FAPSO parameters as follows: initial value of inertia facto $w = 0.85$, acceleration constant $c_1 = c_2 = 2$, dimension is 2 (2 parameters are to be optimized), particle swarm scale is 20, the maximum number of iterations is 100, the minimum fitness value is negative infinity, speed range in $[-1,1]$, the range of the two parameters to be optimized is $[0,1]$, $[0,1]$ respectively. Optimal parameters can be achieved after setting parameters and semi-physical simulation. The boost converter actual output voltage and inductor current waveform is shown in Fig. 3 (b).

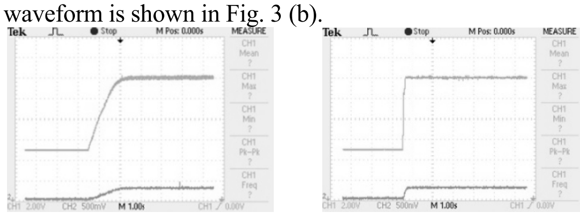

(a) (b)

Fig. 3.The boost converter output voltage (top) and inductor current (bottom) waveforms((a)before optimization,(b) after optimization).

As we can be seen from Fig.3(a)and Table 3, under the set of parameters, the rising process of the output voltage is slower, the output voltage has no overshoot and reaches steady state after 1.824s, steady-state voltage is 12.08V. Control voltage doesn't overshoot, the steady-state value is 2.215V. The value of fitness function ITAE is 0.0012.

As we can see from Fig. 3 (b) and Table 3, the rising process of the output voltage is fast, the output voltage has no overshoots and reaches steady state after 0.160s, and steady-state value is 12.08V. Control voltage doesn't overshoot, steady state is 2.208V. When the output voltage reaches a steady state, the duty cycle of the PWM wave is 0.5813, approximately equal to the theoretical value 0.5833. The value of fitness function ITAE is $3.131*10^{-5}$.

Table3.The Control Results Before Optimization and After Optimization

Index	Before optimization	After optimization
ρ_k	0.0001	0.0210
λ	0.001	0.7422
t_s(s)	1.824	0.160
V_{CS}(V)	2.215	2.208
V_S(V)	12.08	12.08
e_{ss}(%)	0.67	0.67
I_{LS}(A)	0.32	0.32
J	0.0012	$3.131*10^{-5}$

e_{ss}—Steady-state error, J—Fitness function value

I_{LS}—Inductor current's steady-state value, t_s—Adjustment time

V_{CS}—Steady-state value of control voltage

V_S—The output voltage of steady-state value

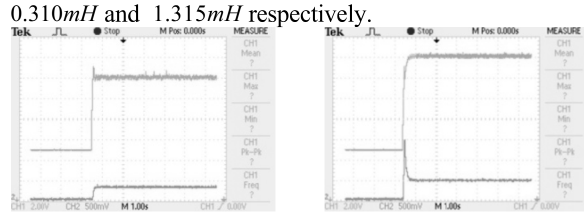
From the control results before optimization and after optimization, it can be seen that the optimized controller performance is significantly better than previous optimization controller.

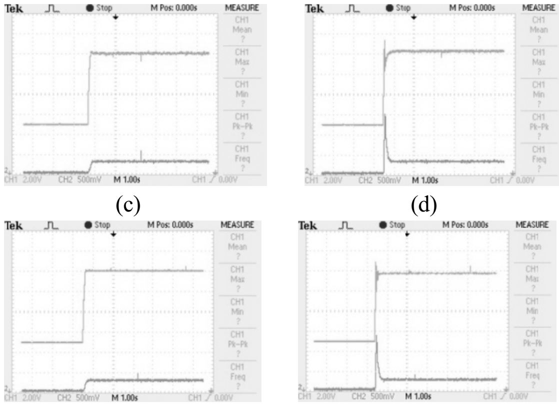
4.3 The Simulation Study of Model Mismatch Loop

Because of the boost converter topology inductance's position is special, the inductance value will change due to temperature and electromagnetic interference. Load resistor will also changes as the temperature changes. Thus, boost converter model will change. To study boost converter in the case of model mismatch, separately change the inductance and resistance, and the rest of the parameters remain unchanged.

1) The inductance mismatching

The boost converter inductance value changes to $0.125mH$, $0.310mH$ and $1.315mH$ respectively.


(a) (b)



(c) (d)

(e) (f)

Fig. 4.The actual output voltage and inductor current waveform of the boost converter (model-free adaptive control: (a)L=0.125mH,(c)L=0.310mH, (e)L=1.315mH. classical state feedback exact linearization control: (b) L=0.125mH, (d)L=0.310mH ,(f) L=1.315mH).

From Table4 and Table5, when the boost converter inductance value mismatches, the output voltage steady-state value of the model-free adaptive control keeps the same, adjustment time is always around 0.2s, and the current doesnot overshoot. The influence of the inductance change on control result is little. The output voltage steady-state value of the state feedback exact linearization control changes, especially the inductance value is $0.125mH$, steady-state error reaches to 17.3%, adjustment time is slower. And the inductor current start peak is larger, about 1.5A. Therefore, when the boost converter inductance value mismatches, the control result of the model-free adaptive control is better than that of the state feedback precise linearization control.

Table4.The Control Comparison Results of Boost Converter When the Inductor Mismatches Under Model-free Adaptive Control

L(mH)	0.125	0.310	0.5(match)	1.315
t_s(s)	0.0001	0.0210	0.160	0.14
V_{PP}(V)	0.001	0.7422	12.08	12.08
σ%	1.824	0.160	——	——
V_S(V)	2.215	2.208	12.08	12.08
e_{ss}(%)	12.08	12.08	0.67	0.67
I_{LP}(A)	0.67	0.67	0.32	0.32
I_{LS}(A)	0.32	0.32	0.32	0.32

Table5.The Control Comparison Results of Boost Converter When the Inductor Mismatches Under State Feedback Exact Linearization Control

L(mH)	0.125	0.310	0.5(match)	1.315
t_s(s)	0.448	0.504	0.396	0.28
V_{PP}(V)	14.08	13.36	11.92	12.88
σ%	——	8.4	——	9.5
V_S(V)	14.08	12.32	11.92	11.76
e_{ss}(%)	17.3	2.7	0.67	2
I_{LP}(A)	1.5	1.52	1.4	1.4
I_{LS}(A)	0.52	0.36	0.32	0.3

I_{LS}—Inductor current's steady-state value, t_s—Adjustment time

V_{PP}—Output voltage's peak value , e_{ss}—Steady-state error

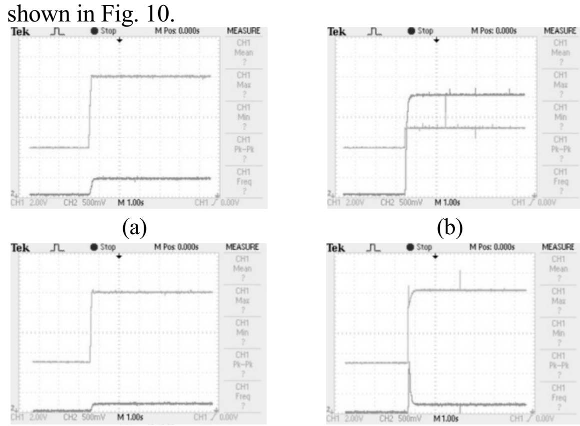
I_{LP}—Inductor current's peak value

σ%—Output voltage overshoot

V_S—Output voltage's steady-state's value

2) The load resistor mismatching

In this paper, the boost converter load resistor value changes to 65Ω and 150Ω respectively. The actual output voltage and inductor current waveform of the boost converter under model-free adaptive control and the classical state feedback exact linearization control are shown in Fig. 10.



(a) (b)

(c) (d)

Fig. 5. The output voltage and inductor current of the boost converter(Model-free adaptive control: (a)R= 65Ω , (c)R= 150Ω . classical state feedback linearization control: (b)R= 65Ω ,(d)R= 150Ω)

Table6.The Control Comparison Results of Boost Converter When the Load Resistor Mismatches UnderModel-free Adaptive Control

R(Ω)	65	100(match)	150
t_s(s)	0.136	0.160	0.176
V_{PP}(V)	12.08	12.08	12.32
σ%	——	——	2.0
V_S(V)	12.08	12.08	12.08
e_{ss}(%)	0.67	0.67	0.67
I_{LP}(A)	0.48	0.32	0.22
I_{LS}(A)	0.48	0.32	0.22

Table7. The Control Comparison Results of Boost Converter When the Load Resistor Mismatches UnderState Feedback Exact Linearization Control

R(Ω)	65	100(match)	150
t_s(s)	0.048	0.396	0.3

V_{PP}(V)	6.96	11.92	12.72
σ%	——	——	3.9%
V_S(V)	6.96	11.92	12.24
e_{ss}(%)	42	0.67	2.0
I_{LP}(A)	2.56	1.4	1.3
I_{LS}(A)	2.56	0.32	0.24

t_s—Adjustment time

e_{ss}—Steady-state error

σ%—Output voltage overshoot

V_{PP}—Output voltage's peak value ,

I_{LP}—Inductor current's peak value

I_{LS}—Inductor current's steady-state value,

V_S—Output voltage's steady-state's value

From Table 6 and Table 7, when the load resistor of boost converter mismatches, the output voltage steady-state value of the model-free adaptive control keeps the same, adjustment time is always from 0.1s to 0.2s, and the current doesn't overshoot. The influence of the load resistor change on control result is little. The adjustment time of the state feedback exact linearization control is slower, and the inductor current start peak is larger. Therefore, when the boost converter load resistor value mismatches, the control result of the model-free adaptive control is better than that of state feedback precise linearization control.

5 CONCLUSIONS

In this paper, the optimal control for boost converter using model-free adaptive controller (MFAC) and fuzzy particle swarm optimization algorithm (FPSOA) has been proposed to reduce the influence of the model mismatch and the parameter Time-Variation. The data driven-based MFAC has been investigated to design the controller of boost converter. It has avoided the contradiction of establishing accurate model and complex systems design, and restrained the influence of the model mismatch and the parameter Time-Variation. In order to further improve the system response performance and robustness, FPSOA has been used to optimize MFAC controller parameters and of boost converter, and ITAE optimal control performance index has been used as fitness function. Comparing with the classic state feedback exact linearization control, it has better response performance and robustness. Finally, semi-physical simulation has been realized to demonstrate the effectiveness of the proposed optimal control method. for the disadvantages of the proposed method, the accuracy of the algorithm has not been considered and different algorithm computational complexity has not been considered.

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