International Journal of Robotics and Control Systems
Vol. 6, No. 2, 2026, pp. 888-905
ISSN 2775-2658
http://pubs2.ascee.org/index.php/ijrcs

Reinforcement Learning for Electric Vehicle Traction Motor Control: A Comprehensive Review

Anwar Hasni [a,1,*], Abdellah Lassioui [a,2], Hassan El Fadil [a,3], Intidam Abdessamad [a,4], Tasnime Bouanou [a,b,5], Marouane El Ancary [a,6], Yassine El Asri [a,7]

[a] ISA Laboratory, National School of Applied Sciences (ENSA), Ibn Tofail University, Kénitra 14000, Morocco
[b] Research Institute on Solar Energy and New Energies (IRESEN), Rabat 10090, Morocco
[1] hasni.anwar20@gmail.com; [2] abdellah.lassioui@uit.ac.ma; [3] elfadilhassan@yahoo.fr;
[4] intidam.abdessamad@gmail.com; [5] bouanou.t@gmail.com; [6] marouane.elancary@gmail.com;
[7] elasriyassine@yahoo.com
* Corresponding Author

ARTICLE INFO

Article history
Received January 08, 2026
Revised February 04, 2026
Accepted April 01, 2026

Keywords
Artificial Intelligence;
Electric Motors;
Reinforcement Learning;
Model-Free Control;
Electric Vehicles;
Adaptive Control;
Nonlinear Control

ABSTRACT

The control of traction motors is a key element of speed and torque regulation loops in electric vehicle traction systems, where high efficiency, low torque ripple, and strong robustness to disturbances are required. Conventional control methods show limitations when faced with strong nonlinearities, parametric variations, and unmodeled dynamics. Reinforcement Learning is therefore investigated as a data-driven solution capable of learning optimal control laws without relying on an explicit analytical model of the system. The contribution of the research is a structured and original review dedicated to the application of RL to the control of electric vehicle traction motors. It proposes a systematic classification of algorithms, application domains, and performance objectives. The methodology is based on a bibliographic analysis of works published between 2018 and 2025. RL methods are classified according to the learning paradigm, the control level, and the type of validation. The analyzed algorithms include classical approaches such as Q-learning and SARSA, as well as deep reinforcement learning methods such as DQN, DDPG, and PPO. Control architectures, reward functions, and learning environments are systematically compared. Several studies report superior performance compared to conventional control laws under transient conditions and in the presence of disturbances. Deep learning-based approaches are particularly effective for highly nonlinear systems. However, challenges remain in terms of stability, safety, and computational cost. Experimental validations also confirm the feasibility of real-time implementation within specific hardware constraints. In conclusion, this review highlights the strong potential of RL for traction motor control and outlines perspectives toward safe learning, embedded implementation, and hybrid model-data control strategies.

1. Introduction

The global transition toward sustainable mobility has profoundly transformed the automotive industry, placing electric vehicles (EVs) at the heart of decarbonization strategies. Rapid advances in

https://dx.doi.org/10.31763/ijrcs.v6i2.2505

electric machines, power electronics, and energy storage technologies have enabled EVs to reach a level of maturity that now gives them performance, operating costs, and energy efficiency comparable and sometimes even superior those of internal combustion engine vehicles [1]. Whether hybrid (HEV, PHEV) or fully electric (BEV), these systems rely on a propulsion chain that includes an energy source, a static converter, an electronic controller, and a traction motor, whose behavior directly determines overall efficiency and driving quality [2]. At the heart of this propulsion chain, traction motors, such as induction motors (IM), brushless DC motors (BLDC), reluctance machines (SRM, SynRM), and especially permanent magnet synchronous motors (PMSM), play a decisive role in the overall efficiency, power density, and driving comfort of EVs [3]. PMSMs, in particular, are increasingly favored in traction applications due to their high-power density, high torque density, low noise and vibration levels, and excellent dynamic performance [4].

However, these systems show strongly nonlinear, multivariable, and coupled dynamics with respect to parameters and load disturbances and unmodeled dynamics, making the design of optimal control laws quite complex [5]. In the past, traction motor controls employed quite established techniques such as FOC and DTC, which are known for their potential to decouple flux and torque dynamics and for their high-precision dynamics with high speed, while more recent techniques such as MPC allowed for the direct exploitation of constraints through finite-horizon optimization problems [6], [7]. However, whether it comes to PMSMs, induction motors, BLDC motors, SRMs, or SynRMs, all types of such machines are known to be strongly nonlinear and coupled. This complexity can be further increased due to parametric variations, magnetic saturation, friction, external disturbances, and un-modeled dynamics [8]. In this scenario, a degradation in the performance of traditional controllers, especially the popular PI controller, which is much appreciated for its simplicity, may be witnessed [9]. To overcome this issue, a number of efficient techniques using robust control [10], adaptive control [11], predictive control [12], sliding mode control [13], fuzzy logic [14], neural networks [15], and other machine learning-based techniques [16] have already been examined. Still, despite almost all of their significant contributions, these methods experience some limitations regarding the establishment of strong stability, overall optimal performance, and adequate adaptability within practical industrial settings, where uncertainties and nonlinearity are mostly prevalent [17].

In current years, the use of deep reinforcement learning for traction motor control attracts more and more research interests. This can be observed from Fig. 1, which shows the number of publications devoted to control of electric motors using the method of reinforcement learning from 2018 to 2025. The sharp increase after 2021 represents the corresponding advancement of deep learning techniques and their suitability for the nonlinearly coupled dynamics that exist in a traction system. In this regard, discrete control algorithms like DQN fit naturally with direct control methods like DTC, and algorithms with continuous control like DDPG or TD3 are best suited for current or speed regulation control methods [18]. At the same time, numerous studies have explored hybrid approaches combining DRL with classical techniques (PI, MPC, SMC), in order to simultaneously leverage the robustness of physics-based models and the adaptability provided by learning agents. These developments open the door to more flexible, more autonomous, and potentially higher-performing control structures under real-world operating conditions [19], [20].

From an algorithmic point of view, RL-based control has progressed from discrete-action RL, such as DQN, which is naturally associated with finite state control and DTC, towards continuous-action actor-critic RL, such as DDPG and TD3. The latter has the potential to provide direct control of smooth references for the FOC of PMSM and induction motors, thereby improving the accuracy of the motor current control, minimizing torque ripple, and increasing overall efficiency. Nevertheless, even though these RL-based control approaches offer better performance compared to their predecessors, they are essentially "black-box" models, and this has raised important issues related to automotive functional safety standards such as ISO 26262. The standard requires interpretability, traceability, and verifiability of control decisions, and this has created a major problem related to explainable AI (XAI) for RL-based control.

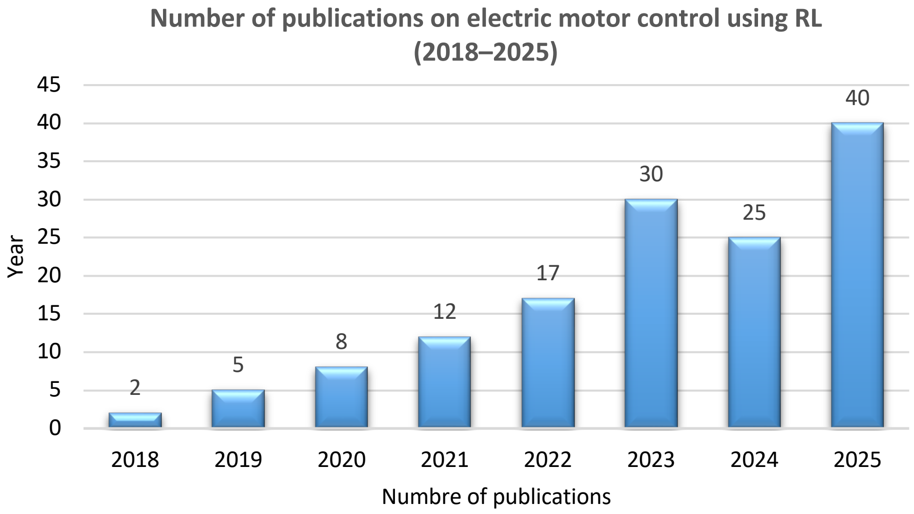

Fig. 1. Number of publications related to traction motors control using Reinforcement Learning, identified through a Scopus search using the keywords ''reinforcement learning'' and ''traction motors''

This article provides a comprehensive review of traction motor control techniques based on Deep Reinforcement Learning. It presents an overview of the different motor topologies used in electric vehicles as well as the various reinforcement learning based control strategies. After an introduction devoted to presenting the subject and its various dimensions, Section 2 presents the types of motors found in electric vehicles, as well as an evaluation of their performance, while Section 3 provides a theoretical description of the principles underlying DRL, as well as the algorithms most often used for controlling nonlinear systems. Section 4 focuses on an in-depth discussion of the role of DRL in motor speed control, while Section 5 is reserved for the advantages and limitations of RL for motor control. Finally, the last section provides a general summary, accompanied by recommendations for future developments in this emerging field.

2. Electric Vehicle Motors

Below you will find an overview of the types of traction motors utilized for electric vehicles. Following this you will find a comparison that will present the pros and cons of each type of traction motor. Each type of traction motor has benefits and drawbacks, which are illustrated through the application of a variety of parameters such as; efficiency, density, torque, power and cost etc.

2.1. Traction Motor Overview

Traction motor drives are an essential part in the progress of electric vehicles. Each of the motors has unique advantages and challenges. The major motor drive systems used in electric vehicles are direct current motors, induction motors, permanent magnet motors, and reluctance motors, as shown in Fig. 2. Each motor has its unique properties and challenges [21], [22].

DC motors were traditionally used in electric vehicles because of simple design principles and their high torque capability even at slower speeds. These motors produce high torque even at slower speeds, can be easily controlled, and enjoy a well-established technology base. However, their relatively lower efficiency and high maintenance requirements due to brushes, which wear out quite frequently, remain significant drawbacks [23].

The use of induction motors is widespread in electric vehicles because of their simplicity, reliability, and relatively low price. Induction motors are also known to be robust and require less maintenance. Nonetheless, compared to other types of motors such as permanent magnet motors and reluctance motors, the efficiency of induction motor is less, and its size is larger [24].

Permanent Magnet motors are known to offer excellent torque control, maintenance costs are minimal, and they are characterized by their significantly high efficiency levels and relatively higher power density. In addition to the excellent torque control and efficiency levels, the smooth operation of such motors also improves the comfort levels of the driver. Even though PM motors are largely employed in electric vehicles, the major disadvantages of such motors include relative high costs and lower production volumes. In addition to that, the use of rare earth materials that are highly susceptible to the effects of higher temperatures and are prone to demagnetization increases costs to a large extent [25].

Recently, there has been growing interest in reluctance motors, thanks to their cost-effective nature and ability to provide a high torque density. Advances in modern control theory and power electronics have made it possible to overcome the limitations associated with constant speeds, thereby controlling motor speeds, which was difficult due to the rigidity of the motor [26]. In fact, the efficiency and compactness of brushless DC motors are notable advantages, adding to their increased appeal for use within electric vehicles. Another method for the propulsion of electric vehicles could be variable reluctance motor drives [27]. Comparative Analyses of Electric Vehicle Drive Systems as Attractive Technology. The fault tolerance, cost-effectiveness, lightweight characteristics, and relatively high efficiencies of an SRM motor are some of the benefits of this type of electric vehicle drive system as shown in comparison analyses performed by numerous researchers [28]. These are reliable, cost-effective, and capable of operating in harsh environments; this has made their popularity high in a wide range of applications. Their open platform with no magnets and flexible controls is of great benefit to electric vehicles. However, some of the challenges that are worth focusing on in modern research fields include torque ripple, vibration noise, and drag caused by their speed [29]. Reluctance motors rely on differences in magnetic reluctance to create torque, making them inherently simple and economical. However, their biggest disadvantage is the low power factor, which requires complex control algorithms to achieve maximum performance. In fact, transverse flux machines are also believed to be very suitable for electric vehicle applications due to the preliminary comparative study, which revealed them to have among the highest power density at low speeds [30].

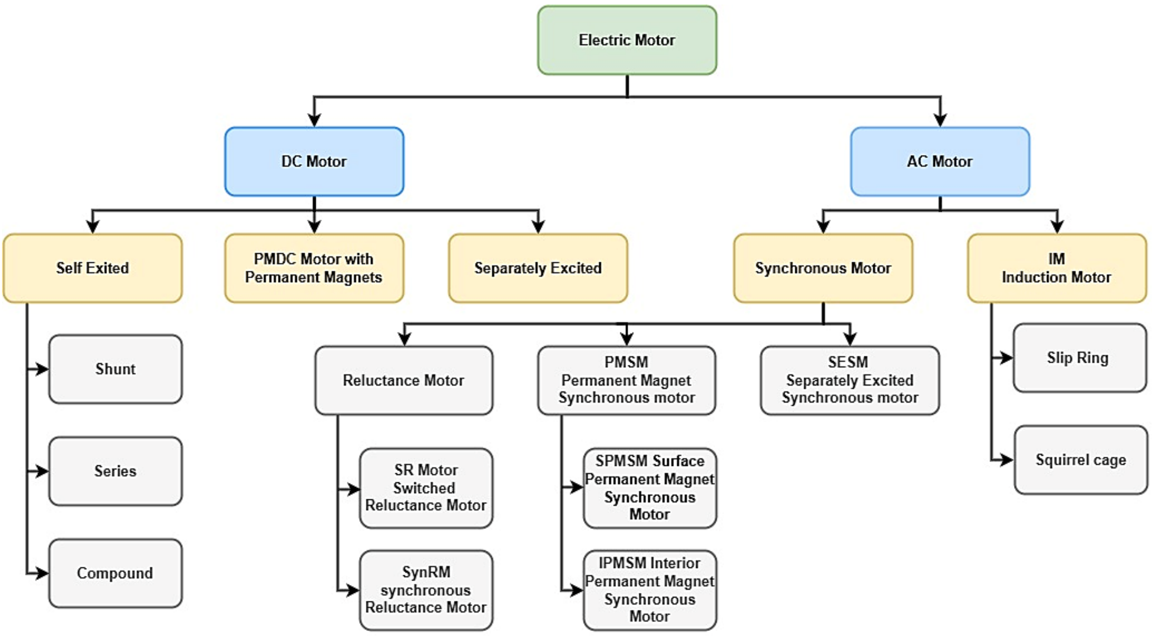

Fig. 2. Types of traction motors for electric vehicles [31]

2.2. Motors Comparison

Electric vehicles need high starting torque and minimal power consumption at higher speeds. From Fig. 3, the relationships between torque, speed, and power of an electric traction motor are identified. The major factors that need to be taken into consideration while choosing a motor in an electric propulsion system are listed in Table 1. These factors include cost, size, speed range, efficiency, power density, maximum torque, reliability, and maturity of technology [32]. The comparison study focuses on five types of motors: brushless DC motors, synchronous reluctance motors, variable reluctance motors, induction motors, and permanent magnet synchronous motors. Analyzing these factors in detail, as presented in Table 1, helps to highlight the pros and cons of each technology [33]. It must be stated that induction motors, permanent magnet synchronous motors, and so forth have come up as serious competitors that perform much better compared to other options and are among those best suited for electric propulsion [34].

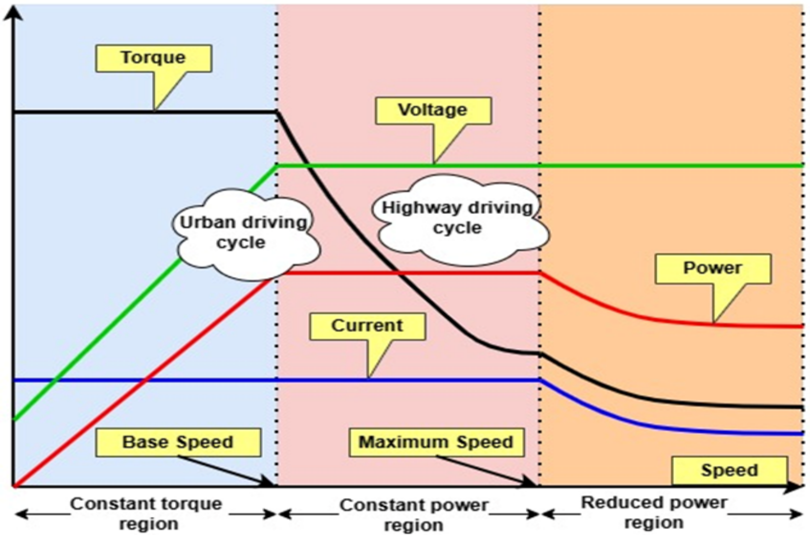

Fig. 3. Performance Attributes of Electric Traction Motors [35]

Table 1. Electric motors criteria [36]

Parameters	BLDC	SynRM	SRM	PMSM	IM
Cost	3	2	3	2	4
Size	2	2	1	4	3
Efficiency	2	3	3	4	2
Fault tolerance	1	4	4	3	2
Overload capacity	2	2	1	2	3
Power density	1	3	2	4	2
Speed range	1	3	4	2	2
Torque ripple	4	3	1	3	4
Control simplicity	4	2	2	3	4
Noise level	3	3	1	4	3
Reliability	2	4	4	3	4

Low = 1: Medium = 2: High = 3: Very high = 4

3. Theoretical Basis and Algorithmic Approaches of DRL

Reinforcement learning represents the third major paradigm of machine learning. Unlike supervised or unsupervised learning, it does not necessarily rely on a pre-established dataset: the agent, modeled here by a neural network, learns directly from its interactions with its environment. As illustrated in Fig. 4, the agent observes the environment, generates an action, and receives a reward value in return that evaluates the relevance of that action [37]. This exchange mechanism forms the basis of the learning process: the reward function simultaneously encodes the overall objective and the characteristics of the environment, gradually guiding the agent toward optimal behavior. One of the key advantages of RL is the absence of fixed input data, since learning emerges directly from accumulated experience. However, the performance of the algorithm depends heavily on the quality of the environment modeling and the definition of the reward function, the design of which often remains one of the main challenges [38].

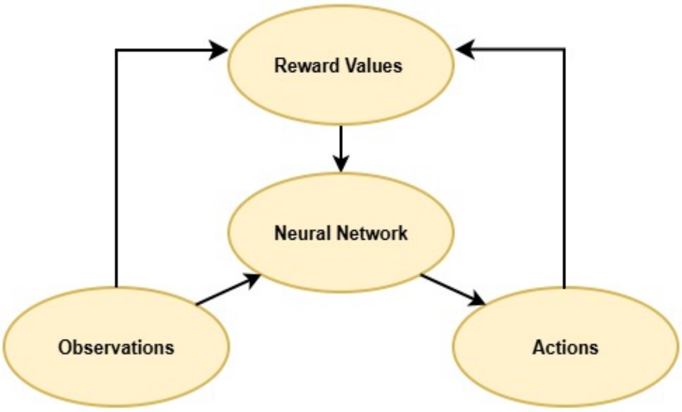

Fig. 4. Reinforcement learning structure [39]

3.1. Fundamental reinforcement learning

After presenting reinforcement learning, which belongs to the field of artificial intelligence, as well as the three main categories of neural networks, it is now time to introduce a more in-depth theoretical framework dedicated to this learning paradigm. This framework will serve as the basis for the following sections of this article. The general configuration of a reinforcement learning system is illustrated in Fig. 5. A reinforcement learning system is essentially based on two elements: the environment and the agent. The environment represents, often in a simplified but sufficient manner, the real system that we wish to model and control [40]. At each time step t, it provides a state s_t and a reward r_t, which serve as inputs to the agent. It is important to distinguish the state from the observation: the state corresponds to the complete set of information characterizing the environment's situation, while the agent generally perceives only a subset of it, called the observation o_t. Depending on the amount of information available, the environment may be fully or partially observable, which directly influences the agent's performance during learning. By convention, most works use the state notation rather than the observation notation, a choice we follow here. Based on the received information, the agent generates an action a_t that it sends to the environment in order to modify its evolution. This decision is produced by a policy $\pi_\theta(s_t)$, a function parameterized by θ and continuously optimized based on the rewards obtained. The policy can be deterministic, one action for a given state or stochastic, in which case actions are sampled from a learned distribution, and the log-likelihoods $\log\pi_\theta(a \mid s)$ then play a central role in the optimization. The reward function, defined by $r_t = R(s_t, a_t, s_{t+1})$ It depends on the current state, the action performed, and the state obtained in return [41]. This function, specific to each application, formalizes the objective to be achieved and guides the agent toward the desired behavior. The agent's objective is to maximize the cumulative reward obtained along a trajectory $\tau = (s_0, a_0, s_1, a_1, \dots)$. Generally formulated within a finite, non-discounted time horizon or according to other equivalent criteria depending on the application. Two types of cumulative rewards are generally distinguished: the finite-horizon undiscounted return and the infinite-horizon discounted return [42].

The first is simply the sum of rewards over a fixed time window:

$$R(\tau) = \sum_{t=0}^{T} r_t \tag{1}$$

For the infinite-horizon cumulative reward, we introduce a discount factor $\gamma \in (0,1)$, which gives less weight to rewards obtained farther in the future:

$$R(\tau) = \sum_{t=0}^{\infty} \gamma^{t} r_{t} \tag{2}$$

Using a discount factor is justified by two simple reasons. First, as in real life, an immediate reward is more valuable than a delayed one. Second, an infinite sum may not converge; discounting ensures convergence and allows the expression to be used in mathematical derivations [43].

After establishing the fundamental definitions of RL, it is time to introduce the core problem: finding a policy that maximizes the expected return when the agent acts according to it. If both the policy and the state transitions are stochastic, the probability of a trajectory can be written as follows:

$$P(\tau \mid \pi) = p_0(s_0) \prod_{t=0}^{T-1} P\left(s_{t+1} \mid s_t, a_t\right) \pi(a_t \mid s_t) \tag{3}$$

From this, the expected return J(π) is expressed as:

$$J(\pi) = \int_{\tau} P\left(\tau \mid \pi\right) R(\tau) = \mathbb{E}_{\tau\sim\pi}[R(\tau)] \tag{4}$$

The fundamental objective of RL can now be summarized in a single line:

$$\pi^{*} = \underset{\pi}{\operatorname{argmax}} J(\pi) \tag{5}$$

where π^{*} is the optimal policy, we seek.

Using this formal framework, multiple valuable functions can be established. They play a key role in the RL algorithms presented in the next section, as they evaluate the quality of a state or state action pair in terms of the expected future reward when the agent follows a given policy [44].

These value functions quantify the value of a state or a state action pair, defined as the expected return obtained when starting from that position and following a given policy thereafter. Four fundamental types of value functions are commonly distinguished, each forming the basis of a major class of RL algorithms.

The first is the On-Policy Value Function, $V_{\pi}(s)$, which represents the expected return when starting in state s and consistently acting according to policy π:

$$V_{\pi}(s) = \mathbb{E}_{\tau\sim\pi}[R(\tau) \mid s_0 = s] \tag{6}$$

The second is the On-Policy Action-Value Function, $Q_{\pi}(s,a)$, which extends the previous definition by considering an arbitrary initial action a that may not come from the policy itself:

$$Q_{\pi}(s,a) = \mathbb{E}_{\tau\sim\pi}[R(\tau) \mid s_0 = s,\ a_0 = a] \tag{7}$$

From these definitions, one can also introduce the optimal counterparts. The Optimal Value Function, $V^{*}(s)$, represents the maximum expected return achievable from state s when following the optimal policy thereafter:

$$V^{*}(s) = \max_{\pi} \mathbb{E}_{\tau\sim\pi}[R(\tau) \mid s_0 = s] \tag{8}$$

Similarly, the Optimal Action-Value Function incorporates an arbitrary initial action:

$$Q^{*}(s,a) = \max_{\pi} \mathbb{E}_{\tau\sim\pi}[R(\tau) \mid s_0 = s,\ a_0 = a] \tag{9}$$

Two important relationships linking value and action-value functions follow directly from their definitions:

$$V_\pi(s) = \mathbb{E}_{a\sim\pi}[Q_\pi(s,a)],\ \ V^*(s) = \max_a Q^*(s,a) \tag{10}$$

There is also a key relationship between the optimal action-value function and the action selected by the optimal policy. Since the optimal policy always chooses the action that maximizes the expected return in state s, the optimal action $a^*(s)$ can be directly obtained from the optimal Q-function:

$$a^*(s) = \operatorname*{argmax}_a Q^*(s,a) \tag{11}$$

Multiple actions may achieve the same maximal value; in such cases, all are considered optimal, though there always exists at least one optimal policy that selects deterministically [45].

With these definitions in mind, we can now bring in the formalism that pervades all reinforcement learning algorithms the Bellman equations. The Bellman equations formalize the consistency principle that the value of a state is equal to the discounted reward received in that state and the value of the next state.

For on-policy value functions, the Bellman equations are:

$$\begin{gathered} V_\pi(s) = \mathbb{E}_{a\sim\pi,\ s'\sim P}[\,r(s,a) + \gamma V_\pi(s')\,] \\ Q_\pi(s,a) = \mathbb{E}_{s'\sim P}[\,r(s,a) + \gamma\, \mathbb{E}_{a'\sim\pi}[Q_\pi(s',a')]] \end{gathered} \tag{12}$$

where $s' \sim P(\cdot|\ s,a)$ denotes sampling the next state from the environment dynamics; $a \sim \pi(\cdot|\ s)$ denotes sampling an action from the policy; and $a' \sim \pi(\cdot|\ s')$ denotes the next action under the same policy.

The Bellman equations for optimal value functions are written as:

$$\begin{gathered} V^*(s) = \max_a \mathbb{E}_{s'\sim P}[\,r(s,a) + \gamma V^*(s')\,] \\ Q^*(s,a) = \mathbb{E}_{s'\sim P}\left[r(s,a) + \gamma \max_{a'} Q^*(s',a')\right] \end{gathered} \tag{13}$$

The key distinction here is the presence of the maximization operator, which reflects the requirement that an optimal agent must always select the action yielding the highest value. Solving these equations is the central objective of reinforcement learning algorithms, making them fundamental to the training of any RL agent [46].

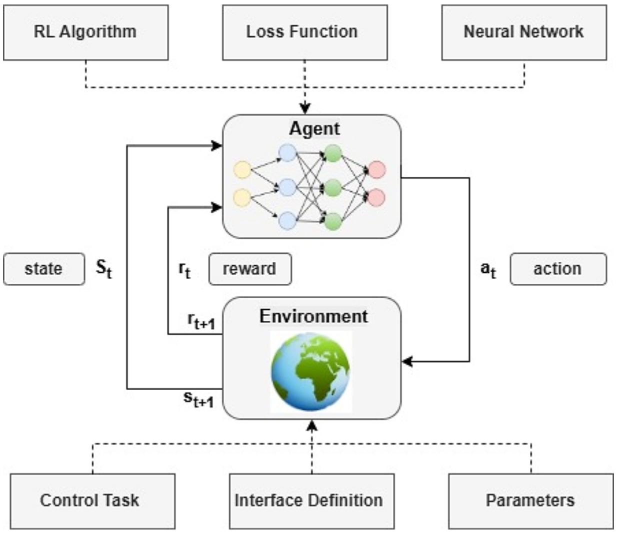

Fig. 5. Fundamental architecture of the RL environment [47]

3.2. Algorithms for reinforcement learning

After introducing the fundamental concepts of reinforcement learning, it is useful to briefly review the algorithms based on these formulations. Fig. 6 provides an overview of their classification, as well as some of the most commonly used algorithms in each category.

RL methods can be divided into two main categories depending on whether or not they use an internal model of the environment. Model-based approaches rely on a model of the environment, either provided before learning or learned gradually during learning. Their main advantage is greater learning efficiency; however, obtaining a model that accurately reflects real dynamics is often complex, a well-known problem in conventional model-based control techniques. Furthermore, when the model is learned in parallel with training, the desired accuracy and convergence speed can be significantly affected. Because of such shortcomings and the increased complexity of electric control, model-free solutions are considered preferable in general [48].

Model-free reinforcement learning solutions can be divided into three categories depending on the strategy of the agent to select the next action. The first category is value-based methods. These methods seek to estimate the value function defined beforehand and use the value function as a basis to build the policy. A good representation of value-based methods is Q-learning [49]. This solution is based on the use of Q-tables and a value function that is estimated through the Temporal-Difference learning method. It makes a calculation of the difference between the estimated value and the value expected by the next state, which makes it a more efficient sampling strategy. It has good convergence properties but lacks the ability to be applied to a continuous state space [50]. In that respect, the Deep Q-Network approach was proposed to make use of neural networks and the Q-learning strategy to estimate policy in continuous state spaces. However, DQN is inclined to overestimate the value of Q. To remove such a drawback, the Double DQN strategy [51] was proposed. In that strategy, a neural network is utilized to estimate the value of Q. In short, value-based reinforcement learning algorithms are highly efficient and robust against getting trapped at local optima.

However, the approach faces challenges when applied to the continuous state space. The second predominant reinforcement learning approach is policy-based methods. As the name signifies, the methodology focuses on learning the optimal policy without making use of any value function. The reinforcement learning approach [52] is the most prominent example: the approach makes use of Monte Carlo learning to estimate the gradient value regarding the policy. This helped in achieving relatively stable learning but low efficiency regarding the sampling updates. It was later improved through Trust Region Policy Optimization [53] and eventually through the approach called Proximal Policy Optimization [54], where the hyperparameters were accurately tuned such that the updates remained within a smaller magnitude. In other words, the approach is guaranteed to show improvement at every iteration, ensuring that the overall performance would be non-decreasing. However, compared to value-based approaches, they are less efficient in terms of sampling, exhibit greater variance, and are more prone to falling into local optima.

The last major category of model-free reinforcement learning methods includes actor-critic algorithms, which currently occupy a central place in reinforcement learning research. Their fundamental principle is to merge value-based and policy-based approaches in order to combine their strengths within a single algorithmic framework. An AC algorithm typically relies on two neural networks: a critic, responsible for estimating and updating the value function via TD-type updates, and an actor, which optimizes the policy based on the evaluations produced by the critic. Convergence can be improved using the Deep Deterministic Policy Gradient method [55], which is based on the DQN algorithm described above while extending it to the AC framework in order to handle continuous state spaces. However, the DDPG method can suffer from overestimation phenomena, which led to the development of the Twin Delayed DDPG method [56], a variant that uses six neural networks to provide more reliable estimates. Another widely used AC algorithm is the Asynchronous Advantage Actor-Critic algorithm, or A3C for short [57], which was designed to improve the efficiency of exploration via the reduction of correlation within training data. Taken together, actor-critic algorithms combine the advantages of value-based methods and policy-based methods, and as a result, they are able to achieve a smoother estimate of the value functions and improve the efficiency of exploration. On the other hand, these algorithms also inherit some disadvantages possessed by the individual methods, which can be very sensitive to hyperparameter settings. To simplify the process of implementing an AC algorithm, a set of hyperparameter settings within the RL Zoo database [58] can be used, depending on the task at hand.

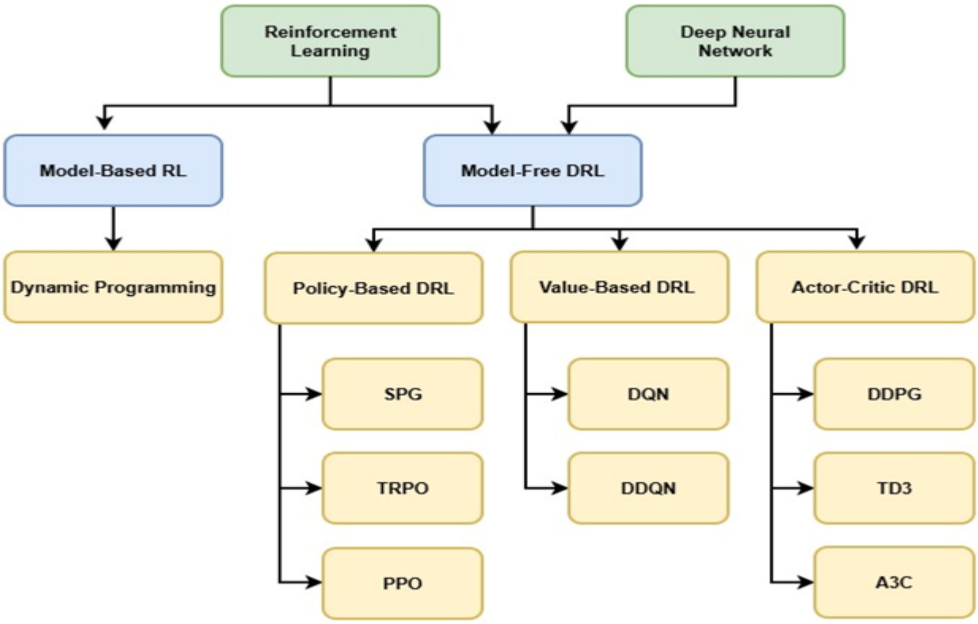

Fig. 6. Classification of reinforcement learning algorithms [59]

4. Reinforcement Learning Based Control of Traction Motors

In this section, an assessment of the control techniques suggested in the literature using reinforcement learning is given in Table 2. The type of algorithms used, the controls selected, and the developments obtained using RL for the control of traction motors are addressed. In particular, this section is aimed at recognizing, categorizing, and summarizing the various techniques suggested for the control of electric machine systems, focusing on the type of controls applied and, on the algorithms, implemented. This assessment includes a wide range of algorithms, going from classical reinforcement learning to advanced reinforcement learning techniques using deep Q-Network, Double Deep Q-Network, Proximal Policy Optimization, Soft Actor-Critic, and TD3. These elements are summarized using a table that classifies the contributions for a wide range of machine types, namely induction machines, permanent magnet synchronous motors, brushless DC motors, switched reluctance motors, and synchronous reluctance motors. In these studies, the machine type, algorithm type, and type of suggested controller are given. This presentation is focused on presenting the main trends existing in the literature, particularly on the use of advanced algorithms capable of performing the optimal controller's self-learning directly, reducing, to a certain point, the dependency on explicit machine modeling. In fact, some studies include a combination of the use of conventional controls (PI, MPC, fuzzy, and optimization) with reinforcement learning to take advantage from the stability offered by these classical techniques combined with the versatility offered by the self-learning abilities offered by the RL techniques. The recent increase of the number of studies on TD3 controller applied to BLDC motors is a good representation of these changes, highlighting the growing interest for these techniques, particularly for complex conditions. It can be noted that according to the synthesis of the various studies analyzed, the reinforcement learning represents a particularly appropriate approach for the advanced control techniques for the current applications related to the electric machine systems.

Table 2. Summary of reinforcement learning algorithms for traction motor control

Motors	RL Algorithm	Proposed Solution	Reference
IM	Adaptive Q-Learning	RL policy replacing the PI controller for automatic torque/speed adjustment.	[60]
	Deep Q-Network	Model-free speed control based on discrete states and online learning.	[61]
	DDPG	Continuous control learning the torque current law to limit oscillations.	[62]
	PPO	Policy optimization via proximal gradient for robust control under uncertainty.	[63]
	SAC	Off-policy controller simultaneously learning value and policy to improve transients.	[64]
PMSM	Actor–Critic	Actor-critical architecture replacing PI flow/speed with automatic gain adaptation.	[65], [66]
	DDPG	Continuous control law learning the optimal torque at different speeds.	[67]
	DQN + Observer	State observer + RL to compensate for disturbances and parameter uncertainties.	[68]
	PPO	Stable drive for direct speed control.	[69]
	Hybrid RL + MPC	RL for adjusting the horizons/weights of a classic MPC online.	[70]
BLDC	Q-Learning	Dynamic Q table to adapt switching according to inertia.	[71]
	DQN	Sensorless control using deep Q network to select control actions.	[72]
	DDPG	Continuous policy learning the current waveform to smooth the torque.	[73], [74]
	PPO	Mandatory policy update to track variable load profiles.	[75]
	RL + Fuzzy	RL adjusts the rules/factors of a fuzzy controller in real time.	[76], [77], [78]
	TD3	A controller using a TD3 agent trained through simulation shows good tracking of the target position and good performance for varying torques, with response times from about 1.2 to 1.9 seconds.	[79]
SRM	Q-Learning	Adaptation of excitation angles via discrete learning.	[80]
	Actor Critic	Torque current control via actuator + evaluator network.	[81]
	DDPG	Continuous policy explicitly managing the nonlinearities of the SRM.	[82]
	PPO	Stabilized update to control speed and torque under disturbances.	[83]
	RL + Optimization	RL coupled with optimization to simultaneously adjust speed and efficiency.	[84]
SynRM	Actor Critic	Learning excitation laws that take rotor variation into account.	[85]
	DDPG	Continuous control aimed at minimizing steady-state error.	[86], [87]
	DQN	Approach without a model that directly learns the speed–current policy.	[88]
	PPO	Stable policy implemented to compensate for network disruptions.	[89]
	Hybrid RL + PI	RL dynamically adjusts PI gains according to the operating state.	[90]

5. Considerations and Limitations

After summarizing the use of reinforcement learning algorithms for the improvement of electric controllers’ performance, it can be observed that, when considered within the traction motor control domain, reinforcement learning entails a number of significant advantages, which are contributing to the increased interest shown by the scientific community within recent times. Specifically, as a data-driven approach, RL enables the formulation of control methods capable of learning through direct interaction with the system, without necessarily needing an accurate analytical model. Additionally, this makes it even more appealing for being applied to electric vehicles’ drive trains, as well as other industrial applications, wherein nonlinearities, parametric uncertainties, as well as external disturbances, prevail. Between 2018 and 2025, numerous works have demonstrated the ability of RL to provide a superior level of adaptability when considering variable circumstances and the capability of jointly optimizing more-than-one objective, especially within the domain of efficiency, dynamics, and robustness. Nonetheless, the application of RL within the traction motor domain remains accompanied by a number of significant challenges, including the difficulty of migrating learning policies within the simulator setting to the actual system, significant requirements related to safety and stability, as well as issues associated with high computational complexity when considering real-time issues, as well as generalization and scalability challenges. The aforementioned challenges have, however, currently led to the exploration of novel research trends, which include robust RL methods, RL and Conventional Control hybrid methods, offline learning, domain randomization, the use of digital twins, as well as online adaptation methods.

6. Conclusion

Since 2018, the use of reinforcement learning for controlling electric vehicle traction motors has grown rapidly, driven by the limitations of conventional approaches, which are highly dependent on precise models and are not very robust in the face of nonlinearities, parametric uncertainties, and external disturbances. This study shows that value-oriented, policy-oriented, or hybrid methods offer remarkable potential for multi-objective optimization of dynamic performance, and compliance with electromagnetic constraints, while benefiting from a largely model-free nature. In parallel with these advances, major obstacles remain: discrepancies between simulation and reality, stability guarantees, operational safety, robustness in extreme conditions, and computational complexity for embedded systems. The theoretical contributions presented, in particular the explicit integration of physical constraints into the cost function and the comparative analysis of constrained learning schemes, shed new light on the design of safer and more interpretable RL controllers. Promising perspectives are emerging around secure RL, offline learning, hybrid models combining RL and predictive control, and federated learning enabling fleets of vehicles to collectively improve their policies based on shared driving data, while respecting confidentiality. However, industrial validation of these controllers will require methodological frameworks that comply with automotive safety standards (ISO 26262, ASPICE), including formal verification, closed-loop testing, stability testing, and certification of learning processes. The limitations of this work lie in the fact that the evaluation is still mainly based on simulation and in the absence of large-scale real-time deployment. Future work will focus on sim-to-real transfer through domain randomization, extension to multi-engine architectures, overall vehicle energy management, and interaction with ADA systems. In summary, this article highlights that, despite scientific and industrial challenges that remain unresolved, reinforcement learning is a major technological lever with the potential to profoundly transform the control and embedded intelligence architectures of next-generation electric and autonomous vehicles.

Author Contribution: All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Acknowledgment: This work was carried out with the support of the Centre National de la Recherche Scientifique et Technique (CNRST), as part of the "PhD-Associate Scholarship - PASS" program.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Z. Gao, H. Xie, X. Yang, L. Zhang, H. Yu, W. Wang, Y. Liu, Y. Xu, B. Ma, X. Liu, and S. Chen, "Electric vehicle lifecycle carbon emission reduction: A review," *Carbon Neutralization*, vol. 2, no. 5, pp. 528–550, 2023, https://doi.org/10.1002/cnl2.81.

[2] H. Tahir, H. E. Gelani, S. El-Ferik, M. Tayyab, and N. Khosravi, "Electric vehicles and renewable energy for sustainable mobility: Insights from bibliometric, topic modeling, and societal impact analyses," *Energy Strategy Reviews*, vol. 61, p. 101827, Sep. 2025, https://doi.org/10.1016/j.esr.2025.101827.

[3] K. T. Chau and W. Li, "Overview of electric machines for electric and hybrid vehicles," *International Journal of Vehicle Design*, vol. 64, no. 1, p. 46, 2014, https://doi.org/10.1504/IJVD.2014.057775.

[4] W. Cai, X. Wu, M. Zhou, Y. Liang, and Y. Wang, "Review and development of electric motor systems and electric powertrains for new energy vehicles," *Automotive Innovation*, vol. 4, no. 1, pp. 3–22, Feb. 2021, https://doi.org/10.1007/s42154-021-00139-z.

[5] D. Tavernini, M. Metzler, P. Gruber, and A. Sorniotti, "Explicit nonlinear model predictive control for electric vehicle traction control," *IEEE Transactions on Control Systems Technology*, vol. 27, no. 4, pp. 1438–1451, 2018, https://doi.org/10.1109/TCST.2018.2837097.

[6] C. A. Lúa, S. Di Gennaro, A. B. F. Jiménez, and A. N. Guzmán, "Robust dynamic control for electric vehicles with estimation of parametric uncertainties and external disturbances," *IEEE Access*, vol. 12, pp. 170011–170026, 2024, https://doi.org/10.1109/ACCESS.2024.3475990.

[7] S. A. Saleh, E. Ozkop, M. Ş. Ayas, K. M. Muttaqi, and B. Nahid-Mobarakeh, "Survivability-based protection for electric motor drive systems—Part I: Three-phase induction motor drives," *IEEE Transactions on Industry Applications*, vol. 58, no. 2, pp. 1797–1808, Mar. 2022, https://doi.org/10.1109/TIA.2022.3145772.

[8] M. Aktas, K. Awaili, M. Ehsani, and A. Arisoy, "Direct torque control versus indirect field-oriented control of induction motors for electric vehicle applications," *Engineering Science and Technology, an International Journal*, vol. 23, no. 5, pp. 1134–1143, 2020, https://doi.org/10.1016/j.jestch.2020.04.002.

[9] L. Svensson, M. Bujarbaruah, A. Karsolia, C. Berger, and M. Törngren, "Traction adaptive motion planning and control at the limits of handling," *IEEE Transactions on Control Systems Technology*, vol. 30, no. 5, pp. 1888–1904, 2021, https://doi.org/10.1109/TCST.2021.3129373.

[10] J.-H. Heo, J.-K. Kang, and J. Hur, "Verification of shaft voltage reduction effect using layered shield in EV traction motors," *IEEE Access*, vol. 12, pp. 136825–136836, 2024, https://doi.org/10.1109/ACCESS.2024.3465492.

[11] S. Zhang, A. Shen, X. Luo, Q. Tang, and Z. Li, "An adaptive strategy for PMSM-based disturbance estimation and online parameter identification," *IEEE/ASME Transactions on Mechatronics*, vol. 29, no. 4, pp. 2522–2533, 2023, https://doi.org/10.1109/TMECH.2023.3333382.

[12] G. Fang, F. P. Scalcon, D. Xiao, R. P. Vieira, H. A. Gründling, and A. Emadi, "Advanced control of switched reluctance motors (SRMs): A review on current regulation, torque control and vibration suppression," *IEEE Open Journal of the Industrial Electronics Society*, vol. 2, pp. 280–301, 2021, https://doi.org/10.1109/OJIES.2021.3076807.

[13] L. Wu, J. Liu, S. Vazquez, and S. K. Mazumder, "Sliding mode control in power converters and drives: A review," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 3, pp. 392–406, 2022, https://doi.org/10.1109/JAS.2021.1004380.

[14] R. Pusca, Y. Ait-Amirat, A. Berthon, and J. M. Kauffman, "Fuzzy logic based control for electric vehicle with four separate traction drives," in *Proceedings of the IEEE 55th Vehicular Technology Conference (VTC Spring)*, 2002, pp. 2089–2096, https://doi.org/10.1109/VTC.2002.1002991.

[15] J. Guo, T. Kawaguchi, and S. Hashimoto, "A discrete space vector modulation MPC-based artificial neural network controller for PMSM drives," *Machines*, vol. 13, no. 11, pp. 1–14, Oct. 2025, https://doi.org/10.3390/machines13110996.

[16] W. Zine, Z. Makni, E. Monmasson, L. Idkhajine, and B. Condamin, "Interests and limits of machine learning-based neural networks for rotor position estimation in EV traction drives," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 5, pp. 1942–1951, 2017, https://doi.org/10.1109/TII.2017.2765398.

[17] M. Drakaki, Y. L. Karnavas, I. A. Tziafettas, V. Linardos, and P. Tzionas, "Machine learning and deep learning based methods toward Industry 4.0 predictive maintenance in induction motors: State of the art survey," *Journal of Industrial Engineering and Management*, vol. 15, no. 1, pp. 31–57, 2022, https://doi.org/10.3926/jiem.3597.

[18] A. Mastanaiah, T. Ramesh, S. V. K. Naresh, and P. K. Bonthagorla, "Deep reinforcement learning agent-based speed controller for DTC-SVM of PMSM drive," *IET Power Electronics*, vol. 18, no. 1, p. e70130, Jan. 2025, https://doi.org/10.1049/pel2.70130.

[19] A. Pinosky, I. Abraham, A. Broad, B. Argall, and T. D. Murphey, "Hybrid control for combining model-based and model-free reinforcement learning," *The International Journal of Robotics Research*, vol. 42, no. 6, pp. 337–355, May 2023, https://doi.org/10.1177/02783649221083331.

[20] C. Jia, X. Li, H. Wang, and Z. Song, "Sliding mode-based integral reinforcement learning event-triggered control," *International Journal of Control, Automation and Systems*, vol. 23, no. 1, pp. 315–331, Jan. 2025, https://doi.org/10.1007/s12555-024-0231-7.

[21] T. A. Zarma, A. A. Galadima, and M. A. Aminu, "Review of motors for electric vehicles," *Journal of Scientific Research and Reports*, vol. 24, no. 6, pp. 1–6, 2019, https://doi.org/10.9734/jsrr/2019/v24i630170.

[22] K. Deepak, M. A. Frikha, Y. Benômar, M. El Baghdadi, and O. Hegazy, "In-wheel motor drive systems for electric vehicles: State of the art, challenges, and future trends," *Energies*, vol. 16, no. 7, p. 3121, 2023, https://doi.org/10.3390/en16073121.

[23] A. Singh, S. Yadav, N. Tiwari, and S. Patel, "Performance enhancement of DC motor drive for electric vehicle application by using deep neural network," *International Journal of Innovative Computing and Applications*, vol. 15, no. 3, pp. 145–155, Jan. 2025, https://doi.org/10.1504/IJICA.2025.148630.

[24] A. Hasni, H. El Fadil, A. Lassioui, Y. El Asri, M. El Ancary, H. Abbade, and M. Mouyane, "Enhancing scalar control of induction motors using super-twisting sliding mode control: Experimental validation," *Journal Européen des Systèmes Automatisés*, vol. 58, no. 8, pp. 1767–1776, 2025, https://doi.org/10.18280/jesa.580820.

[25] H. Yang, P. Wu, D. Liu, Y. Zhu, S. Fang, and H. Lin, "A less-rare-earth permanent magnet machine with hybrid magnet configuration for electric vehicles," *Energies*, vol. 18, no. 12, p. 3051, 2025, https://doi.org/10.3390/en18123051.

[26] Y. Lan, Y. Benomar, K. Deepak, A. Aksoz, M. El Baghdadi, E. Bostanci, and O. Hegazy, "Switched reluctance motors and drive systems for electric vehicle powertrains: State of the art analysis and future trends," *Energies*, vol. 14, no. 8, p. 2079, 2021, https://doi.org/10.3390/en14082079.

[27] L. Feng, X. Sun, G. Bramerdorfer, Z. Zhu, Y. Cai, K. Diao, and L. Chen, "A review on control techniques of switched reluctance motors for performance improvement," *Renewable and Sustainable Energy Reviews*, vol. 199, p. 114454, 2024, https://doi.org/10.1016/j.rser.2024.114454.

[28] A. L. Saleh, F. Al-Amyal, and L. Számel, "Control techniques of switched reluctance motors in electric vehicle applications: A review on torque ripple reduction strategies," *AIMS Electronics and Electrical Engineering*, vol. 8, no. 1, pp. 104–145, 2024, https://doi.org/10.3934/electreng.2024005.

[29] A. Hasni, A. Lassioui, H. El Fadil, Y. El Asri, M. El Ancary, I. Bentalhik, S. El Jeilani, and S. Nady, "Cruise control of an electric vehicle propelled by a BLDC motor," *EPJ Web of Conferences*, vol. 330, 2025, https://doi.org/10.1051/epjconf/202533006008.

[30] B. Kaiser and N. Parspour, "Transverse flux machine-A review," *IEEE Access*, vol. 10, pp. 1–1, 2022, https://doi.org/10.1109/ACCESS.2022.3150905.

[31] M. Megrini, A. Gaga, and Y. Mehdaoui, "Review of electric vehicle traction motors, control systems, and various implementation cards," *Journal of Operation and Automation in Power Engineering*, vol. 13, no. 3, pp. 238–247, 2025, https://www.researchgate.net/publication/380518707.

[32] S. Guo, H. Zhao, Y. Wang, X. Yin, H. Qi, P. Li, and Z. Lin, "A design technique of traction motor for efficiency improvement based on multiobjective optimization," *World Electric Vehicle Journal*, vol. 12, no. 4, p. 260, 2021, https://doi.org/10.3390/wevj12040260.

[33] K. S. Mohammad and A. S. Jaber, "Comparison of electric motors used in electric vehicle propulsion system," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 1, pp. 11–19, 2022, https://doi.org/10.11591/ijeecs.v27.i1.pp11-19.

[34] M. Gobbi, A. Sattar, R. Palazzetti, and G. Mastinu, "Traction motors for electric vehicles: Maximization of mechanical efficiency - A review," *Applied Energy*, vol. 357, p. 122496, Mar. 2024, https://doi.org/10.1016/j.apenergy.2023.122496.

[35] A. K. Venkitaraman and V. S. R. Kosuru, "Trends and challenges in electric vehicle motor drivelines - A review," *International Journal of Electrical and Computer Engineering Systems*, vol. 14, no. 4, pp. 485–495, Apr. 2023, https://doi.org/10.32985/ijeces.14.4.12.

[36] M. Yılmaz and S. Özdemir, "Review of motors used in commercial electric vehicles," in *Proceedings of the 5th International Mediterranean Science and Engineering Congress (IMSEC 2020)*, 2020, pp. 585–591, https://www.researchgate.net/publication/348153072.

[37] S. Tufenkci, B. B. Alagoz, G. Kavuran, C. Yeroglu, N. Herencsar, and S. Mahata, "A theoretical demonstration for reinforcement learning of PI control dynamics for optimal speed control of DC motors

by using Twin Delay Deep Deterministic Policy Gradient Algorithm," *Expert systems with applications*, vol. 213, p. 119192, 2023, https://doi.org/10.1016/j.eswa.2022.119192.

[38] A. Hasni, H. El Fadil, A. Lassioui, Y. El Asri, and M. El Ancary, "Precise induction motor parameters identification for robust electric vehicle cruise control using dSPACE 1104," in *Proceedings of the 2025 11th International Conference on Optimization and Applications (ICOA)*, Oct. 2025, pp. 1–6, https://doi.org/10.1109/ICOA66896.2025.11236866.

[39] L. A. Moulai, F. M. Zaihidee, S. Mekhilef, J. R. Tang, and M. Mubin, "Implementation of deep reinforcement learning in permanent magnet synchronous motors control: A review," *Annual Reviews in Control*, vol. 60, p. 101014, Jan. 2025, https://doi.org/10.1016/j.arcontrol.2025.101014.

[40] C. Liu, G. Luo, Z. Chen, and X. Ding, "Overview on active disturbance rejection control for electro-mechanical actuation servo drive," *Chinese Journal of Aeronautics*, vol. 38, no. 7, p. 103292, Jul. 2025, https://doi.org/10.1016/j.cja.2024.11.002.

[41] M. Schenke, W. Kirchgässner, and O. Wallscheid, "Controller design for electrical drives by deep reinforcement learning: A proof of concept," *IEEE Transactions on Industrial Informatics*, vol. 16, pp. 4650–4658, Jul. 2020, https://doi.org/10.1109/TII.2019.2948387.

[42] Z. Deng, X. Huo, Q. Du, and Q. Liu, "Reinforcement learning-based data-driven control design for motion control systems," in *Proceedings of the 2024 36th Chinese Control and Decision Conference (CCDC)*, May 2024, pp. 5745–5749, https://doi.org/10.1109/CCDC62350.2024.10587783.

[43] Q. Guan, X. Yao, Z. Lin, J. Wang, H. H. C. Iu, T. Fernando, and X. Zhang, "A robust control scheme for PMSM based on integral reinforcement learning," *IEEE Transactions on Transportation Electrification*, vol. 11, no. 1, pp. 4214–4223, Feb. 2025, https://doi.org/10.1109/TTE.2024.3455574.

[44] M. F. Elnaggar, A. Flah, C. Z. El-Bayeh, and M. M. Alrashed, "Optimized FOC control strategy for dual stators permanent magnet machine," *Scientific Reports*, vol. 15, no. 1, p. 34010, Sep. 2025, https://doi.org/10.1038/s41598-025-11435-7.

[45] A. Raffin, A. Hill, A. Gleave, A. Kanervisto, M. Ernestus, and N. Dormann, "Stable-baselines3: Reliable reinforcement learning implementations," *Journal of Machine Learning Research*, vol. 22, no. 268, pp. 1–8, 2021, http://jmlr.org/papers/v22/20-1364.html.

[46] M. El Ancary, A. Lassioui, H. El Fadil, T. Bouanou, Z. El Idrissi, A. Rachid, A. Hasni, and Y. El Asri, "Control of a wireless power transfer charger powered by renewable energies," in *Proceedings of the 2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, May 2024, pp. 1–6, https://doi.org/10.1109/IRASET60544.2024.10548631.

[47] N. Szécsényi and P. Stumpf, "Reinforcement learning based control approach for PMSM drives - Theory, concept, design and realizations," *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 13, p. 101095, Sep. 2025, https://doi.org/10.1016/j.prime.2025.101095.

[48] C. J. C. H. Watkins and P. Dayan, "Q-learning," *Machine Learning*, vol. 8, no. 3, pp. 279–292, May 1992, https://doi.org/10.1007/BF00992698.

[49] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg, and D. Hassabis, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, pp. 529–533, Feb. 2015, https://doi.org/10.1038/nature14236.

[50] H. van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double Q-learning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 30, no. 1, pp. 2094–2100, Mar. 2016, https://doi.org/10.1609/aaai.v30i1.10295.

[51] R. J. Williams, "Simple statistical gradient-following algorithms for connectionist reinforcement learning," *Machine Learning*, vol. 8, no. 3, pp. 229–256, May 1992, https://doi.org/10.1007/BF00992696.

[52] S. Zhao, F. Blaabjerg, and H. Wang, "An overview of artificial intelligence applications for power electronics," *IEEE Transactions on Power Electronics*, vol. 36, no. 4, pp. 4633–4658, Apr. 2021, https://doi.org/10.1109/TPEL.2020.3024914.

[53] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep reinforcement learning for power system applications: An overview," *CSEE Journal of Power and Energy Systems*, vol. 6, no. 1, pp. 213–225, Mar. 2020, https://doi.org/10.17775/CSEEJPES.2019.00920.

[54] H. Yoo, B. Kim, J. W. Kim, and J. H. Lee, "Reinforcement learning based optimal control of batch processes using Monte-Carlo deep deterministic policy gradient with phase segmentation," *Computers and Chemical Engineering*, vol. 144, p. 107133, Jan. 2021, https://doi.org/10.1016/j.compchemeng.2020.107133.

[55] M. Zanon and S. Gros, "Safe reinforcement learning using robust MPC," *IEEE Transactions on Automatic Control*, vol. 66, no. 8, pp. 3638–3652, Aug. 2021, https://doi.org/10.1109/TAC.2020.3024161.

[56] H. Huang, J. Xu, J. Wang, and X. Chen, "Reinforcement learning-based secure synchronization for two-time-scale complex dynamical networks with malicious attacks," *Applied Mathematics and Computation*, vol. 479, p. 128840, Oct. 2024, https://doi.org/10.1016/j.amc.2024.128840.

[57] G. Book, A. Traue, P. Balakrishna, A. Brosch, M. Schenke, S. Hanke, W. Kirchgässner, and O. Wallscheid, "Transferring online reinforcement learning for electric motor control from simulation to real-world experiments," *IEEE Open Journal of Power Electronics*, vol. 2, pp. 187–201, 2021, https://doi.org/10.1109/OJPEL.2021.3065877.

[58] A. Hasni, H. El Fadil, A. Lassioui, M. El Ancary, Y. El Asri, A. Hamed, and S. El Jeilani, "Optimized speed regulation of BLDC motors: A comparative performance study of artificial neural networks and super-twisting sliding mode controllers," *International Journal of Robotics and Control Systems*, vol. 5, no. 4, pp. 2360–2378, 2025, https://pubs2.ascee.org/index.php/IJRCS/article/view/2046.

[59] A. Hasni, A. Lassioui, H. El Fadil, M. El Ancary, Y. El Asri, S. Nady, A. Fhail, H. Abbade, and M. Chiheb, "A comprehensive review of advanced control strategies of adaptive cruise control system in electric vehicles," in *Proceedings of the 2025 5th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, May 2025, pp. 1–7, https://doi.org/10.1109/IRASET64571.2025.11008174.

[60] H. Alharkan, S. Saadatmand, M. Ferdowsi, and P. Shamsi, "Optimal tracking current control of switched reluctance motor drives using reinforcement Q-learning scheduling," *IEEE Access*, vol. 9, pp. 9926–9936, 2021, https://doi.org/10.1109/ACCESS.2021.3050167.

[61] Q. Abdullah, N. Farah, M. S. Ahmed, N. S. Mohd Shah, Ö. Aydoğdu, M. H. N. Talib, Y. M. Al-Moliki, A. Uğurenver, M. A. A. Al-Mekhalfi, M. Z. Aihsan, and A. Salh, "Sensorless speed control of induction motor drives using reinforcement learning and self-tuning simplified fuzzy logic controller," *IEEE Access*, vol. 12, pp. 136485–136501, 2024, https://doi.org/10.1109/ACCESS.2024.3435529.

[62] U. U. Korpe, M. Gokdag, and O. Gulbudak, "Speed control of IM using RL-based TD3 agent," in *Proceedings of the IEEE Global Power, Energy and Communication Conference (GPECOM)*, 2024, pp. 173–178, https://doi.org/10.1109/GPECOM61896.2024.10582561.

[63] H.-T. Yau, P.-H. Kuo, P.-C. Luan, and Y.-R. Tseng, "Proximal policy optimization-based controller for chaotic systems," *International Journal of Robust and Nonlinear Control*, vol. 34, no. 1, pp. 586–601, 2024, https://doi.org/10.1002/rnc.6988.

[64] A. Traue, G. Book, W. Kirchgassner, and O. Wallscheid, "Toward a reinforcement learning environment toolbox for intelligent electric motor control," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 3, pp. 919–928, 2022, https://doi.org/10.1109/TNNLS.2020.3029573.

[65] N. Farah, G. Lei, G. Bramerdorfer, and J. Zhu, "A review of machine-learning-based control methods for permanent magnet synchronous machines," *IET Electric Power Applications*, vol. 19, no. 1, p. e70126, 2025, https://doi.org/10.1049/elp2.70126.

[66] F. F. M. El-Sousy, M. M. Amin, and A. Al-Durra, "Adaptive optimal tracking control via actor-critic-identifier based adaptive dynamic programming for permanent-magnet synchronous motor drive system," *IEEE Transactions on Industry Applications*, vol. 57, no. 6, pp. 6577–6591, Nov. 2021, https://doi.org/10.1109/TIA.2021.3110936.

[67] Z.-X. Fan, L. Tang, S. Li, and R. Liu, "Modified deep deterministic policy gradient based optimal speed tracking strategy for PMSMs," in *Proceedings of the IEEE Data Driven Control and Learning Systems Conference (DDCLS)*, 2024, pp. 2206–2211, https://doi.org/10.1109/DDCLS61622.2024.10606656.

[68] Z. Song, J. Yang, X. Mei, T. Tao, and M. Xu, "Deep reinforcement learning for permanent magnet synchronous motor speed control systems," *Neural Computing and Applications*, vol. 33, no. 10, pp. 5409–5418, May 2021, https://doi.org/10.1007/s00521-020-05352-1.

[69] Y. Zhang, J. Li, H. Zhou, C.-B. Chng, C.-K. Chui, and S. Zhao, "Comprehensive evaluation of deep reinforcement learning for permanent magnet synchronous motor current tracking and speed control applications," *Engineering Applications of Artificial Intelligence*, vol. 149, p. 110551, Jun. 2025, https://doi.org/10.1016/j.engappai.2025.110551.

[70] B. Karg and S. Lucia, "Efficient representation and approximation of model predictive control laws via deep learning," *IEEE Transactions on Cybernetics*, vol. 50, no. 9, pp. 3866–3878, 2020, https://doi.org/10.1109/TCYB.2020.2999556.

[71] X. Wu, H. Yan, Y. Wang, and C. Lin, "Analysis of brushless DC motor control strategy based on Q-learning algorithm," in *Proceedings of the 2024 11th International Forum on Electrical Engineering and Automation (IFEEA)*, Nov. 2024, pp. 1182–1187, https://doi.org/10.1109/IFEEA64237.2024.10878709.

[72] B. T. Sayed, P. Rodrigues, A. Chammam, A. K. Kareem, T. Trivedi, and A. Singh, "A Bayesian machine learning-driven control algorithm for one-phase winding permanent-magnet brushless DC machines," *International Journal of Dynamics and Control*, vol. 13, no. 1, p. 12, 2024, https://doi.org/10.1007/s40435-024-01526-0.

[73] A. Sardashti and J. Nazari, "A learning-based approach to fault detection and fault-tolerant control of permanent magnet DC motors," *Journal of Engineering and Applied Science*, vol. 70, no. 1, p. 109, Sep. 2023, https://doi.org/10.1186/s44147-023-00279-5.

[74] P. Lu, W. Huang, and J. Xiao, "Speed tracking of brushless DC motor based on deep reinforcement learning and PID," in *Proceedings of the 2021 7th International Conference on Condition Monitoring of Machinery in Non-Stationary Operations (CMMNO)*, Jun. 2021, pp. 130–134, https://doi.org/10.1109/CMMNO53328.2021.9467649.

[75] S. M. Ghamari, M. Ghahramani, D. Habibi, and A. Aziz, "Design of a robust adaptive cascade fractional-order proportional-integral-derivative controller enhanced by reinforcement learning algorithm for speed regulation of brushless DC motor in electric vehicles," *Energies*, vol. 18, no. 19, pp. 1–27, 2025, https://doi.org/10.3390/en18195056.

[76] R. İnan, B. Aksoy, and O. K. M. Salman, "Estimation performance of the novel hybrid estimator based on machine learning and extended Kalman filter proposed for speed-sensorless direct torque control of brushless direct current motor," *Engineering Applications of Artificial Intelligence*, vol. 126, p. 107083, Nov. 2023, https://doi.org/10.1016/j.engappai.2023.107083.

[77] I. Tunc and M. T. Soylemez, "Fuzzy logic and deep Q learning based control for traffic lights," *Alexandria Engineering Journal*, vol. 67, pp. 343–359, Mar. 2023, https://doi.org/10.1016/j.aej.2022.12.028.

[78] S. Moazzami, A. Mirzaei, M. Aminian, R. Karimi, and N. Mikaeilvand, "A hybrid fuzzy logic and deep reinforcement learning algorithm for adaptive task scheduling and resource allocation in heterogeneous fog-cloud environments," *Sustainable Computing: Informatics and Systems*, vol. 49, p. 101260, Jan. 2026, https://doi.org/10.1016/j.suscom.2025.101260.

[79] A. Hasni, H. El Fadil, A. Lassioui, A. Intidam, M. El Ancary, Y. El Asri, and S. Nady, "Reinforcement learning-based control strategy for BLDC motors," *Journal Européen des Systèmes Automatisés*, vol. 58, no. 6, pp. 1111–1121, 2025, https://doi.org/10.18280/jesa.580603.

[80] D. Ramasamy and S. Maruthachalam, “Deep Deterministic Policy Gradient-Based Actor–Critic Reinforcement Learning for Torque Ripple Minimization in Switched Reluctance Motors,” *Machines*, vol. 14, no. 3, p. 333, 2026, https://doi.org/10.3390/machines14030333.

[81] Alharkan, H. “Machine Learning Structure for Controlling the Speed of Variable Reluctance Motor via Transitioning Policy Iteration Algorithm,” *World Electric Vehicle Journal*, vol. 15, no. 9, p. 421, 2024, https://doi.org/10.3390/wevj15090421.

[82] E. Fantin Irudaya Raj and M. Balaji, "Analysis and classification of faults in switched reluctance motors using deep learning neural networks," *Arabian Journal for Science and Engineering*, vol. 46, no. 2, pp. 1313–1332, Feb. 2021, https://doi.org/10.1007/s13369-020-05051-y.

[83] G. X. Prestes, W. K. Moreira, F. P. Scalcon, C. Rech, A. M. Knight, and R. P. Vieira, "Reinforcement learning-based current controller for switched reluctance motor drives," in *Proceedings of the 2025 IEEE International Electric Machines and Drives Conference (IEMDC)*, May 2025, pp. 71–76, https://doi.org/10.1109/IEMDC60492.2025.11061049.

[84] M. Omar, E. Sayed, M. Abdalmagid, B. Bilgin, M. H. Bakr, and A. Emadi, "Review of machine learning applications to the modeling and design optimization of switched reluctance motors," *IEEE Access*, vol. 10, pp. 130444–130468, 2022, https://doi.org/10.1109/ACCESS.2022.3229043.

[85] H. M. Ahmed, I. Jlassi, A. J. Marques Cardoso, and A. Bentaallah, "Model-free predictive current control of synchronous reluctance motors based on a recurrent neural network," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 11, pp. 10984–10992, Nov. 2022, https://doi.org/10.1109/TIE.2021.3120480.

[86] E. Kiliç, "Deep reinforcement learning-based controller for field-oriented control of SynRM," *IEEE Access*, vol. 13, pp. 2855–2861, 2025, https://doi.org/10.1109/ACCESS.2024.3524156.

[87] S. Mishra and B. Singh, "An adaptive forward compensation for enhanced PLL based position estimation of Syn-RL motor drive," in *Proceedings of the IEEE Region 10 Symposium (TENSYMP)*, 2024, pp. 1-6, https://doi.org/10.1109/TENSYMP61132.2024.10752228.

[88] A. Khan, C. Midha, and D. Lowther, "Reinforcement learning for topology optimization of a synchronous reluctance motor," *IEEE Transactions on Magnetics*, vol. 58, no. 9, pp. 1–4, Sep. 2022, https://doi.org/10.1109/TMAG.2022.3184246.

[89] O. Zeb, A. Rehman, I. Ahmad, H. Iqbal Sherazi, and S. Osman Madbouly, "Deep reinforcement learning-driven robust adaptive control for hybrid energy storage in SynRM-based light electric vehicle drives," *IEEE Access*, vol. 14, pp. 1439–1467, 2026, https://doi.org/10.1109/ACCESS.2025.3648165.

[90] R. Jafari, P. Sarhadi, A. Paykani, S. S. Refaat, and P. Asef, "Integrated energy optimization and stability control using deep reinforcement learning for an all-wheel-drive electric vehicle," *IEEE Open Journal of Vehicular Technology*, vol. 6, pp. 2583–2606, 2025, https://doi.org/10.1109/OJVT.2025.3606120.