Comparison of ANN- and GA-based DTC eCAR

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Abstract

In this paper, an artificial intelligence (AI)-integrated direct torque control (DTC) scheme is developed for an electric vehicle (EV or eCAR) propulsion motor drive. In addition, a comparison is made between adaptive neural network (ANN) and genetic algorithm (GA)-based torque controllers. The integration of AI into EVs has attracted the attention of many researchers in terms of drive control, dynamic stability, speed estimation, and energy management strategies. Amidst the various motor drive control strategies, DTC schemes with space vector pulse width modulation (SVPWM) have gained prominence due to its fast torque (speed) control capability. The smooth control of a DTC-eCAR propulsion motor is accomplished by the use of AI algorithms. The applications of ANN and GA algorithms for tuning the torque controller are tested and the behavior of an eCAR in terms of drive range, percentage of state of charge (SOC), and energy consumption for different driving conditions is observed using MATLAB simulations.

Keywords Adaptive neural network · Artificial intelligence · Direct torque control · Electric vehicle · Genetic algorithm · Powertrain · Vehicle dynamics

1 Introduction

Nowadays, human survival is being adversely affected due to environmental perils. Globally, the Coronavirus (COVID-19) pandemic has pushed down the GDP and caused the loss of many human lives. The majority of auto-manufacturers have put off the production of vehicles due to the COVID-19 crisis and there is a drastic decrease in the auto market growth rate. After this pandemic, there will be a huge demand for EVs in view of their eco-friendly nature. In EVs, the choice of a propulsion motor and its control strategy play a vital role, especially for battery-powered vehicles (eCAR). EVs are gaining popularity due to their silent, smooth, and zero emission operation, as well as their portable charging

and higher fuel economy. In addition, the cost of fuel/unit charge is less when compared to combustion vehicles. However, these vehicles have challenges such as excessive charging time and poor energy density, which provide areas of possible research for their improvement. These limitations can be overcome by implementing an efficient control strategy.

In modern research, the integration of artificial intelligence (AI)-based motor control schemes has gained prominence due to the need for most suitable parameter selection. The grey wolf optimization (GWO) algorithm is a recently developed algorithm that imitates the grey wolf community hierarchy and hunting mechanisms. It has the major advantage of reducing the number of the search parameters. The authors of [1] proposed an optimal control strategy for a bearing less permanent-magnet synchronous machine (BPMSM) drive. The weighting matrices K_d are obtained by employing the GWO algorithm. In [2], an optimal control strategy for a permanent-magnet synchronous hub motor (PMSHM) drive using the state feedback control method plus the GWO algorithm was proposed. The GWO algorithm is employed to acquire the weighting matrices Q and R in the linear quadratic regulator optimization process. In [3], the parameters of a PI are tuned using an ANN and a GA for a DTC scheme. The DTC can increase the dynamic stability, mitigate torque and flux

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ripples, and increase the energy efficiency of the induction motor drive under different operating conditions. In [4], an improved direct instantaneous torque control (DITC) based on adaptive terminal sliding mode control (ATSMC) was proposed. It is a novel DTC for motors. The authors of [5] proposed an improved direct torque control (DTC) with a sliding mode controller and an observer to reduce the torque ripples of a four-phase SRM. In [6], the appropriateness of a DTC scheme for a typical EV propulsion system was predicted. In addition, a search control method for a precise flux and torque estimator, and an efficiency optimizer using offline loss model for EV parameter optimization were derived. In [7], a review of DTC schemes integrated with intelligent algorithms was given and a comparative analysis was made with respect to algorithm intricacy, speed tracking, parameter variations, switching losses, and ripples reduction. In [8], a stator flux optimization algorithm-based DTC scheme to increase the drive range of an EV in terms of the full charge driving of a 3 kW induction motor is tested by considering the effect of core loss and leakage inductance. In [9], a DTC scheme for battery and fuel cell powered front wheel drive (FWD) EV with an ANN speed PI controller, tracks the reference speed accurately when compared to traditional PI controllers in terms of the U.S. Environmental Protection Agency (EPA) and the New European Driving Cycle (NEDC). In [10], a GA-based DTC-IM drive, to regulate PI controller parameters was discussed. In [11], a DTC space vector-modulated (SVM) control strategy for the speed control of a three-phase IM using a GA to optimize the speed PI controller parameters was discussed, and the behaviors of GA-PI and traditional PI were compared.

In this paper, an AI-integrated DTC scheme is developed for an eCAR propulsion motor drive, and a comparison is made between ANN- and GA-tuned torque controllers. The responses of the two intelligent algorithms are observed in terms of torque ripple, battery SOC, and drive range under different driving conditions. The remainder of this paper is organized as follows. In Sect. 2, the DTC scheme for an eCAR propulsion system is explained. In Sect. 3, the integration of an ANN torque controller for the DTC scheme is discussed. In Sect. 4, the integration of a GA torque controller for the DTC scheme is discussed. In Sect. 5, a comparative simulation study is made among the conventional PI-, ANN- and GA-based controllers to validate their performances. Section 6 recapitulates the conclusions of the work done.

2 Direct torque-controlled eCAR propulsion

In the 1980s, Takahashi Isao and Depenbrock Manfred published an article with the title Direct Torque Control (DTC), to contest with traditional vector controls. The DTC scheme has good dynamic stability and robustness in the presence of induction motor parameter variations. In DTC, the control

pulses generated for the switches of the voltage source inverter are resolved directly. In modern studies, a great deal of research has been carried out on DTC schemes [12–14]. The classical DTC scheme using hysteresis controllers is widely used for the torque and flux control of an induction motors. However, at lower speeds and operating at a low switching frequency, they produce high flux and torque ripples, which cause acoustic noise and reduce the control performance. Later, a number of DTC schemes came into existence to overcome the impediments of the classical DTC scheme. Most of these schemes concentrated on torque and flux ripple minimization. An optimal advanced discontinuous PWM (ADPWM) algorithm for a DTC-controlled induction motor drive is used to depict the actual value of gamma (γ) given a set policy frequency. The space vector PWM (SVPWM) technique provides solutions to a few of the hardships found in traditional PWM schemes. The sequence of three switching states yields eight output voltage vectors. At any given instance, the inverter has to drive one of these voltage vectors. Of the eight voltage vectors, V_0 and V_7 are zero-voltage vectors, and V_1 , V_2 , V_3 , V_4 , V_5 , and V_6 are active voltage vectors, and they are presented in the space vector plane in Fig. 1, [15]. In this approach, the overall time interval of the zero-voltage vector is uniformly distributed between V_0 and V_7 . In addition, the zero-voltage vector time is distributed proportionally at the initial and final parts of a sub-cycle in a symmetrical way. The frontier for the modulation index is 0.866, while 0127–7210 is utilized in the first sector, 0327–7230 is utilized in the second sector, and so on [16].

A VSI is used to develop a three-phase voltage vector with a regulated amplitude and frequency. A block diagram of the VSI, and the output voltage, switching pulses, and sectors are shown in Figs. 2, 3, respectively.

In Fig. 4, a block diagram of a direct torque control scheme integrated with intelligent control algorithms (ANN and GA) for the torque control of an eCAR propulsion motor is shown. Initially, the size and rating of

Fig. 1 Two-level space vector representation

the propulsion motor are determined based on the vehicle mass, acceleration rate, and maximum speed limit. Later, the induction machine is modeled in a synchronously rotating reference frame using Clark's and Park's transformations. The d-q axis voltage and current magnitudes are measured to estimate the actual speed, torque, and flux of the motor using an adaptive motor model [17].

The set speed ω_r^* is compared with the estimated speed ω_r , and the speed error is regulated by a speed PI controller also termed as a driver model since it gives the percentage of the accelerator pedal position (APP) or reference torque magnitude T_e^* . The speed controller output T_e^* is then compared with the torque T_e , which is computed by an adaptive motor model. Then, the torque error is processed through the proposed intelligent torque controller (ANN and GA) to obtain the synchronously rotating reference slip speed ω_{sl}^* . The summation of ω_{sl}^* , ω_r and its integration denotes theta θ_e^* . Then, the reference input d-q axis voltage vectors are manipulated by the reference voltage vector calculator (RVVC) block using the following equation, and the output is fed to SVPWM [18–20]:

$$F_{ref} = \frac{2\pi f_1}{V_{ref}} \sqrt{\frac{3}{\pi} \int_0^{\frac{\pi}{3}} F_{seq}^2 d\alpha}, \quad (1)$$

where F_{seq}^2 is the RMS stator flux ripple of a specific sequence, and V_{ref} is the reference voltage vector at the angle α .

3 Artificial intelligence-based torque controller

i. ANN-tuned torque controller

The integration of an AI-based DTC scheme is introduced for the enrichment of eCAR performance in view

Fig. 3 Two-level VSI voltage, SVPWM pulses, and sector

of a higher acceleration rate, maximum speed, drive range, and fuel economy. The ANN algorithm has a simple structure, simple learning practices, and can resolve higher order nonlinear function. However, it is ineffective for motor parameter variations. The feed forward multilayer neural network and the recursive neural network are two typical ANN networks. In the literature, ANN-based DTC schemes have been used for control parameter identification, state estimation, tuning speed controllers, torque controllers, sensorless speed estimation, and voltage vector selection. An online ANN speed estimator that keeps V/f constant for a DTC-controlled IM drive is discussed and observed. It is observed that the steady-state operation of the ANN speed estimator

Fig. 2 Three-phase voltage source inverter

Fig. 4 Block diagram of an intelligent ANN- and GA-based DTC eCAR powertrain

provides a fast-dynamic response, but is not effective during transient operation [21]. The pros and cons of the ANN-based DTC scheme are described. It has been shown that the ANN controller experiences reductions in the settling time at starting and in speed reversal [22]. An ANN-based speed controller for a SVM-DTC-controlled IM was developed to mitigate steady-state speed errors as well as transient torque and flux ripples [23]. In this paper, an ANN-based torque controller for a DTC-controlled eCAR is implemented to minimize the torque ripple and to enhance the performance of the eCAR. First, the ANN network is constructed by the input data, output data, target data, and error data attained by the response of a step-input signal. The network is selected in a 2, 40, 1 manner, with two neurons in the input layer, 40 neurons in the hidden layer, and one neuron in the output layer. The input data are the torque error and the change in torque error, and the output is the steady-state torque error. The process of the ANN network is shown in Fig. 5.

Once the ANN is constructed with the available data, it is trained using the Levenberg–Marquardt back propagation algorithm [24]. In Simulink, the ANN network is designed by typing “nntool” in the MATLAB command window, and the ANN structure is depicted in Fig. 6. In addition, the Simulink

model of the ANN is originated by the command “genism(network)”, as shown in Fig. 7.

The subsystems of the ANN network are shown in Fig. 8.

ii. GA-tuned torque controller

Genetic algorithms (GA) make up a branch of the AI tree that has great prominence in global parameter optimization procedures. The first GA was brought into existence by John Holland in 1970 and it is one of the most robust optimization algorithms. The integration of a GA into drive control made it possible to easily solve complex control systems by searching a set of possible solutions in parallel using a fitness function as a mean of selective among different sets of possible solutions and using randomize operators instead of derivative information. A GA create new generations to increase the population of the former population. Crossover and mutation are the two major elements for generating a new solution. In the crossover process, the chromosomes are split into two new chromosomes and swapped in the mutation process. This occurs during natural selection and natural evaluations to produce new generations. A GA is more robust to parametric variations, yields better solutions in a shorter period of time, and requires less computing power. The drawback of a GA is the selection of parameters

Fig. 5 Process of an adaptive neural network

Fig. 6 Simulink structure of an ANN

Fig. 7 Simulink model of an ANN

Fig. 8 Subsystem of an ANN

since they are strongly subject to user knowledge and the investigation process. Recently, with the introduction of GA-based DTC control schemes, the dynamic stability of induction motor drives has improved, and the GA is adapted to optimize the torque controller gain values to achieve accurate speed tracking

as well as significant reductions in the torque, flux, and current ripples. In this paper, a GA is employed to optimize the parameters of the torque controller to attain minimal torque ripples. A GA is a global search method utilized for computing the best or near solutions from a group of complex solutions. The process of a GA is described as follows.

Step 1: Build up a set of chromosomes (arbitrarily). The generated chromosomes are the present nominated solutions of the problem.

Step 2: Compute fitness values (integral time absolute error (ITAE)) for all of the chromosomes.

Step 3: Assemble the chromosomes starting from the better solution (i.e., the least fitness value).

Step 4: Clone the best chromosomes to obtain better attributes in the population.

Step 5: Perform a crossover process for the parent chromosomes to obtain a new population.

Step 6: Mutate chromosomes with a small predetermined value.

Step 7: Compute the new fitness values for all of the chromosomes.

Step 8: Restart Step 3 through Step 7 until the minimum error criterion is met.

A basic block diagram of a GA for the tuning of torque controller parameters is shown in Fig. 9. In addition, the properties involved in this GA are represented in Table 1.

The optimized best output values of the GA-based PI controller are shown in Fig. 10. It can be seen that the values of K_p and K_i are 0.5 and 1.8, respectively.

Fig. 9 Block diagram of GA-based PI tuning

Table 1 GA properties

GA properties	Value
Population size	20
Generations	10
Crossover	0.6
Mutation	0.2
Number of variables	2
Higher boundary [Kp, Ki]	[300, 300]
Lower boundary [Kp, Ki]	[0, 0]
Objective function	ITAE

4 Simulation analysis

An intelligent ANN- and GA-based DTC-controlled front wheel drive (FWD) eCAR propulsion system was designed to analyze the behavior of an eCAR with vehicle dynamics under different driving conditions. The propulsion system of the eCAR incorporates several apparatuses such as a 35 kW, 100 Ah, 400 V Lithium-ion (Li-ion) battery stack, a 4 kW, 400 V AC/DC/AC bidirectional on-board charger, a 90 kW three-phase squirrel-cage induction motor, an intelligent ANN- and GA-integrated SVPWM-based microcontroller, a two-level IGBT-based three-phase VSI, a simple gear with a gear ratio of 10.8, a differential transmission, and a drive axel. The mass of the vehicle is 1680 kg, with a frontal area of 1.2 square meters and a wheel radius of 0.2794 m. A parametric analysis is performed for pre-sizing the components of the eCAR powertrain to increase the acceleration rate and driving range [25]. The components of the eCAR are modeled with the help of mathematical equations, and the vehicle dynamics are considered by adding force due to inertia, aerodynamic drag, rolling friction, and hill climbing or a gradient slope, where all these forces are

Fig. 10 Current best individual and fitness values of a GA

represented in terms eCAR parameters [26]. The road load is determined by means of a quadratic equation relating to the eCAR speed. This equation is given by the following equation:

$$F_{rl} = A_1 + B_1 V + C_1 V^2. \quad (2)$$

The environmental protection agency (EPA) constants A_1 , B_1 , and C_1 correspond to inertial force, gradient force, and aerodynamics, respectively. These constraints are definite for each eCAR configuration. All these forces add to the total tractive effort given by the following equation:

$$F_{tr} = F_{rl} + m * a, \quad (3)$$

Fig. 11 Model-based design of an intelligent ANN- and GA-based direct torque-controlled eCAR

where “ F_{tr} ” is the tractive force, “ m ” is the mass, and “ a ” is the acceleration. The acceleration value is given by the following equation:

$$a_x = \frac{dv}{dt} = \frac{F_{TR} - (F_{rl})}{m_i}. \quad (4)$$

The proposed ANN- and GA-based DTC eCAR propulsion system is modeled using R2019b MATLAB simulation software, and is shown in Fig. 11.

Simulation results obtained for both the ANN and GA intelligent torque controllers are analyzed and compared with the

conventional PI controller as follows. Initially, the response of the developed AI-integrated DTC eCAR Simulink model was analyzed with the step input as a set speed. In Fig. 12a, it is observed that the time taken to reach a vehicle speed of 25 m/s or 90 km/h is 5.2 s, which is one of the customer desires. This can be achieved with an acceleration rate of 4.8 m/s², a motor angular speed of 314 rad/s at a maximum output power of 90 kW, and a torque of 290 N-m. Figure 12b represents the torque response of the PI-, ANN- and GA-based DTC schemes for a step input. It is seen that the GA torque controller has smoother and lower torque ripple. Figure 13a represents speed

Fig. 12 Step input: **a** motor speed characteristics; **b** motor torque characteristics

Fig. 13 Step change input: **a** motor speed characteristics; **b** motor torque characteristics

Fig. 14 European cycle: **a** motor speed characteristics; **b** motor torque characteristics

responses of the PI-, ANN- and GA-based DTC schemes for a step change input. The step change input represents rural, urban, and highway-driving conditions with the speeds of 40 km/h, 80 km/h, and 120 km/h. Figure 13b represents the torque response of the PI-, ANN- and GA-based DTC schemes for a step change input. It is seen that the GA torque controller has a low torque ripple. Figure 14a represents the speed response of an eCAR in terms of the European Cycle (ECE-R15). Figure 14b represents the torque response of the PI, ANN and GA. It is seen that the GA torque controller has accurate speed tracking and low torque ripple. Figure 15a represents the

Fig. 15 European cycle: **a** fuel economy; **b** lithium-ion battery %SOC

energy consumption of an eCAR over one European Cycle. It is seen that the GA has a low energy consumption of about 210 W-s while the PI and ANN have 255 W-s and 260 W-s, respectively. Figure 15b represents the percentage state of charge (SOC) of a Lithium-ion battery over one European Cycle. It is seen that the GA has a higher %SOC of about 95.5% when compared to those of the PI and ANN. A comparative analysis is made among the PI-, ANN- and GA-tuned torque controllers. This comparison is tabulated in Table 2 in terms of maximum torque ripple.

Thus, from the above simulation analysis, it is clear that the proposed GA-tuned torque controller is best suited

Table 2 Maximum torque ripple for different controllers

Ref. input	Step			Step change			European cycle		
	PI	ANN	GA	PI	ANN	GA	PI	ANN	GA
Torque ripple	100	20	8	120	40	20	60	10	5

for DTC eCAR since it provides a low torque ripple, an increased drive range, and low fuel consumption.

5 Conclusion

An AI-integrated DTC scheme was proposed for an eCAR propulsion system. A comparative analysis is made among PI-, ANN-, and GA-tuned torque controllers under different driving conditions. Each component of the eCAR propulsion system is modeled using mathematical relations. In this paper, a 90 kW three-phase cage IM is used to attain a maximum speed of 90 km/h in 5.2 s, which is a desirable characteristic for an eCAR. The proposed AI-integrated DTC scheme was designed in simulation software and the behaviors of the PI-, ANN-, and GA-tuned torque controllers were analyzed. From the obtained simulation results, it is observed that the performance of the GA torque controller is much better than those of the PI and ANN controllers, since it offers a low torque ripple at higher speeds, while consuming less power. Thus, the performance of an eCAR in view of fuel economy, energy efficiency, and driving range is improved with the integration of a GA torque controller into its DTC scheme.

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