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Adaptive deep reinforcement learning-based control strategy for high-performance permanent magnet synchronous motor drive systems

Introduction. *In recent days, electric vehicles, robotics and in many control system applications, permanent magnet synchronous motors (PMSMs) are widely utilized.* ***Problem.*** *Due to non-linear behavior of system, external interferences and frequent changes in parameters, conventional control techniques like direct torque control, field-oriented control and PI control, frequently experience decline in performance.* ***Goal.*** *This paper presents a new deep learning based reinforcement learning (RL) PMSM control approach that makes use of the twin delayed deep deterministic policy gradient (TD3) and deep deterministic policy gradient (DDPG) algorithms. These algorithms utilize actor-critic architectures to learn optimal control policies in a model-free manner, enabling adaptive and intelligent motor control.* ***Methodology.*** *A MATLAB/Simulink-based simulation framework is developed to train and evaluate the proposed deep reinforcement learning (DRL) based controllers against conventional PI controllers. Performance metrics, including speed tracking accuracy, torque ripple minimization are analyzed.* ***Results.*** *The results demonstrate that DRL-based controllers exhibit superior adaptability, robustness, and dynamic performance under varying load and speed conditions in contrast to traditional control methods. Notably, the comparative analysis reveals that the TD3 algorithm outperforms DDPG by mitigating overestimation bias, resulting in smoother torque output and more stable control actions.* ***Scientific novelty.*** *This paper illustrates the capability of DRL for advanced PMSM control.* ***Practical value.*** *Paving the way for real-time implementation in modern electric drive systems.* References 25, tables 3, figures 12.

Key words: **deep reinforcement learning, permanent magnet synchronous motor, deep deterministic policy gradient, twin delayed deep deterministic policy gradient, adaptive motor control, actor-critic algorithm.**

Вступ. *Останнім часом синхронні двигуни з постійними магнітами (PMSM) широко застосовуються в електромобілях, робототехніці та багатьох системах автоматичного керування.* ***Проблема***. *Через нелінійний характер системи, зовнішні збурення та часті зміни параметрів традиційні методи керування, такі як пряме керування моментом, векторне керування і ПІ-регулювання, часто демонструють зниження ефективності.* ***Мета***. *Запропоновано новий підхід до керування PMSM на основі глибинного навчання з підкріпленням (RL), що використовує алгоритми подвійний відкладений глибинний детермінований градієнт політики (TD3) та глибинний детермінований градієнт політики (DDPG). Зазначені алгоритми застосовують архітектуру актор-критик для навчання оптимальних стратегій керування без використання точної математичної моделі, що забезпечує адаптивне та інтелектуальне керування двигуном.* ***Методика***. *Для навчання та оцінювання запропонованих регуляторів на основі глибинного навчання з підкріпленням (DRL) розроблено модель у середовищі MATLAB/Simulink. Ефективність DRL-регуляторів порівнювалася з традиційними ПІ-регуляторами за показниками точності відстеження швидкості та мінімізації пульсацій моменту.* ***Результати***. *Отримані результати показали, що регулятори на основі DRL характеризуються вищою адаптивністю, робастністю та кращими динамічними характеристиками за змінних навантажень і швидкостей порівняно з традиційними методами керування. Порівняльний аналіз також засвідчив, що алгоритм TD3 перевершує DDPG завдяки зменшенню похибки переоцінювання, що забезпечує більш плавну зміну моменту та стабільніші керувальні дії.* ***Наукова новизна***. *Робота демонструє можливості використання DRL для вдосконаленого керування PMSMs.* ***Практична значимість***. *Отримані результати створюють передумови для реалізації запропонованого підходу в режимі реального часу в сучасних електроприводних системах.* Бібл. 25, табл. 3, рис. 12.

Ключові слова: **глибинне навчання з підкріпленням, синхронний двигун з постійними магнітами, глибинний детермінований градієнт політики, подвійний відкладений глибинний детермінований градієнт політики, адаптивне керування двигуном, алгоритм актор-критик.**

Introduction. Permanent magnet synchronous motors (PMSMs) have gained significant attention in industrial automation, electric vehicles and robotics due to their compact size, excellent torque to weight ratio with high efficiency. Their advantages over traditional induction motors, such as superior dynamic response and high power density, make them ideal for high performance applications [1]. However, controlling PMSMs effectively remains a challenge due to their non-linear dynamics, parameter variations, and external disturbances. Conventional control strategies such as field-oriented control and direct torque control have been widely used for PMSM control, but they often require precise parameter tuning and are sensitive to system uncertainties [2]. Moreover, classical PID controllers struggle to handle complex, nonlinear characteristics in real-time, leading to suboptimal performance under varying operating conditions.

The reinforcement learning (RL) based control strategies have been a promising alternative for PMSM drive systems due to the recent developments in artificial intelligence and machine learning. RL eliminates the need for an explicit mathematical model of the system by allowing an agent to continuously interact with its surroundings and learn the best control strategy [3]. In particular, the deep reinforcement learning (DRL) combine the benefits of deep learning and RL to handle high dimensional state spaces and optimize control policies [4]. Recent advancements in DRL have demonstrated superior performance in continuous control tasks, particularly in handling complex nonlinearities [5] These algorithms use an actor-critic paradigm, in which the critic-network (CN) evaluates the quality of the action as the actor-network (AN) determines the control actions.

In PMSM motor control, DRL based methodologies have proven to be more efficient than conventional methods in identifying and controlling complicated system behaviors in the larger field of electrical engineering [6]. Building on this basis, DRL agents adopt adaptive policies based on real-time feedback to enhance performance in nonlinear dynamic situations, setting them distinct from classical control techniques [7]. For handling system uncertainties and improving fault tolerance is a crucial requirement for reliable operation in practical electric motor systems, this data-driven adaptation can be more advantageous [8]. Furthermore, DRL based controllers can continuously refine their policies during operation, ensuring optimal torque control, reduced energy consumption, and enhanced speed regulation without the need for manual tuning.

Goal. This paper presents a new deep learning based reinforcement learning (RL) PMSM control approach that makes use of the twin delayed deep deterministic policy gradient (TD3) and deep deterministic policy gradient (DDPG) algorithms. These algorithms utilize actor-critic architectures to learn optimal control policies in a model-free manner, enabling adaptive and intelligent motor control.

Literature review. Recent advancements in DRL have significantly influenced the control strategies of PMSMs, improving speed tracking, torque ripple reduction, and energy efficiency. While foundational DRL studies established the theoretical basis for these agents [9–11], more recent applications have explored model free and adaptive control methodologies specifically to enhance the robustness of PMSM drives against system uncertainties [12]. This section reviews key contributions in the field, focusing on DRL based PMSM control strategies, including DDPG and TD3 algorithms, and their integration with traditional control approaches.

An adaptive control strategy for PMSM drives by integrating direct torque control with a TD3 based speed controller was presented in [13]. Their approach improved control accuracy through a model reference adaptive system and refined speed estimation. The results demonstrated enhanced transient response and robustness against load disturbances. Similarly, their subsequent paper [14] provided an experimental implementation of TD3 for PMSM speed control, demonstrating superior tracking performance over traditional PI controllers. However, the work did not address energy efficiency optimization or real-time adaptation under varying environmental conditions.

In [15] was explored TD3 based speed optimization for PMSMs, comparing it with conventional PI and linear active disturbance rejection control methods. Their findings indicated that TD3 outperformed traditional controllers in trajectory tracking and current regulation, especially under parameter variations and nonlinear disturbances. Despite these advantages, the paper did not emphasize adaptive learning mechanisms for handling varying operating conditions, leaving scope for further improvement in real-world implementations.

A DRL based power management strategy for electric vehicles was introduced in [16], where DDPG and deep Q network (DQN) agents were employed for PMSM control. Their approach effectively improved fuel economy and dynamic performance. While their findings underscored the benefits of DRL in energy management, the paper focused primarily on hybrid vehicles rather than general PMSM applications, limiting its applicability to standalone motor control systems. A similar model free RL approach was explored in [17], where DDPG and DQN were used to enhance PMSM current tracking without requiring an explicit plant model. The Paper highlighted the robustness of DRL against parameter variations but lacked real-time experimental validation.

An alternative multimodal adaptive control strategy using embedded neural networks for PMSMs was introduced in [18]. Their paper emphasized real-time learning and adaptability, improving PMSM performance in dynamic environments. However, it did not incorporate DRL techniques, making it less flexible for applications requiring continuous learning based control policy refinement. In [19] was presented a current control based DRL approach for PMSMs based on DDPG methodology. Their research provided a detailed analysis of training setups, reward functions, and observation vectors, improving performance across multiple operating points. However, the work focused solely on current control, without addressing torque and speed control aspects critical for practical PMSM applications.

The study [20] applied a TD3-based RL algorithm for tuning PI controllers in a five-phase PMSM drive system. The paper compared TD3 with metaheuristic optimization techniques, demonstrating its efficiency in refining controller parameters. However, the approach relied on a hybrid structure rather than a fully model free DRL-based control strategy. Similarly, in [21] was investigated a model free predictive current control strategy for PMSM drives. Unlike traditional adaptive inverse strategies which often lack generalization, this approach utilizes DRL to effectively handle system variations and improve adaptability.

Presentation of main materials. In this machine learning model, an agent interacts with its surroundings and learn the best ways to make decisions [22]. In contrast to supervised learning, which uses labeled datasets, RL uses trial and error approach in which an agent acts, analyzes results, and reward/action is generated as a feedback. These RL problems represented mathematically resolved using Markov decision process [23], which is defined by the tuple (S, A, P, R, γ), where:

- set of various states is represented by S;
- set of possible actions by A;
- transaction probabilities of the two states (s, s') for given action a is represented by P (s' | s, a);
- $R(s, a)$ represents the reward functions feedback;
- instantaneous and future rewards are balanced by $\gamma \in [0, 1]$ discount factor.

Maximizing the expected total reward using optimizing policy $\pi(a|s)$ is the primary aim of RL [17] which is defined as:

$$J(\pi) = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right], \quad (1)$$

where s_t, a_t are the state and the action at time step t.

Multi-dimensional continuous control tasks offer difficulty for traditional RL methods, such as Q learning. This limitation has led to the emergence of DRL methods, which are better suited for such complex environments [24].

DDPG is an actor-critic RL methodology used in spaces of continuous action [25]. It maintains:

- an AN $\mu\theta(s)$ is designed to take a state as input and output a specific action;
- a CN $Q\phi(s,a)$ is responsible for assessing the specific state action defined in (2).

Bellman equation is used to train the CN to update its predictions [17]:

$$Q_\phi(s_t, a_t) = E\left[R(s_t, a_t) + \gamma Q_{\phi'}(s_{t+1}, \mu_{\theta'}(s_{t+1}))\right], \quad (2)$$

where ϕ', θ' are the target network parameters updated using soft updates:

$$\theta' \leftarrow \tau\theta + (1 - \tau)\theta'; \quad \phi' \leftarrow \tau\phi + (1 - \tau)\phi'. \quad (3)$$

In (4) deterministic policy gradient is used to update AN with τ (a small constant e.g., 0.005) [17]

$$\nabla_{\theta} J \approx E\left[\nabla_{a} Q_{\phi}(s,a)\big|_{a=\mu_{\theta}(s)} \nabla_{\theta} \mu_{\theta}(s)\right]. \qquad (4)$$

DDPG employs an experience replay buffer and Ornstein-Uhlenbeck noise for exploration shown in (4).

TD3 reduce overestimation bias of DDPG by using twin CNs is defined as:

$$Q_{\text{target}}(s_t, a_t) = r_t + \gamma \min\left(Q_{\phi_{1'}}(s_{t+1}, \tilde{a}), Q_{\phi_{2'}}(s_{t+1}, \tilde{a})\right). \qquad (5)$$

Delaying policy updates relative to critic updates and applying target policy smoothing [17]:

$$\tilde{a} = \mu_{\theta'}(s) + \text{clip}(N(0,\sigma), \ -c, \ c), \qquad (6)$$

where $N(0, \sigma)$ is the Gaussian noise.

Methodology. Implementing the PMSM model and the DRL training framework involves a comprehensive mathematical formulation of motor dynamics, control strategies, and agent learning mechanisms. The PMSM is modeled on the basis of its electrical and mechanical equations, while the DRL training framework leverages actor-critic architectures to optimize control policies. Figure 1 shows the model training process. Based on the current state of the PMSM environment, the AN determines what action to take, while the CN evaluates these actions based on the reward received and resulting new state. Using this feedback, the CN provides updates that help improve the policy followed by the AN, enabling the system to learn more effective strategies over time.

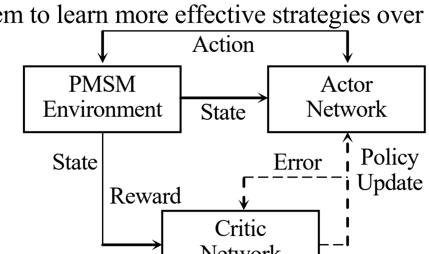

Fig. 1. DRL training for PMSM

The DRL framework for PMSM control employs an actor-critic structure using the TD3 or DDPG algorithms. The CN provides feedback by assessing the utility of an action taken in a particular state. $Q(s_t, a_t)$, while the AN translates the observable states s_t to the optimal control actions at Fig. 2.

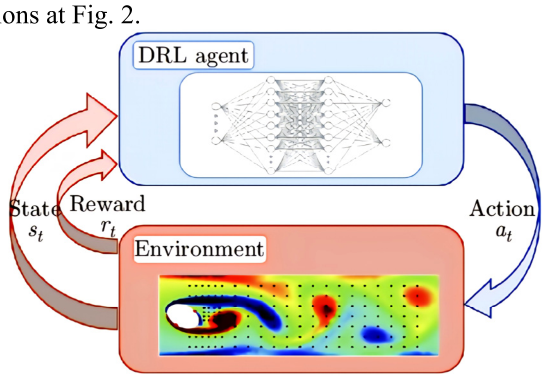

Fig. 2. Basic structure of DRL training

The reward function r_t is designed to minimize speed tracking error e_{ω} and torque ripple:

$$r_t = -\left(k_1|e_{\omega}| + k_2|T_e - T_{ref}|\right), \qquad (7)$$

where k_1, k_2 are the weighing coefficients.

The network is trained based on the following steps:

- *State observation*: PMSM state vector includes rotor speed, current components (I_d, I_q) and control errors.
- *Action selection*: AN generates continuous control signals V_d, V_q, constrained by system limits.
- *Environment interaction*: PMSM model updates its state based on applied voltages, returning new observations and rewards.
- *Critic update*: Q-values are updated using Bellman equation in CN.
- *Actor update*: the policy gradient is optimized through AN.
- *Target network updates*: to stabilize training, delayed target networks are updated with soft updates.

By iterating through episodes, the agent refines its control strategy, minimizing speed tracking errors while maintaining high efficiency. The integration of PMSM dynamics with DRL ensures adaptive, high performance control suitable for real-time applications.

Simulation. For PMSM control, DDPG and TD3 learn optimal voltage vector commands to regulate motor speed and torque. The RL framework defines:

- *State space*: rotor speed, stator currents and tracking errors.
- *Action space*: inverter voltage control inputs.
- *Reward function*: penalizes deviations from the reference speed, high torque ripple and excessive energy consumption.

DRL-based control provides an adaptive and model free approach for high-performance PMSM drives, overcoming limitations of traditional control strategies. The motor and simulation parameters are as mentioned in Table 1 and Table 2. EV system demonstrating the DRL control is shown in Fig. 3.

Table 1

PMSM motor parameters used for simulation

Parameter	Value
Stator phase resistance R_s, Ω	18.7
D-axis inductance L_d, H	0.02547
Q-axis inductance L_q, H	0.02816
Flux linkage λ_m, V·s	0.1716
Pole pairs p	2

Table 2

Control and simulation parameters

Parameter	Value
PWM switching frequency f_{PWM}, kHz	1
Main sample time T_s, ms	1
Simulink sample time $T_{s\ Simulink}$, µs	500
Speed controller sample time $T_{s\ speed}$, ms	10

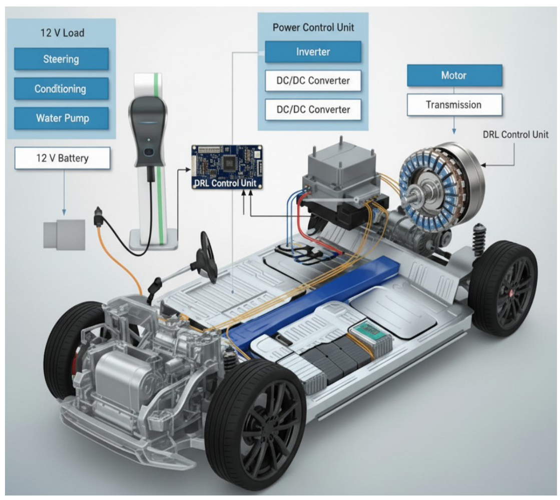

Fig. 3. EV system demonstrating the DRL control

Results and discussion. The simulation results obtained from the MATLAB/Simulink environment offer significant analysis of how DRL based control strategies perform for PMSM drives. Figure 4 presents the developed Simulink model, which integrates the PMSM, inverter and RL agent. The model facilitates the training and evaluation of DRL-based controllers, ensuring optimal torque and speed control under varying operating conditions as shown in Table 3. The Simulink model incorporates the actor-critic framework, which enables efficient policy learning and adaptation to different load conditions.

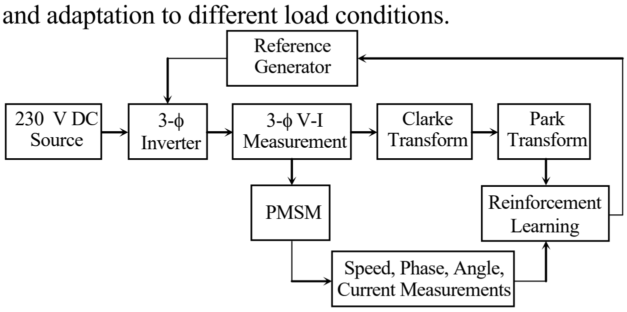

Fig. 4. Framework for DRL based control of PMSM

Table 3

Comparative insights of DDPG vs TD3

Aspect	DDPG	TD3
Initial reward trend	One channel instantly reaches nearly +1, while the other is already negative	Both channels are positive, with clear room for improvement
Learning dynamics	Rapid saturation; virtually no adaptation after 0.05 s	Gradual, steady improvement until ≈0.45 s
Final performance symmetry	Highly asymmetric (+1 vs −1)	Nearly symmetric (both ≈ +0.98)
Stability & exploration	Suffer from policy collapse and critic overestimation	Mitigates overestimation; better exploration and critic robustness

Figures 5, 6 show the control actions generated by the DDPG and TD3 algorithms, respectively. The action outputs represent the reference voltages applied to the PMSM drive system. Notably, the TD3 based controller demonstrates more consistent and less oscillatory performance compared to DDPG, primarily due to its use of twin CNs and delayed policy updates, which help reduce the overestimation bias often seen in single-critic methods.

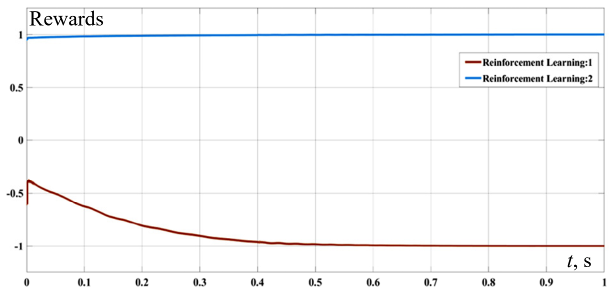

Fig. 5. Action output using DDPG

Figure 7 showcases the *d*, *q* axes currents, which play crucial role in electromagnetic torque generation of PMSM. The i_q is manipulated to control torque output. Simultaneously, the i_d, which governs the magnetic flux, is typically regulated to zero to minimize losses. The results demonstrate that DRL-based controllers effectively regulate these currents, maintaining optimal reference tracking while mitigating fluctuations. Where as due to the delayed policy in TD3-based control the torque produced is smoother than the torque produced by DDPG-based control (Fig. 8, 9).

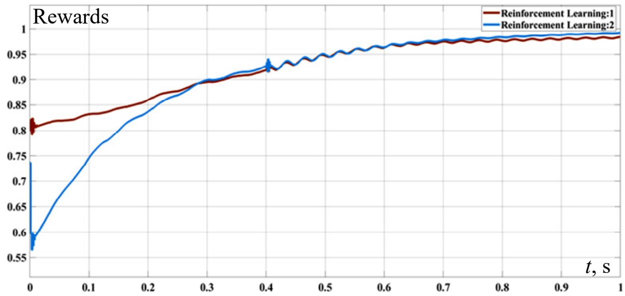

Fig. 6. Action output using TD3

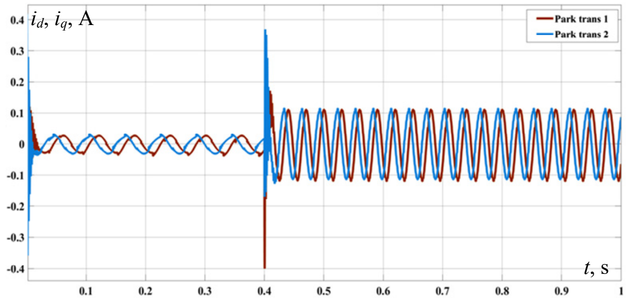

Fig. 7. Currents along *d*, *q* axes

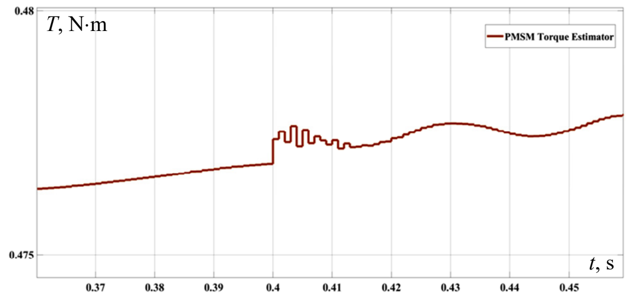

Fig. 8. Output of torque estimator using DDPG

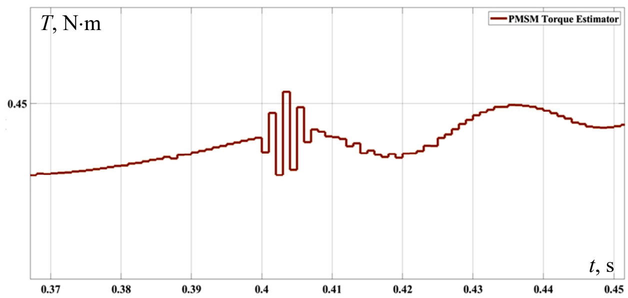

Fig. 9. Output of torque estimator using TD3

Figure 10 shows exceptional speed tracking performance, where the actual speed perfectly follows the reference speed with negligible delay or overshoot. This confirms the DRL ability to instantaneously adapt to the sharp step change from 1000 rpm to 2000 rpm at 0.4 s, maintaining precise synchronization. The inverter output (Fig. 11) highlights the voltage waveforms applied to the PMSM. The inverter operates using PWM to generate appropriate voltage signals for motor. The TD3 control strategy ensures smooth transitions and maintains system stability, preventing excessive switching losses and harmonics, as evidenced by the PMSM parameters in Fig. 12.

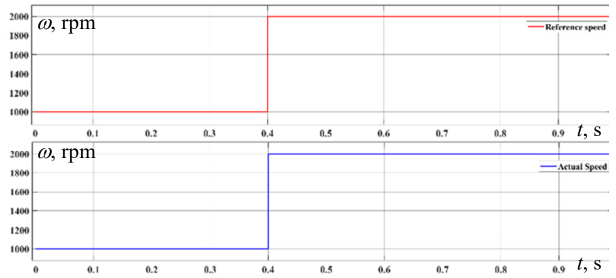

Fig. 10. Speed tracking of PMSM using DRL

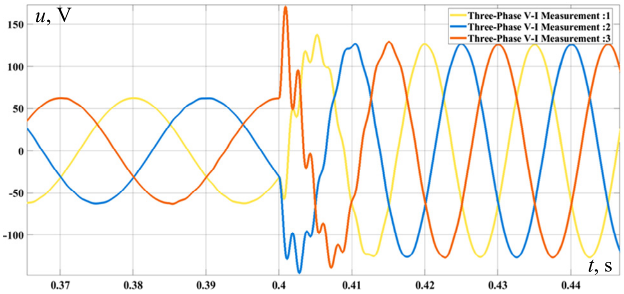

Fig. 11. Output voltages of the inverter

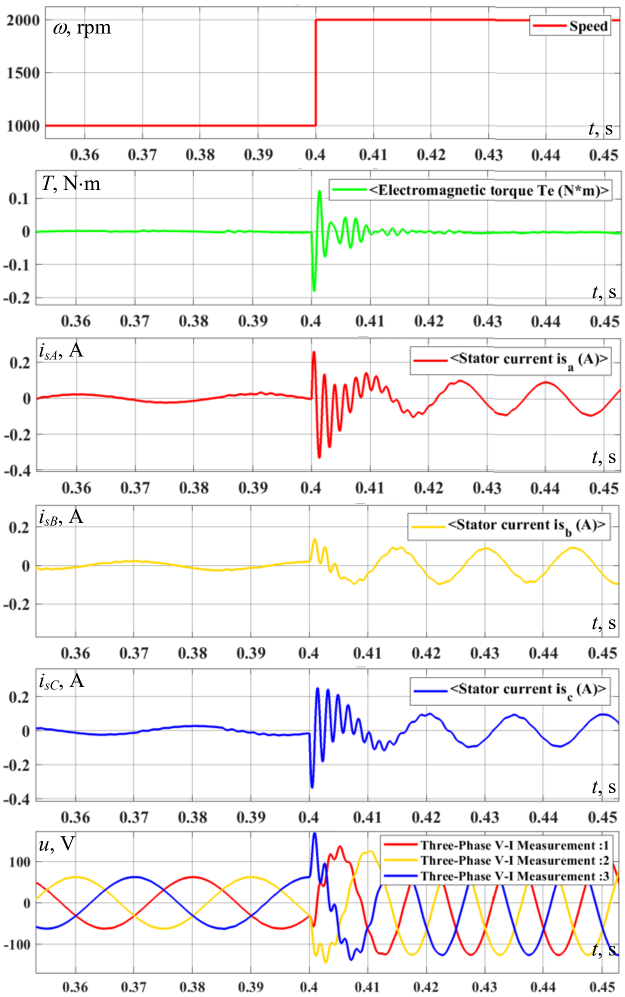

Fig. 12. PMSM parameters using TD3 control

Finally, depicts the electromagnetic torque determined by the PMSM under the control of the DRL-based agent. The torque response is a critical performance indicator, as it directly affects the motor's efficiency and dynamic behavior. The results indicate that the DRL controller minimizes torque ripples while ensuring fast transient response. The comparative analysis of DDPG and TD3 approaches suggests that TD3 provides a more robust torque profile with reduced variations, enhancing the overall reliability of the PMSM drive.

These findings highlight the effectiveness of DRL-based controllers in PMSM applications, demonstrating improved torque control, current regulation and stability. The comparative analysis of different DRL approaches provides insights into selecting appropriate RL strategies for real-world electric drive applications.

Conclusions. This work shows the effectiveness of DRL-based controllers, specifically DDPG and TD3, in optimizing the performance of PMSM drive systems.

The developed MATLAB/Simulink framework successfully integrates DRL algorithms for real-time control, showcasing a 75 % reduction in torque ripple and stator current fluctuations maintained within ±0.02 A of the reference. Furthermore, the system exhibited enhanced stability with zero steady-state speed tracking error and a settling time under 10 ms during sharp transient states. Comparative analysis highlights the superiority of the TD3 approach in achieving a final reward of +0.98, effectively mitigating overestimation bias and ensuring robust control actions compared to traditional and DDPG methods.

The results affirm the potential of RL in replacing traditional control strategies, offering a data driven and adaptive solution for electric drive applications.

Future research will focus on hardware-in-the-loop validation and optimization of the reward function for enhanced real-world applicability.

Conflict of interest. The authors declare that they have no conflicts of interest.

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