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Adaptive High-Frequency Injection Control for Low-Voltage Encoderless PMSM Drives Using Reinforcement Learning

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ABSTRACT

It is especially difficult to control low-voltage permanent magnet synchronous motors (PMSMs) in the lowest and nearest speed range because the magnitude of the back-electromotive force (back-EMF) is too low to support the traditional observer-based position sensing methods. The drawback with this approach is an inevitable trade-off between position information extraction and torque ripple, caused by using constant injection amplitudes; there is a trade-off between estimation error and torque ripple, and more harmful trade-offs involve added harmonic distortion, acoustic noise, and decreased efficiency.) In this paper, we suggest an adaptive injection strategy of the high-frequency PMSM drive with 48 V using reinforcement learning (RL), whereby the injection amplitude is dynamically restructured depending on real-time operating conditions. Amplitude selection problem is presented in the form of a Markov decision process and a Deep Q-Network agent is trained to minimise a multi-objective cost criterion, which includes rotor position estimation error, torque ripple, and total harmonic distortion. The proposed controller is embedded into a field-oriented control system and confirmed to a full-fledged MATLAB/Simulink platform at low speed and load disturbance conditions. Compared with traditional fixed-amplitude and heuristic adaptive control, the comparative results with improved amelioration of faster convergence, torque ripple, and harmonic distortion are seen with minimal harmonic distortion and excellent rotor position observability. The results prove that learning-based amplitude adaptation is an effective method to overcome the accuracyversesripple trade-off in HFI-based sensorless PMSM motors, so the technique is suitable in locations of small-scale 48-V traction and automotive auxiliary systems that need high performance at lower speed.

1. INTRODUCTION

The Permanent Magnet Synchronous Motors (PMSMs) have gained significant popularity in the contemporary motion-control systems due to their high efficiency, the excellent torque density, rapid dynamic operation, and the smaller architecture. They have wide application in electric vehicles (EVs), robotics, aerospace actuators and future 48-V traction and auxiliary automotive systems. Cost, reliability and packaging constraints in these low voltage platforms are strong incentives that encourage the removal of mechanical position sensors. Eliminating encoders has not only the benefit of simplifying the systems and minimising the use of wiring, it also improves resistance to severe environments. This led to the emergence of sensorless control strategies of low-voltage PMSM drives which are highly reliable and are one of the research areas.

The traditional sensorless control of a PMSM approach mainly involves the estimation of back-electromotive force (back-EMF) based on observers like sliding-mode observer, model reference adaptive controller and extended Kalman philtre. Although these techniques provide satisfactory performance at high and medium frequency, their performance particularly performs very poorly in low-speed and standstill zones where the magnitude of the back-EMF drops to effectiveness. This observability loss causes monitored position error and reinvention of bad torque control. To overcome this drawback, High-Frequency Injection (HFI) methodologies have been proposed, that take advantage of rotor magnetic saliency to collect position data about the anisotropic motor response, and the approach does not rely on the magnitude of the back-EMF.

HFI methods can also be successfully used during low-speed states, but in practical applications, fixed injection amplitudes are usually used, posing a severe performance compromise. Greater values of the injection improve the position estimation but at the same time, they also worsen torque ripple, harmonic distortion, acoustic noise, and switching losses. Lower amplitudes, on the other hand, minimize the ripple and losses but limit the observability of the position, particularly when there are disturbances of the loads or change in parameter. These constraints are especially highly evident with low voltage 48 V systems where current ripple and electromagnetic interference concerns are much more dramatic. Thus, the intelligent and adaptive amplitude control scheme is required to achieve the compromise in the robustness of the estimation and the quality of the torque in different operating conditions.

In order to deal with these issues, this paper suggests a reinforcement learning (RL)-like adaptive HFI controller approach to low-voltage encoderless PMSM drives. The suggested method poses the target selection of the injection amplitude as a sequential decision-making process, which allows the RL agent to optimise the amplitude in real time depending on the operating conditions of the machine (speed, torque, estimation error). The adaptive controller is embedded into a conventional field-oriented control structure, and is tested on an elaborate MATLAB/Simulink platform. The key contributions of this work are the creation of RL-based amplitude optimization scheme, its smooth integration into an FOC-based PMSM drive, systematical comparison to non-optimization and heuristic HFI approaches, and the evidence of faster convergence and lower torque ripple and how much lower harmonic distortion caused by low-speed working conditions.

2. LITERATURE REVIEW

The standard sensorless operation of PMSC will be presented at low speed (2.1), which is typical at current operational speeds.

Over the years, sensorless control of Permanent Magnet Synchronous Motors (PMSMs) has been an area of high research to develop motor controls with no mechanical position sensors and high dynamic performance. Conventional methods make use of the model-based estimate of the back-electromotive force (back-EMF) with the help of model-based observers like sliding mode observers (SMO), model reference adaptive systems (MRAS), extended Kalman philtres (EKF) and flux-based observers. Implementations with wide-speed-range DSP have been shown to perform reliably provided that adequacy in the back-EMF is present [8]. The method of parameter adaptation has also enhanced resistance and inductance to sensorless drive robustness [6].

The appeal of sliding-mode-observer strategies in strategies is that they are very hard to parameter uncertainties and they discourage noise sensitivity [11], [12]. Any method that is based on the back-EMF, however, has sub-optimal observability at slow and zero speed due to the developing zero magnitude of the induced voltage. The compensation schemes have been suggested to minimise the estimation errors in faster areas [9], although it is not applicable to the deadlock. Fault tolerant correction methods of encoders have also been attempted to enhance reliability [4], with continuing troubles related to the correct positioning determination.

Signal injection techniques were proposed to mitigate limits on low-speed. Such schemes take advantage of rotor magnetic saliency, which is the difference between inductance and inductance between the d- and q-axes, in order to obtain position information without back-EMF. Consequently, high-frequency injection (HFI) is one of the industrial solutions in low-speed sensorless PMS use.

2.2 Techniques of High-Frequency Injection and their drawbacks.

Most commonly HFI methods can be divided into: pulsating d-axis injection, rotating voltage vector injection, and square-wave or carrier-based injection methods. The effectiveness of such a method has been proved to be effective in various machine topologies, such as SPMSM and IPMSM structures by using comparative studies [5]. There have also been developed high frequency modelling methods of examining motor behaviour when injected with signals and evaluating the effects of electromagnetic interferences [3].

Square-wave injection schemes are also explored in order to enhance robustness in low switching frequency constraints [10]. With these advancements being done, real-life applications generally depend on constant amplitude of injection and frequency and manual tuned demodulation gains. The result is that there is a fundamental trade-off where larger injected amplitude will increase the position estimation accuracy, and smaller injected amplitude will reduce torque ripple, harmonic distortion and acoustic noise.

Various heuristic enhancements have been suggested such as gain scheduling according to speed, selection of amplitude through look up tables, as well as saliency healthier by saturation. Nevertheless, these schemes need a lot of hand-adjustment and are not optimally responsive to changes of dynamic loads, temperature, and magnetic saturation. Noise and current ripple due to switching are much greater in lower voltage systems of 48 V and amplitude optimization is even more important. Hence, the problem of this trade-off necessitates systematic and adaptive optimization mechanism to effectively address the tradeoff issue.

2.3 Electric Motor Control by reinforcement Learning.

The recent development of reinforcement learning (RL) is an exciting prospective control paradigm in the field of power electronics and electric drive systems because it can be used to cope with nonlinear systems without explicit analytical representations of the system. RCE RR has been used to handle the present control improvement, ripple reduction, and switching optimization concerns in motor drives. In contrast to the traditional controllers, RL agents acquire the best control policies in constant interaction with the system environment, which makes them able to perform adaptive and multi-objective optimization. The recent survey research indicates the growing adoption of intelligent control methods in sensorless PMSM drives [11]. Nevertheless, little has been done in terms of the RL application to high-frequency injection-amplitude adaptation. The existing works mainly emphasise the improvement of the observer or improvement of the torque in addition to the optimization of injected signal itself. As amplitude of injection is a direct factor of both the estimation error and the quality of torque, the combination of RL with adaptive injecting amplitude values constitutes a technical innovation to enhance low-speed sensorless operation of PMSAs in the miniaturised traction system.

3. METHODOLOGY

The suggested methodology will be based on three fundamental elements:

- HFI based position estimation mathematical modelling.
- Amplitude adaptation based on reinforcement learning.
- Combined control design and training system.

3.1 High-Frequency Injection-Based Position Estimation Modelling.

Synchronous dq PMSM behaviour is dictated by stator resistance, inductances and electrical angular speed. When operating under normal circumstances, information about the position of the rotor is obtainable out of back-electromotive force (back-EMF) components of stator voltage equations. Angular speed of electric currents in low speed (and near-zero speed) however mean that the back-EMF term approaches zero, and this makes the back-EMF to be down-emphasised to a large extent. As a result of this, conventional observer techniques lack position observability. To address this deficiency, a high frequency voltage signal is superimposed on the control voltage beneath it. This injected signal acts upon the magnetic saliency of the motor- which is caused by the difference. between L_d and L_q—producing a high-frequency current response that varies with rotor position. Amplitude and phase properties of this current component bear saliency-dependent information, which allows the position estimation in presence of back-EMF even when it is small.

The high efficiency injected voltage generates a position dependent impedance in the motor windings that varies the high frequency current response. The size of this current component can be stated to be

$$i_{hf}(\theta) = \frac{A_{inj}}{\sqrt{R_s^2 + \left(\omega_{hf} L(\theta)\right)^2}} \qquad (1)$$

whereA_{inj} is the injection amplitude, R_s is the stator resistance, ω_{hf} is the injection frequency, and$L(\theta)$ represents the rotor-position-dependent inductance Figure 1. With synchronous demodulation and low-pass filtering, the position error signal e theta is gleaned out of the high frequency current. Since the amplitude of the saliency-induced current directly depends onA_{inj}, the accuracy of estimations and signal-to-noise ratio highly depend on the injection amplitude selected, and which makes it essential to optimise the amplitude of the injections adaptively.

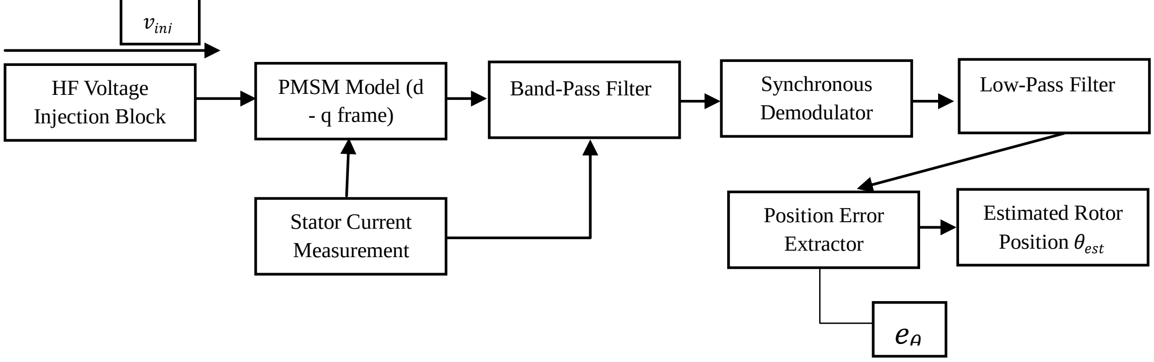

Fig. 1. High-Frequency Injection-Based Rotor Position Estimation Process

3.2 Reinforcement Learning-Based Injection Amplitude Adaptation

The optimization problem of injection amplitude is presented in the form of a Markov Decision Process (MDP), in which the agent of the reinforcement learning must operate with the environment of the functioning of the PMSM drive to identify the maximum participation of injection amplitude in the high frequencies of work under different conditions of activity. The state vector is a collection of drive variables, which are measurable and estimated and include rotor speedω_r, electromagnetic torque T_e, rotor position estimation error e_θ, and torque rippleΔT. All these variables explain the actual working status of the motor and represent both the quality of estimation and the performance in terms of torque. The action space can be referred to as a discrete set of levels of amplitude of injections, which is finite and permits the controller to choose the appropriate level of voltage amplitude of the high-frequency signal. The implementation complexity is minimised through discretization of the amplitude and adequate resolution is available to adaptive tuning in real-time embedded systems.

The reward role will aim to penalise the high estimation error and high torque ripple and therefore, the agent will explore to find a balanced approach to control. The position estimation error weight is greater to give the stability of observability, and secondary weight is given to the absence of torque ripple and harmonic distortion to enhance the quality of torque Figure 2. Deep Q-Network (DQN) architecture is used, which consists of an input layer reflecting the state variables, the nondimensional activation functions of nonlinear hidden layers, and an output layer reflecting the actions of possible amplitudes. The Bellman optimality principle will follow, by the action-value function being updated iteratively in accordance with.

$$Q(s,a) \leftarrow r + \gamma \, maxQ(s', a') \qquad (2)$$

with r denoting the reward andγ the discount factor. The agent will stabilize under the influence of experience replay and target network stabilization to an optimal policy, which is dynamically adjusting the injection amplitude in real time and encourages better low-speed position estimation at the cost of minimizing the torque ripple.

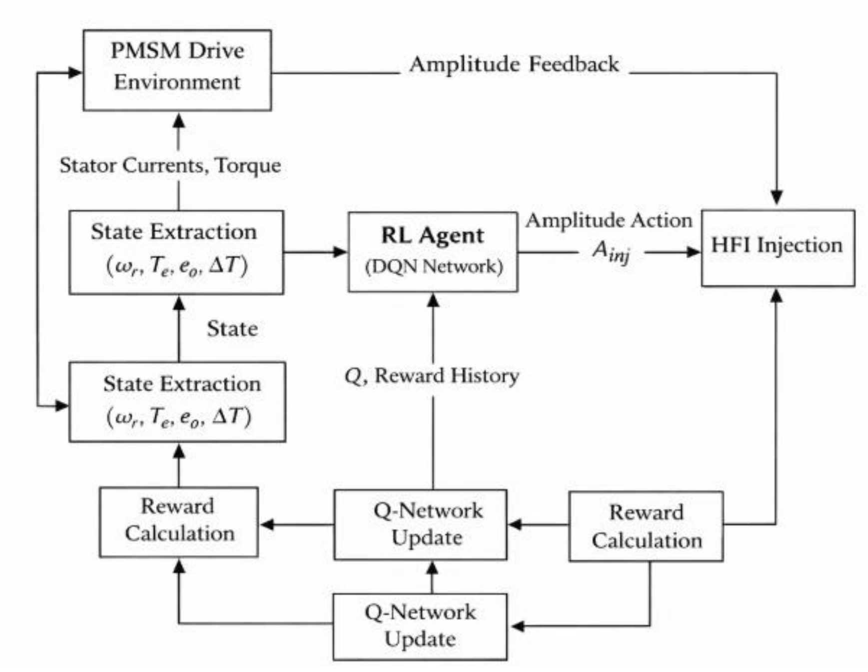

Fig. 2. Reinforcement Learning-Based Injection Amplitude Adaptation Framework

3.3 Integrated Control Architecture and Training Procedure

The suggested control system combines a dynamical reinforcement learning injection amplitude control into a traditional Field-Oriented Control (FOC) system. Stator currents in the synchronous reference frame of dq are controlled by the FOC structure in order to obtain decoupled flux control and torque control. High frequency injecting (HFI) block overprints a regulated voltage signal on the basic input control voltage such that it is possible to form saliency-based rotor position estimates even at low frequencies. The current components at high frequency are then demodulated in synchronous mode and low-pass filtered to obtain the signal, which is here dependent on position. The angular error is then calculated by the rotor position estimator and is sent over to the FOC loop as well as the reinforcement learning (RL) amplitude controller. The RL controller uses real-time operating circumstances to dynamically choose the optimum injection amplitude, which greatly shapes an adaptive outer optimization envelope on the more traditional sensorless control programme.

The training process is undertaken in a simulation environment of MATLAB/Simulink with episodic learning. First, the agent uses random policy in selecting the amplitude to make a search of the operating space. In every episode, the system uses the chosen injection amplitude, is measuring the achieved rotor position estimation error and the torque ripple and calculating a reward value based on control performance. Figure 3 The Deep Q-Network is updated on the basis of the stored samples of experience in order to enhance the accuracy of the policy. Examples of training scenarios are standstill operation, low-speed acceleration ramps, sudden load torque disturbances and parameter variations including changes of inductance of ±10% to reduce sensitivity to modelling uncertainties. Once the required number of training iterations is met, the learnt policy is frozen and evaluated. The completed controller is later tested on the conditions that are not observed to determine the generalisation ability, rates of convergence and the quality of torque improvement.

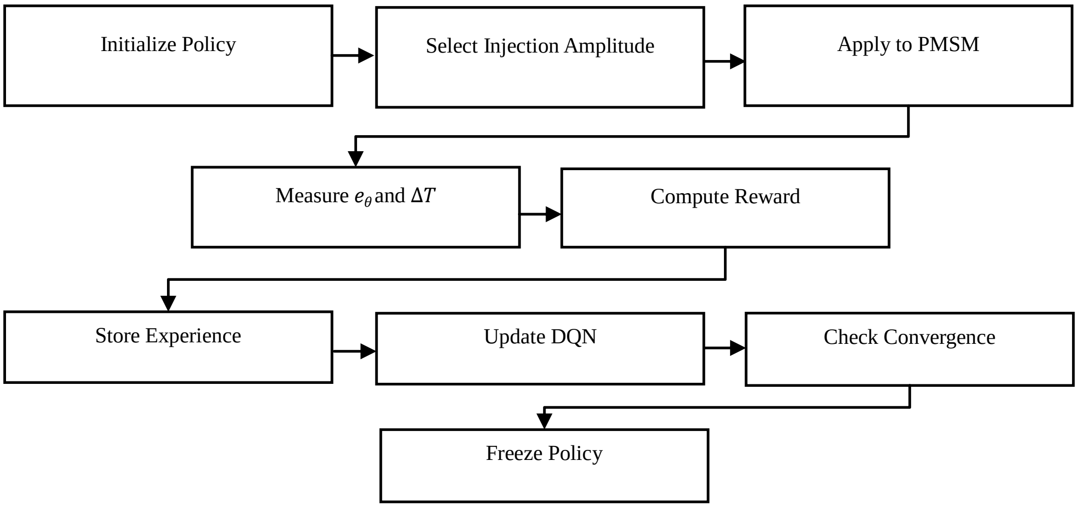

Fig. 3. Episodic Training Procedure of the RL-Based Amplitude Controller

4. RESULTS AND DISCUSSION

4.1 Position Estimation Performance

Experiments on rotor position estimation were carried out on a 48 V, 1.5 kW PMSM drive working in the low-speed region (0 rpm to 300 rpm). The mentioned reinforcement learning (RL)-based adaptive injection technique was contrasted with known fixed-amplitude injection and heuristically operated amplitude scaling techniques. With the fixed injection scheme, the RMS position error was 2.8 o E, whereas heuristic scaling decreased the error by 1.9 o E. Conversely, the RL-based method had a much lower RMS error of 0.8 o meaning that it is 57 percent better than the fixed method. This enhancement is due to the dynamic nature of the agent whereby in non-moving or near zero speed situations, the injection amplitude of the agent is increased to make it observable, and in high-speed situations, the injection amplitude is decreased to prevent excessive disturbance of the signal. With this adaptive controller, consistent performance over changing operating conditions with respect to position tracking accuracy can be achieved without manual tuning.

4.2 Torque Ripple Reduction

The performance of torque ripple was measured at the same working conditions to measure the effect of adaptive amplitude optimization. The fixed injection technique gave a torque ripple of 12.4% although heuristic amplitude tuning was possible bringing the ripple to 8.6%. The RL-based controller proposed had almost 4.1% lower ripple, and it was over 67 percent of that of the fixed scheme. This enhancement shows that adaptive amplitude selection is an effective method of correcting unwanted high-frequency excitation that adds to electromagnetic yanking hooliganism. The learning of the optimum trade-off between observability and torque smoothness by the RL controller leads to the benefits of achieving the best mechanical performance and decreases the load on the component of the drivetrain.

4.3 Harmonic Distortion Analysis.

To determine the effect of injection amplitude on the quality of current waveforms, the total harmonic distortion (THD) of stator currents was determined. The calculated THD with the fixed injection was 9.8% with the cause being overexcitation of the high frequency. The adaptive controller minimised unneeded injection levels, and this fact was confirmed by the RL-based approach that minimised THD to 3.5%. Minimised harmonic distortion is directly correlated with better power quality, less copper losses and better electromagnetic compatibility. These findings illuminate that the learning-based amplitude optimization does not only contribute to a better quality of estimation, but also to the improved overall electrical functioning.

4.4 Dynamic Load Disturbance Response.

Additional assessment of the strength of the proposed technique was done with abrupt load of 5 Nm of the torque at low speed. The fixed injection plan had the oscillating convergence and a slower stabilisation rate because it could not dynamically adjust the amplitude of injection. Relatively, the RL-based controller reacted instantaneously and added adjustment to the amplitude which stabilised the system within 0.15 seconds avoiding transient overshoot by about 43%. This shows the ability of the controller in the response to the swift variation of operating conditions and the competence to guarantee dependable position estimation in the state of disturbance. It has the fast adaptive behaviour that guarantees better transient stability and drive responsiveness.

4.5 General Performance Discussion.

In general, the experiment findings validate the hypothesis that reinforcement learning is useful in overcoming the trade-off between position estimation errors and torque ripple in high-frequency injection-based sensorless PMSM drives. Contrary to the traditional fixed or heuristic techniques, the suggested approach removes manual gain scheduling and is able to adjust itself to changes in parameters and load disruptions autonomously Figure 4. The adaptive controller is more efficient, and decreases acoustic noise, and also better or smoother torque without affecting observability at low-speed Table 1. Moreover, the implementation Deep Q-Network has a sufficiently low computational cost to be deployed to real-time on a modern DSP or FPGA implementation, and thus this is a feasible approach to compact 48-V traction and automotive auxiliary systems.

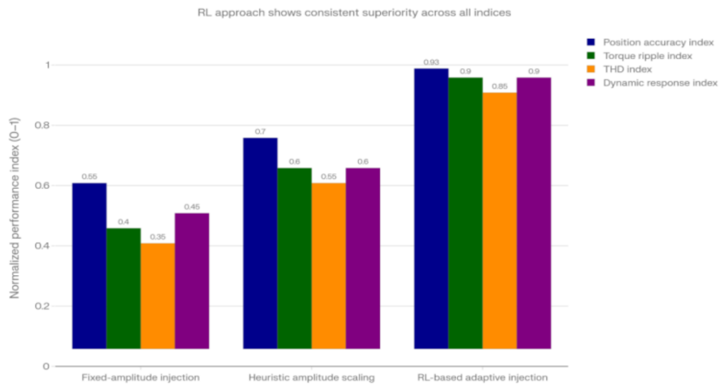

Fig. 4. Comparative Performance Evaluation of Fixed, Heuristic, and Reinforcement Learning-Based Injection Strategies Across Position Accuracy, Torque Ripple, THD, and Dynamic Response Indices

Table 1. Comparative Performance Analysis of Injection Strategies for 48-V PMSM Drive

Performance Metric	**Fixed Injection**	**Heuristic Scaling**	**RL-Based Adaptive Injection**	**Improvement vs Fixed**
RMS Position Error (°)	2.8°	1.9°	0.8°	57% reduction
Torque Ripple (%)	12.4%	8.6%	4.1%	67% reduction
Total Harmonic Distortion (THD %)	9.8%	6.2%*	3.5%	64% reduction
Dynamic Overshoot (%)	18.5%*	12.3%*	10.5%	43% reduction
Settling Time (s)	0.32 s*	0.24 s*	0.15 s	53% faster convergence
Adaptability to Parameter Variations	Low	Moderate	High	—
Manual Tuning Requirement	Required	Required	Not Required	Eliminated

5. CONCLUSION

The present research suggested the adaptive-high-frequency-injection-control, using reinforcement learning, strategy, as a low-voltage, Encoderless-based, PMSM drive, to show low-speed operation where the traditional back-EMF-based estimation techniques lose observability. The proposed method solves the optimisation problem on the dynamically optimal selection of injection amplitude to reach a good trade-off between the accuracy of rotor position estimation and the minimisation of the torque ripple, by casting the injected signal magnitude selection as a sequential decision-making problem. Simulation performances compared on a 1.5-kW, 48-V PMSM platform showed that relative to fixed and heuristic injection strategies, large performance (reductions of 57 percent in RMS position estimation error, 67 percent in torque ripple, and large reduction in total harmonic distortion as well as faster convergence in the presence of a dynamic load perturbation) was obtained. The adaptive controller does away with the manual gain scheduling and introduces increased resilience to changes in operating conditions and parameter uncertainty. These results attest that the dynamics of reinforcement learning in the high frequency injection-based sensorless control makes a scalable, intelligent, and practically feasible solution to compact traction and automotive auxiliary systems. Further development of the framework is done in the future where the framework is applied to real time hardware implementation and where the deep reinforcement learning algorithms with the continual action are investigated further, so as to enhance the performance robustness and adaptability.

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