Design and simulation of braking energy recovery control system for electric vehicle based on adaptive PID

Xi Jia [1, a], Qipeng Nie[2, b], Xiaofeng Yao[3, c]

[1]School of Dalian Jiaotong University, Dalian 116021, China;

[2]School of Dalian Jiaotong University, Dalian 116021, China.

[3]School of Dalian Jiaotong University, Dalian 116021, China.

[a]Jarxi0727@163.com, [b]qipengnie@163.com, [c]YXF811@163.com

Abstract

Regenerative braking technology of electric vehicles (EV) is increasingly becoming one of the key research issues for automobile manufacturers. In view of the electric vehicle braking energy recovery control system of strong nonlinear and strong coupling characteristics, the present research situation was investigated at home and abroad. This paper analyzes the operating environment of electric vehicle, verifies the control characteristics of permanent magnet synchronous motor (PMSM) and the feasibility of BP Neural network on-line tuning PID control, and establishes the vector control model of PMSM, dynamic braking model of EV. The results show that BP Neural network PID control can effectively improve the braking energy recovery efficiency of electric vehicles through MATLAB simulation experiments.

Keywords

Electric vehicle; Permanent magnet synchronous motor; Adaptive PID; BP Neural network; The braking energy recovery; MATLAB simulation.

1. Introduction

With the decrease of non-renewable energy such as fossil fuels and the strengthening of people's environmental awareness. Electric vehicles are gradually occupying the automobile market and it will become the mainstream of the automobile industry. Major automobile manufacturers have invested a lot of manpower and material resources to research electric vehicles. One of the biggest obstacles to carmakers is battery life. Before the big breakthrough in battery technology, the only way to increase range is to convert the heat lost during deceleration and braking into electricity that could be stored in a battery-powered car for recycling. The PMSM with high energy density is widely used in electric vehicle drive motor. But the PMSM control system and the energy recovery control system have strong coupling and nonlinearity and electric vehicles work in kinds of complex environments.

According tothe actual investigation and literature research, EV usually adopt conventional PID control system. It does not have the ability to deal with nonlinear problems , while RBF Neural network has a strong nonlinear function approximation ability and self-learning ability, which can continuously reduce the error caused by uncertain factors in the system. RBF Neural network system has good anti-interference ability and adaptive ability. In this paper, BP neural network is adopted to improve the braking energy recovery efficiency of electric vehicles by online tuning PID control parameters.

2. Regenerative braking

Researches have shown that about one-third to one-half of the energy consumed by cars on urban roads is on the car's braking [1] .Its inertial kinetic energy and mechanical energy are converted into heat energy by mechanical brakes. One of the biggest problems in the development of electric vehicles is the cruising problem. Battery technology can't make a breakthrough in a short time, so it is necessary to recycle the energy consumed during the braking process of the electric vehicle. Because PMSM is reversible, it can be used as both an electric motor and a generator. Therefore, when the electric vehicle brakes, the drive motor can work in the power generation state. During braking, the excess inertial kinetic energy of the car is converted into electric energy and fed back to the energy storage device to increase the cruising range of the electric vehicle. The energy conversion principle of the EV energy regenerative braking system can be represented by Figure 1.

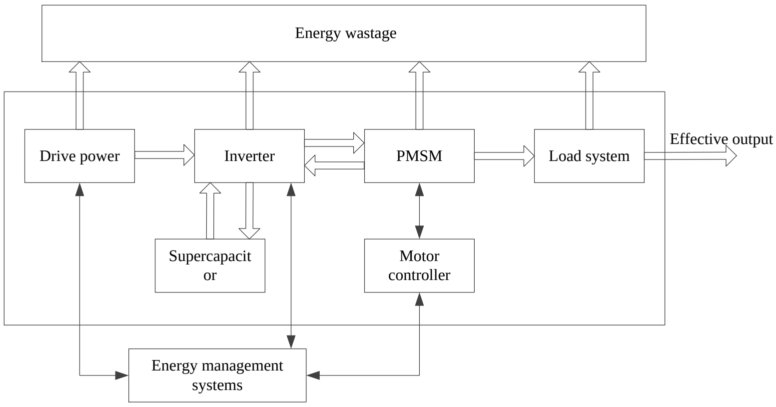

Fig. 1 The energy conversion principle

Take the Tesla Models as an example. 66] The relationship between speed and torque and power is as follows:

$$\mathrm{T}_t = \begin{cases} T_{max} & n \le n_b \\ \dfrac{9549}{n} P_{max} & n > n_b \end{cases}$$

$$T_{rb} \le T_{rbmax} \le T_t$$

$$P_{rb} \le T_{rbmax} n \le P_{cmax}$$

T_{max}: $Maximum\ output\ torque\ of\ the\ motor\ (N \cdot m)$

P_{max}: $Maximum\ output\ power\ of\ the\ motor\ (kW)$

T_{rbmax}: $Maximum\ regenerative\ braking\ torque\ (N \cdot m)$

P_{cmax}: $Maximum\ allowable\ power\ generation\ (kW)$

It can be known that the battery feedback power is related to the electromagnetic torque of the motor and the motor speed. In the direct drive or the drive system configuration with only fixed reduction ratio reducer, since the motor angular velocity is coupled with the vehicle speed, the optimal braking energy feedback can only be achieved by adjusting the output torque of the motor [2]. The main circuit of electric vehicles is designed by the principle of buck and boost chopper circuits. As a system, choosing two sets of circuits is complicated and difficult to control. Therefore, the motor control of electric vehicles is mainly carried out by combing with the characteristics of the two to form a composite chopper circuit. The working environment of the car is more complicated, and the drive motor control system adopts the pulse width modulation (PWM) chopping method, which makes the system become a strong nonlinear system. Therefore, the regenerative braking control system has strong nonlinearity and has a large range of parameters volatility and external interference.

3. Energy recovery system

The EV energy recovery system mainly includes a main PMSM, an energy storage device (lithium battery pack and super capacitor), an inverter rectifying device and an energy recovery control algorithm.

3.1 PMSM

Because the PMSM has the advantages of fast start-up and high power density, it is widely used as a drive motor for electric vehicles. The PMSM has two working modes including generator or electric motor. The mode can be determined by the sign of the mechanical torque: positive for motor mode and negative for generator mode[3]. PMSM consists of a permanent magnet as a rotor. The synchronous rotating magnetic field is generated by the excitation of the permanent magnet, and the three-phase stator winding induces a three-phase symmetrical current through the armature reaction under the action of the rotating magnetic field.

3.2 Inverter

The inverter consists of an inverter bridge, control logic and filter circuits to converts the battery's direct current into alternating current. It is actually a process of voltage inversion with the converter adopting pulse width modulation (PWM) technology [4]. The core part is a PWM integrated controller, which consists of internal reference voltage, error amplifier, oscillator and PWM, overvoltage protection, undervoltage protection, short circuit protection, and output transistor.

DC-AC conversion: It consists of a MOS switch tube and a storage inductor. The input pulse is amplified by a push-pull amplifier and drives the MOS transistor to perform a switching action, so that the DC voltage charges and discharges the inductor, and the other end of the inductor can get AC voltage.The inverter Simulink model is shown in Figure 2.

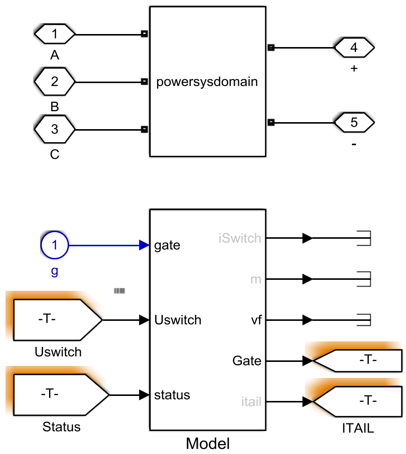

Fig. 2 The inverter Simulink model

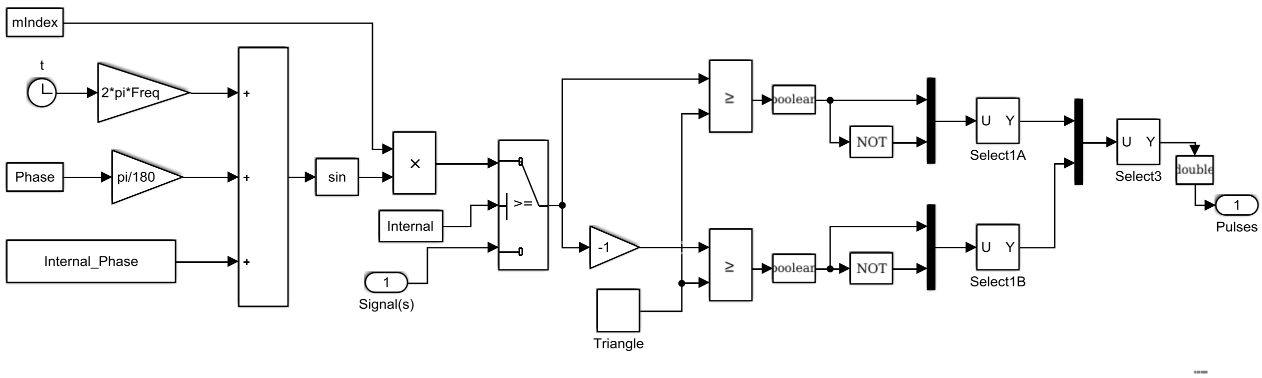

Fig. 3 PWM generator model

3.3 PWM generator

The PWM generator module uses a two-stage topology to generate pulses for a carrier-based PWM converter. This module can be used to trigger a forced commutation device (FET, GTO or IGBT) for a three-phase two-level bridge. The Simulink model of the PWM generator is shown in Figure 3.

3.4 IGBT

IGBT is a semiconductor device that can be controlled by a gate signal. The IGBT is modeled as a series connection of resistor Ron, inductor Lon and DC voltage source Vf ,which is in series with a switch controlled by a logic signal (g > 0 or g = 0). Its internal structure and Simulink model are shown in Figure 4 and Figure 5.

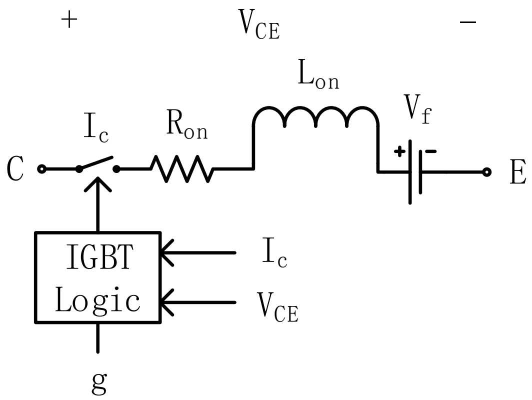

Fig. 4 IGBT simplified equivalent circuit

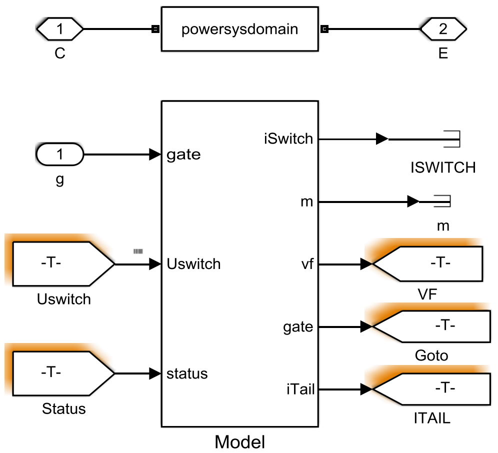

Fig. 5 IGBT Simulink model

3.5 Energy storage device

For electric vehicles, a single power battery is currently selected as the vehicle energy source, but the lithium ion battery with the most comprehensive performance is difficult to meet the power demand of the electric vehicle which is frequently charged and discharge. Its service life and battery pack safety will be seriously weakened. As a novel energy storage device, supercapacitor has high power density and outstanding cycle life, but its low energy density makes it unable to become the main energy source of electric vehicles [5]. The characteristics of the two energy storage devices are shown in Table 1.

Table 1 Comparison of lithium battery and super capacitor parameters

characteristic	lithium battery	Super capacitor
Discharge reversibility	Reversible	Reversible
Charging time	5-6 h	10s

Power density (W/kg)	Low, 100-400 W/kg	High,5000W/kg
Energy Density （WH/kg）	High, 30-500	Low, 3-15
Charge and discharge efficiency	70%-90%	90%-95%
Cycle life	An average of 5,000 to 10,000 times	Up to 500,000 times
Charge retention	Self-discharge	No Self-discharge
Connection method	Series and parallel	parallel

According to the table data, the specific energy of the battery is close to 10 times that of the super capacitor, but the specific power of the super capacitor is nearly 100 times that of the battery. If they are combined to form a mixed dual energy source, the advantages will be fully utilized to satisfy the electric vehicle power demand [6]. As the main energy source of electric vehicles, lithium batteries provide energy for electric motor motors. Super capacitors are used to store the electric energy generated by electric vehicles. When the car starts or suddenly accelerates, super capacitors can provide powerful driving current for the motor with lithium batteries. The supercapacitor Simulink model is shown in Figure 6.

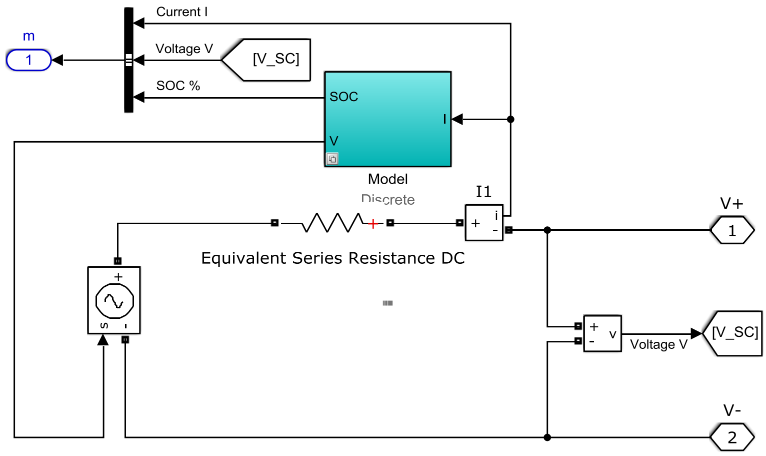

Fig.6 The supercapacitor Simulink model

4. BP Neural network self-tuning PID

The key of PID control is how to adjust the three parameters of proportional(Kp), integral(Ki) and differential(Kd) to achieve a better control effect. There are innumerable combinations between the three parameters, and the relationship among them is not necessarily a simple linear combination. It may be a non-linear combination to achieve optimal control of the controller. The BP (Back Propagation) neural network has good nonlinear expression ability. After learning the system performance, a three-parameter self-learning PID controller can be established [7].

The controller consists of two parts:

Classic PID controller, which directly controls the controlled object in closed loop, and the three parameters are online adjustment mode.

The neural network, according to the operating state of the system, through the self-learning of the neural network and the adjustment of the weighting coefficients, makes the output of the output layer neurons correspond to the three adjustable parameters of the PID controller, in order to achieve the optimization of certain performance indicators.

Classic PID control we use incremental digital PID control, the algorithm is

$$u(k) = u(k-1) + \Delta u(k)$$

$$\Delta u(k)=k_p(error(k)-error(k-1))+k_i error(k)+$$
$$k_d(error(k)-2error(k-1)+error(k-2))$$

Adopt three-layer BP network, its structure is shown in Figure 7.

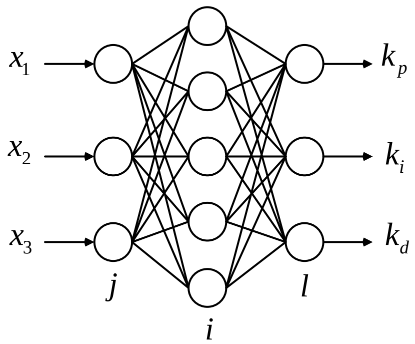

Fig.7 BP network structure

The input to the network input layer is:

$$O_j^{(1)}=x(j) \qquad (j=1,2,\cdots,M)$$

(The number of input variables M depends on the complexity of the controlled system.)

The input and output of the network hidden layer are:

$$net_i^{(2)}(k)=\sum_{j=0}^{M} w_{ij}^{(2)} O_j^{(1)}$$

$$O_i^{(2)}(k)=f(net_i^{(2)}(k)) \qquad i=(1,2,\cdots,Q)$$

$w_{ij}^{(2)}$ Implicit layer weighting factor : the upper corners (1), (2), (3) represent the input layer, the hidden layer, and the output layer, respectively.

The activation function of the hidden layer neurons takes a positive and negative symmetric Sigmoid function:

$$f(x)=\tanh(x)=\frac{e^x-e^{-x}}{e^x+e^{-x}}$$

The input and output of the network output layer is

$$net_l^{(3)}(k)=\sum_{i=0}^{Q} w_{li}^{(3)} O_i^{(2)}(k)$$

$$O_l^{(3)}(k)=g(net_l^{(3)}(k)) \qquad l=(1,2,3)$$

$$O_1^{(3)}(k)=k_p$$

$$O_2^{(3)}(k)=k_i$$

$$O_3^{(3)}(k)=k_d$$

The output layer output nodes correspond to three adjustable parameters respectively. Since they cannot be negative, the activation function of the output layer neurons takes a non-negative Sigmoid function:

$$g(x)=\frac{1}{2}(1+tanh(x))=\frac{e^x}{e^x+e^{-x}}$$

Take the performance indicator function as

$$E(k)=\frac{1}{2}(rin(k)-yout(k))^2$$

The weighting coefficient of the network is modified according to the gradient descent method, that is, the search is adjusted in the direction of the negative gradient of the weighting coefficient, and an inertial term that causes the search to quickly converge globally is added:

$$\Delta w_{li}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{li}^{(3)}} + \alpha \Delta w_{li}^{(3)}(k-1)$$

(η:learning rate; α:inertia coefficient)

$$\frac{\partial E(k)}{\partial w_{li}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial \Delta u(k)} \cdot \frac{\partial \Delta u(k)}{\partial O_l^{(3)}(k)} \cdot \frac{\partial O_l^{(3)}(k)}{\partial net_l^{(3)}(k)} \cdot \frac{\partial net_l^{(3)}(k)}{\partial w_{li}^{(3)}(k)}$$

$$\frac{\partial net_l^{(3)}(k)}{\partial w_{li}^{(3)}(k)} = O_i^{(2)}(k)$$

The above analysis can obtain the learning algorithm of the network output layer weight:

$$\Delta w_{ij}^{(3)}(k) = \alpha \Delta w_{li}^{(3)}(k-1) + \eta \delta_l^{(3)} O_i^{(2)}(k)$$

$$\delta_i^{(3)} = error(k)\operatorname{sgn}\left(\frac{\partial y(k)}{\partial \Delta u(k)}\right) \frac{\partial \Delta u(k)}{\partial O_l^{(3)}(k)} g(net_l^{(3)}(k)) \qquad l = (1,2,3)$$

Learning algorithm for the hidden layer weighting coefficient:

$$\Delta w_{ij}^{(2)}(k) = \alpha \Delta w_{ij}^{(2)}(k-1) + \eta \delta_i^{(2)} O_j^{(1)}(k)$$

$$\delta_i^{(2)} = f(net_i^{(2)}(k)) \sum_{l=1}^{3} \delta_l^{(3)} w_{li}^{(3)}(k) \qquad (i = 1, 2 \cdots Q)$$

$$\left(g'(\cdot) = g(x)(1-g(x)),\ f'(\cdot) = \frac{(1-f^2(x))}{2} \right)$$

The PID controller structure and algorithm model based on BP network are shown in Figure 8and Figure9, respectively.

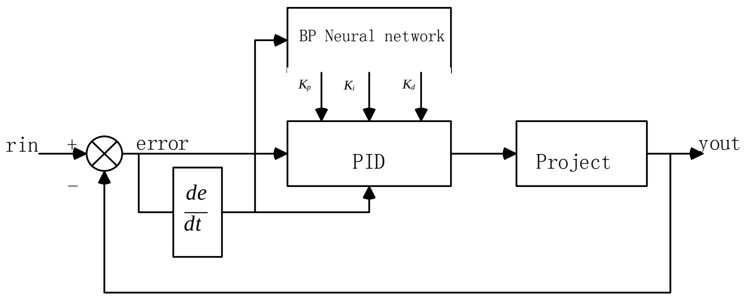

Fig.8 PID controller structure based on BP network

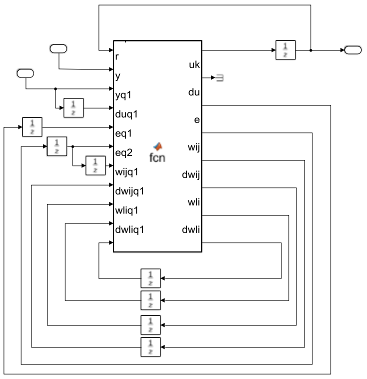

Fig.9 Adaptive PID control algorithm model

5. Control System

5.1 Motor drive control system

When no brake signal is generated, the permanent magnet synchronous motor is normally powered by the lithium battery. The electric vehicle is operated smoothly by a vector control algorithm based on double closed loop of speed and current.

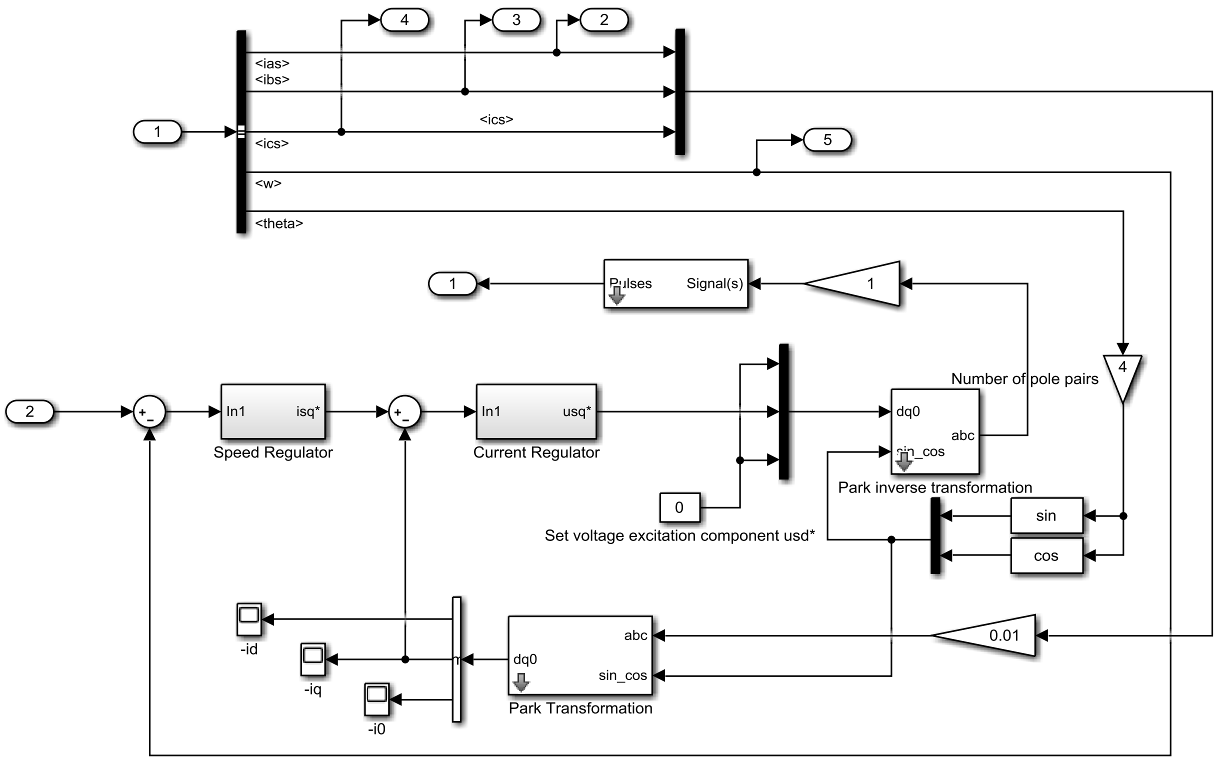

Fig.10 Motor vector control model

5.2 Brake energy recovery control system

The switching of the charging state of the supercapacitor in the electric vehicle energy recovery system is determined by the braking signal. When the system collects the brake pedal sensor signal, the IGBT in the energy recovery circuit is turned on, and the main power supply battery of the driving motor stops supplying power to the driving motor. . In order to facilitate the processing of the brake signal, the signal is normalized and multiplied by the proportional coefficient K to obtain the actual current command value. The model output is the charging current of the super capacitor. At the same time, the current measuring device is used to feed back the current to the energy recovery control algorithm, which is controlled by the algorithm and fed back to the motor. Under the premise of ensuring the smooth running of the vehicle, the proper IGBT turn-on duty ratio is given, so as to achieve the purpose that the response value preferably follows the given value. Maximize the recovery of electrical energy converted from the inertial potential energy of the motor. The car's inertial kinetic energy is converted into electrical energy by the motor and stored in the supercapacitor. The Simulink model of the control system is shown in Figure 11.

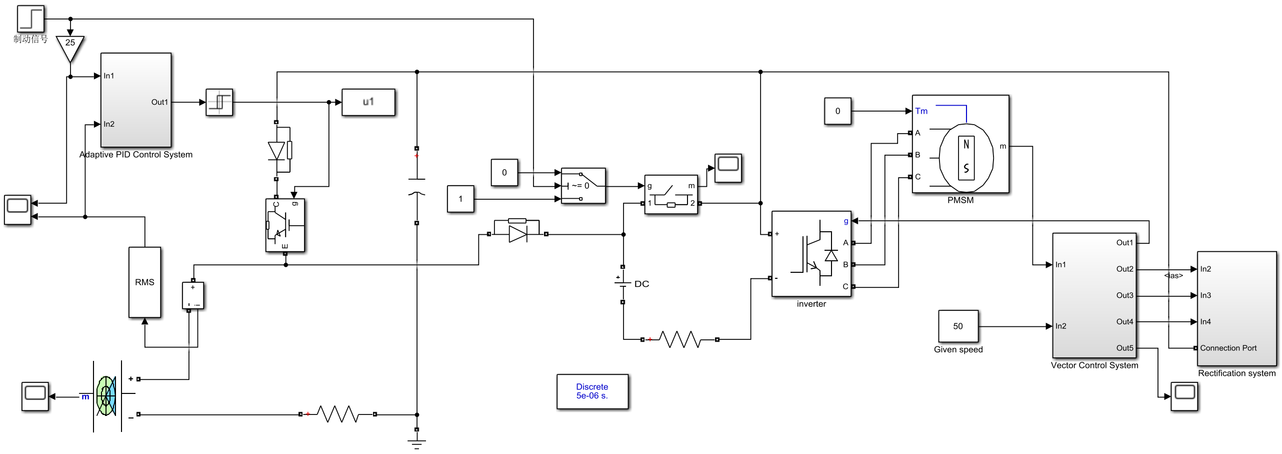

Fig.11 Energy recovery control model

6. Simulation result analysis

Figure12 shows all the files for the entire project. In the simulation experiment, first open the simulink model EVcyclecontrol.slx of the energy recovery system. Then run the main function EVcyclecontrol_main.m, after initializing the sampling time and simulation time, call EVcyclecontrol.slx in the main function. During the running of the model, the adaptive PID control module calls four sub-functions such as the sub-function f_func.m. Test.m is used to debug the performance of the adaptive PID control algorithm. The relationship between the various files is shown in Figure 13.

The change of the speed of the permanent magnet synchronous motor is shown in Figure 14. The motor starts to run normally under vector control. When the system receives the brake signal at 0.5s, the motor starts to decelerate. At about 1.65s, the motor speed is reduced to 0.

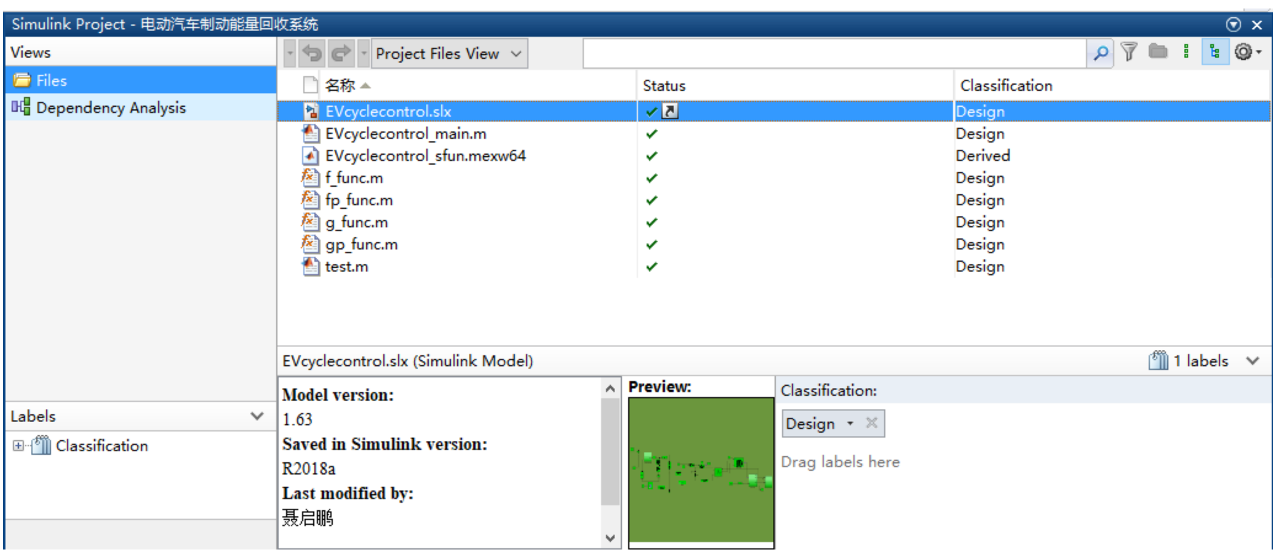

Fig.12 Project file directory

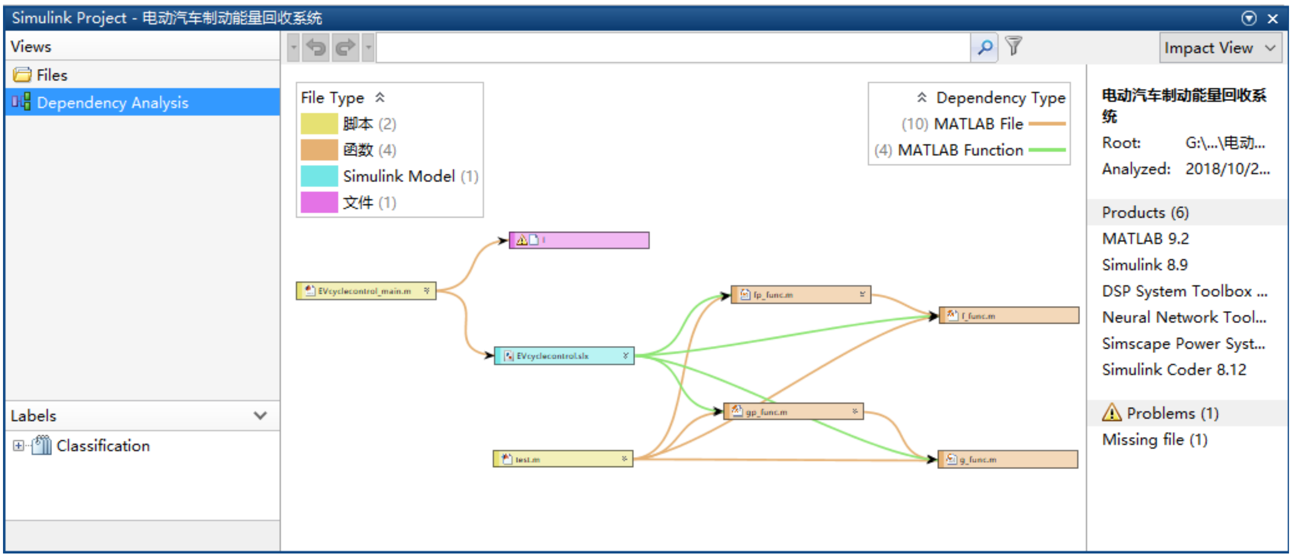

Fig.13 Project file relationship diagram

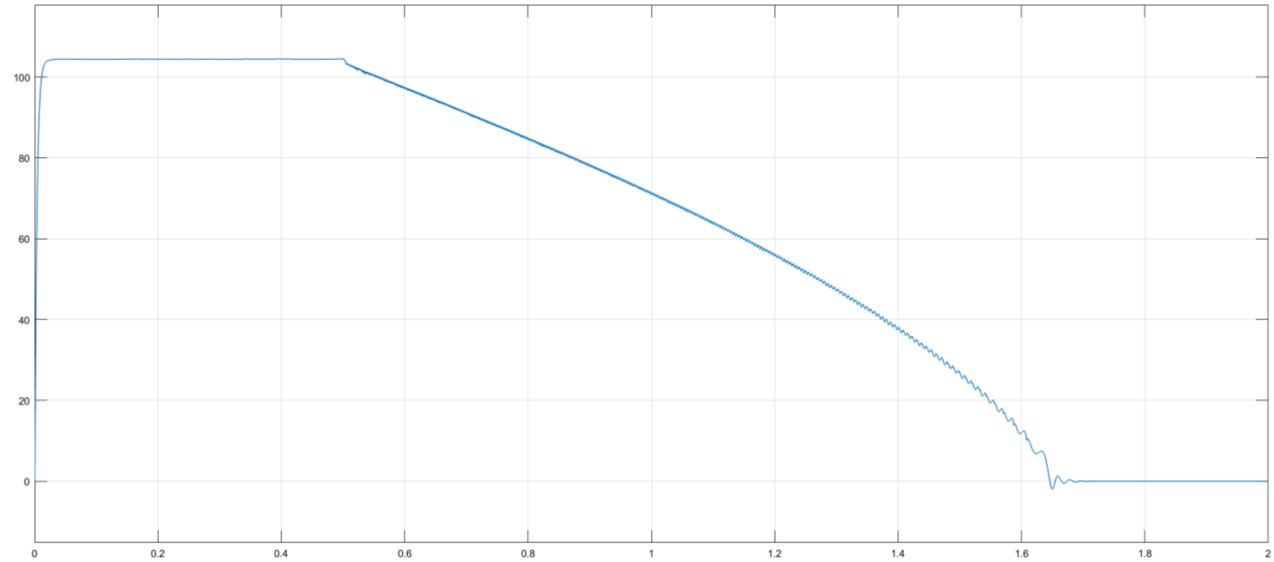

Fig.14 Motor speed curve

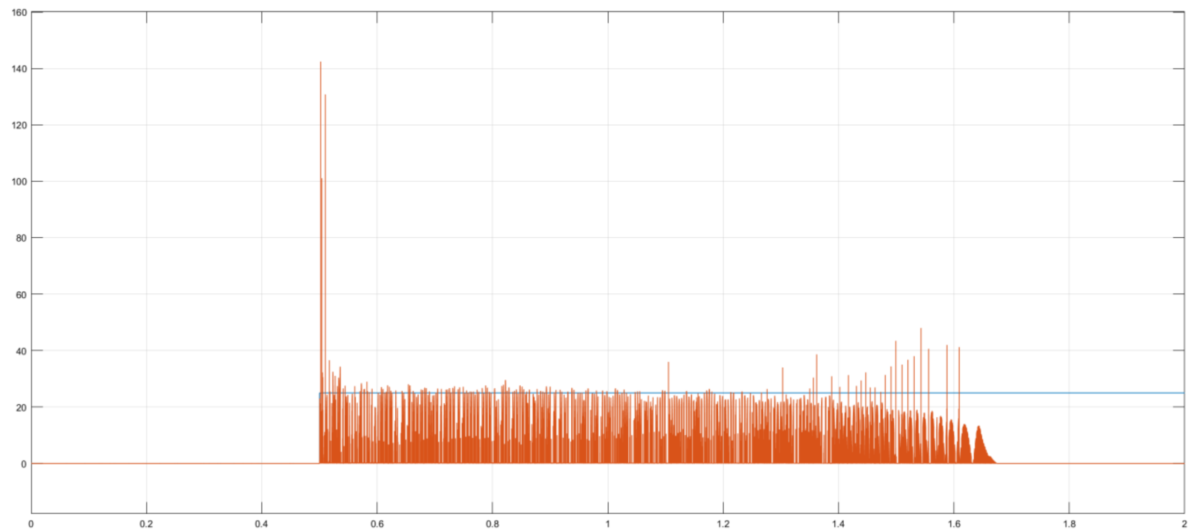

Fig.15 Brake and current signal

At the same time, we observe Figure 15, where the blue line indicates the brake signal and the red line indicates the current. As can be seen from the figure, when the motor is running normally without braking, the current is zero. When the brake signal is applied for 0.5 s, current is generated in the energy recovery loop. And when the motor speed is reduced to zero at about 1.65s, the current disappears.

7. Conclusion

By constructing the energy recovery model, the feasibility of BP tuning PID control algorithm in energy recovery system is verified. The simulation results show that the BP tuning PID control algorithm can stably adjust the current signal fed back in the energy recovery loop. Due to time and condition constraints, we will gradually adjust the optimization control algorithm in order to get better results.

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