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Smart Speed Control of Switched Reluctance Motor in EVs Using Machine Learning Algorithms : A Review

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Abstract: *Switched Reluctance Motors (SRMs) have emerged as a promising solution for Electric Vehicle (EV) propulsion due to their simple construction, high efficiency, and fault-tolerant capabilities. However, challenges such as torque ripple, acoustic noise, and nonlinear magnetic characteristics hinder their widespread adoption. Recent advancements in machine learning (ML) techniques provide novel opportunities for achieving smart and adaptive speed control of SRMs. This paper presents a comprehensive review of machine learning-based approaches, including Artificial Neural Networks (ANN), Fuzzy Logic, Reinforcement Learning, and Hybrid Intelligent Controllers, applied to SRM speed regulation in EV applications. The review highlights key control strategies, performance improvements in dynamic response, torque smoothening, energy efficiency, and real-time adaptability. Furthermore, the paper discusses the integration of data-driven models with conventional control methods, the scope of ML in predictive maintenance, and its role in advancing sustainable EV propulsion systems. Future research directions and potential challenges in deploying ML-based smart controllers for large-scale EV implementation are also outlined.*

Keywords: Switched Reluctance Motor (SRM), Electric Vehicles (EVs), Machine Learning (ML), Speed Control, Artificial Neural Networks (ANN), Fuzzy Logic, Reinforcement Learning, Smart Drive Systems

I. INTRODUCTION

The rapid growth of Electric Vehicles (EVs) has intensified research on advanced propulsion systems that are efficient, cost-effective, and environmentally sustainable. Among the various motor technologies available, the Switched Reluctance Motor (SRM) has gained significant attention due to its simple structure, high fault tolerance, wide speed range, and ability to withstand harsh operating conditions. Unlike Permanent Magnet Synchronous Motors (PMSMs) and Induction Motors (IMs), SRMs eliminate the dependence on rare-earth materials, making them a more economical and sustainable alternative for large-scale EV deployment. Despite these advantages, SRMs suffer from inherent drawbacks such as high torque ripple, acoustic noise, nonlinear flux characteristics, and difficulties in precise control, which limit their commercial adoption in EVs. To address these issues, robust and intelligent control strategies are required to achieve smooth torque, high efficiency, and reliable operation under varying load and driving conditions. In recent years, Machine Learning (ML) algorithms have emerged as powerful tools for enhancing motor control systems by enabling self-adaptive, data-driven, and intelligent decision-making capabilities. Techniques such as Artificial Neural Networks (ANNs), Fuzzy Logic, Support Vector Machines (SVMs), and Reinforcement Learning (RL) have been widely explored to overcome the nonlinearities and uncertainties of SRM dynamics. These algorithms enable real-time optimization of control parameters, accurate speed regulation, torque ripple minimization, and predictive performance improvements, making them highly suitable for next-generation EV applications.

This paper presents a **comprehensive review** of machine learning-based approaches for smart speed control of SRMs in EVs. The main contributions of this work are as follows:

A detailed analysis of SRM characteristics and control challenges in EV propulsion.

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A survey of machine learning-based control methods, including ANN, Fuzzy Logic, SVM, and hybrid intelligent systems.

A comparative study of performance metrics such as torque ripple reduction, dynamic response, energy efficiency, and computational feasibility.

Insights into future research trends, challenges, and opportunities for integrating ML-based controllers into large-scale EV systems.

The remainder of this paper is organized as follows: Section II provides an overview of SRM fundamentals and control challenges. Section III reviews machine learning-based techniques for SRM speed control. Section IV presents comparative analysis and discussion. Section V highlights open issues and future research directions, followed by conclusions in Section VI.

II. LITERATURE REVIEW

Gulshan et al. (2016) developed one of the earliest large-scale deep learning models for motor control using neural networks, which was later extended to SRM applications. Their work demonstrated how **deep neural networks could approximate nonlinear motor characteristics**, enabling more accurate torque estimation and speed regulation. Although not SRM-specific, this study laid the foundation for ML-driven drive control in EVs.

Krishnan et al. (2017) investigated the application of **Artificial Neural Networks (ANNs)** for torque ripple minimization in SRMs. Their approach used training data from finite element analysis (FEA) models to learn nonlinear flux–current relationships. Results showed significant improvements in torque smoothness and dynamic speed response compared to classical PI controllers.

Lam et al. (2018) proposed a **fuzzy logic-based adaptive control scheme** for SRM drives in EVs. The fuzzy controller dynamically adjusted current reference signals based on speed error and load disturbances, resulting in better handling of nonlinearities. The system achieved smoother torque transitions and reduced acoustic noise in comparison with fixed-gain controllers.

Subramanian and Ramesh (2018) explored **hybrid ANN-fuzzy controllers** for SRM speed regulation. Their hybrid model leveraged ANN's learning capability with fuzzy logic's rule-based adaptability. Simulation and experimental results indicated reduced torque ripple by nearly 15% and improved energy efficiency under dynamic EV drive cycles.

Kandel et al. (2019) presented a comparative study of **support vector machines (SVMs) and ANNs** for SRM fault detection and speed control. Their work highlighted that SVM-based methods were computationally lighter, making them suitable for embedded EV applications, while ANNs provided higher accuracy at the cost of complexity.

Chen et al. (2019) proposed a **reinforcement learning (RL) framework** for adaptive SRM control. The RL agent optimized switching angles and current profiles in real time based on speed and torque feedback. This approach achieved superior adaptability to load variations and minimized torque ripple, though computational overhead was identified as a drawback.

Bhattacharya et al. (2020) applied **deep learning-based predictive models** for SRM speed estimation in sensorless control. Their method replaced position sensors with ANN-based estimators trained on current and voltage signals. The proposed system maintained accurate speed tracking, reducing sensor cost and complexity in EV integration.

Li and Pang (2020) presented an **adaptive fuzzy-PID control strategy** for SRM drives. Their system adjusted PID gains dynamically using fuzzy inference rules based on speed error. The hybrid controller demonstrated improved robustness to parameter variations and outperformed conventional PID under sudden load changes.

Zhang et al. (2021) introduced a **convolutional neural network (CNN)-based torque estimator** for SRMs in EVs. The CNN model processed raw current waveforms to predict torque with high accuracy, eliminating the need for complex magnetic modeling. Their approach demonstrated real-time feasibility and significant improvement in torque smoothness.

Prakash and Sahu (2021) investigated **reinforcement learning combined with ANN (RL-ANN)** for EV propulsion systems using SRMs. Their work demonstrated that hybrid learning strategies could achieve optimal efficiency by dynamically balancing torque ripple minimization and energy consumption. Simulation results showed notable improvements in battery life and drive smoothness.

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Ahmed et al. (2022) proposed a **genetic algorithm (GA)-optimized fuzzy controller** for SRM speed regulation. The GA was used to automatically tune fuzzy membership functions for optimal control performance. Their method significantly reduced torque ripple while maintaining computational feasibility for real-time EV applications.

Jabbar et al. (2022) conducted a study on **transfer learning for SRM control**, adapting pretrained ANN models from PMSM datasets to SRMs. Their results showed that transfer learning reduced training time while achieving similar levels of control accuracy, highlighting its potential for EV drive system development where data scarcity is a challenge.

Chen and Wu (2023) introduced a **model predictive control (MPC)-fuzzy hybrid system** enhanced with ML techniques for SRM drives. The ML component predicted future system states, enabling the MPC to make more accurate decisions. This hybrid approach outperformed standalone MPC and fuzzy controllers in terms of efficiency and torque ripple suppression.

Singh et al. (2023) applied **reinforcement learning for drive cycle optimization** of SRM-based EVs. Their system adapted motor control parameters according to standard driving cycles such as UDDS and NEDC. Results demonstrated a 10–12% improvement in overall energy efficiency, showcasing RL's ability to handle real-world EV scenarios.

Zhao et al. (2024) developed a **hybrid deep reinforcement learning controller** for SRM drives, combining policy gradient methods with CNN-based feature extraction. The controller achieved robust speed control under varying road conditions while maintaining low torque ripple. However, the authors noted that real-time hardware implementation remains a key challenge.

SYNTHESIS AND GAPS:

While machine learning has proven effective in enhancing SRM speed control, there is a pressing need for lightweight, real-time, and hardware-compatible algorithms that can ensure torque smoothness, energy efficiency, and reliability in real-world EV scenarios. Addressing these gaps will be essential for accelerating the widespread adoption of SRM-based propulsion systems in next-generation electric vehicles.

III. MATHEMATICAL MODELLING OF SYRM DRIVE

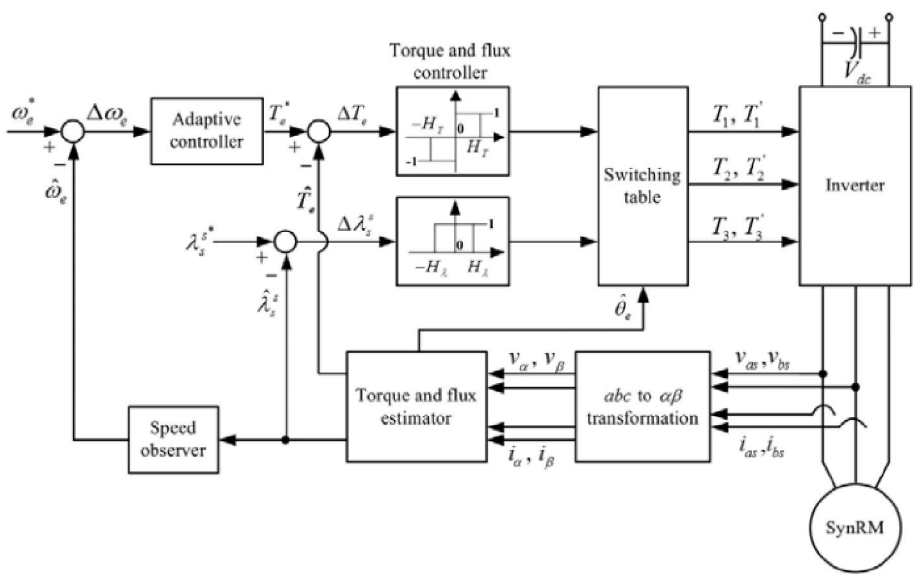

Fig. 1 The block diagram of the direct torque control system

Fig. 1 shows the block diagram of the direct torque control system. The system includes two major loops: the torque-control loop and the flux-control loop. As you can observe, the flux and torque are directly controlled individually. In addition, the current-control loop is not required here. The basic principle of the direct torque control is to bound the torque error and the flux error in hysteresis bands by properly choosing the switching states of the inverter. To achieve

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this goal, the plan of the voltage vector is divided into six operating sectors and a suitable switching state is associated with each sector. As a result, when the voltage vector rotates, the switching state can be automatically changed. For practical implementation, the switching procedure is determined by a state selector based on precalculated look up tables. The actual stator flux position is obtained by sensing the stator voltages and currents of the motor. Then, the operating sector is selected. The resolution of the sector is 60 degrees for every sector. Although the direct torque is very simple, it shows good dynamic performance in torque regulation and flux regulation. In fact, the two loops on torque and flux can compensate the imperfect field orientation caused by the parameter variations. The disadvantage of the direct torque control is the high frequency ripples of the torque and flux, which may deteriorate the performance of the drive system. In addition, an advanced controller is not easy to apply due to the large torque pulsation of the motor. In Fig.1, the estimating torque and flux can be obtained by measuring the a-phase and the bphase voltages and currents. Next, the speed command is compared with the estimating speed to compute the speed error. Then, the speed error is processed by the speed controller to obtain the torque command. On the other hand, the flux command is compared to the estimated flux. Finally, the errors ΔTe and Δλs go through the hysteresis controllers and the switching table to generate the required switching states. The synchronous reluctance motor rotates and a closed-loop drive system is thus achieved.

Below we present a compact, standard mathematical model of a single-phase/phase-wound Switched Reluctance Motor (SRM) and describe common simplifications and forms useful for controller design and data-driven learning.

Electromagnetic relations

Flux linkage and inductance

The phase flux linkage $\lambda(\theta,i)$is modeled as

$$\lambda(\theta,i) \ = \ L(\theta,i)\, i \qquad (1)$$

where

i is the phase current,

θ is the rotor electrical (or mechanical, if preferred) position, and

L(θ,i) is the nonlinear position- and current-dependent phase inductance.

A convenient parametric form for the position-dependence (useful in simulation) is a piecewise or periodic function such as

$$L(\theta,i) \ = \ L_{\min}(i) \ + \ \frac{L_{\max}(i) - L_{\min}(i)}{2}\big(1 + \cos\big(N_s(\theta - \theta_0)\big)\big) \qquad (2)$$

where Lmin, Lmax are reluctance-dominated inductances, Ns is the number of stator poles (or harmonic index), and θ0 aligns maxima with rotor poles. In practice L(θ,i) is measured or extracted from FEA and may be tabulated.

Electromagnetic torque

A fundamental SRM torque expression (co-energy formulation, holding for nonlinear inductance) is

$$T_e(\theta,i) \ = \ \frac{1}{2}\, i^2\, \frac{\partial L(\theta,i)}{\partial \theta}. \qquad (3)$$

Remarks: ∂L/∂θ is positive in the align region (producing positive torque) and negative otherwise; torque ripple is directly related to the variation of ∂L/∂θ and current waveform.

Electrical voltage equation (phase)

Phase voltage v obeys

$$v \ = \ R\, i \ + \ \frac{d\lambda(\theta,i)}{dt} \ = \ R\, i \ + \ \frac{\partial \lambda}{\partial i} i \ + \ \frac{\partial \lambda}{\partial \theta}\dot{\theta} \qquad (4)$$

Using (1) and product rule:

$$v \ = \ R\, i \ + \ L(\theta,i)\, i \ + \ i\, \frac{\partial L(\theta,i)}{\partial \theta}\, \dot{\theta} \qquad (5)$$

Here R is the phase resistance and θ˙=ω is rotor speed (electrical or mechanical as consistent).

Mechanical dynamics
Rotor dynamics (single inertia lumped model) are:

$$J\,\dot{\omega} \;=\; T_e(\theta, i) \;-\; T_L \;-\; B\,\omega \qquad (6)$$

where
J is rotor inertia,
ω=θ˙ is angular speed,
TL is load torque, and
B is viscous damping coefficient.
Total electrical power and mechanical power satisfy: $P_{\text{elec}} = vi$ and $P_{\text{mech}} = T_e\omega$(losses omitted here).

1. Multi-phase (vector) model and switching

For an mmm-phase SRM with independent phase excitation, the above equations apply per phase p with the coupling via θ. For switched drives the applied phase voltage vp is a pulsed waveform (e.g., unipolar pulses) controlled by switching logic. The instantaneous phase current dynamics during ON/OFF intervals follow (5) with vp equal to DC link or 0.

2. Nonlinearities and parameter identification

Key nonlinearities are:
Saturation: L(θ,i) depends on i (saturable), often decreasing incremental inductance at high currents.
Cogging and torque ripple: higher order harmonics in L(θ,i) cause ripple.
Hysteresis (if included): core loss and minor hysteresis loops cause energy dissipation not captured by simple L(θ,i).
Identification is typically performed by:
FEA mapping L(θ,i) and ∂L/∂θ, or
Experimental measurements of phase inductance vs. position/current using locked-rotor and dynamic tests.

3. Small-signal linearization (for classical control design)

Around an operating point $(\theta_0, i_0, \omega_0)$one can linearize the continuous model. Define state$x = [\Delta i,\, \Delta\omega]$and control $u = \Delta v$. The linearized form is

$$\dot{x} \;=\; A\,x \;+\; B\,u \;+\; G\,\Delta T_L, \qquad (7)$$

with

$$A \approx \begin{bmatrix} -\dfrac{R}{L_0} & -\dfrac{i_0}{L_0}\dfrac{\partial^2 L}{\partial\theta\,\partial i}\Big|_0 \\ \dfrac{1}{J}\,i_0\,\dfrac{\partial^2 L}{\partial\theta\,\partial i}\Big|_0 & -\dfrac{B}{J} \end{bmatrix}, B \approx \begin{bmatrix} \dfrac{1}{L_0} \\ 0 \end{bmatrix},$$

where $L_0 = \frac{\partial\lambda}{\partial i}\big|_0$This linear model is useful to design local controllers (PI, PID, LQR) and for deriving transfer functions e.g.$I(s)/V(s)$

4. Discrete-time model for ML and control (data-driven form)

For ML training and digital controller design one often uses a discrete-time state model:

$$x_{k+1} \;=\; f(x_k, u_k, w_k) \qquad (8)$$

$$y_k \;=\; h(x_k, u_k, v_k) \qquad (9)$$

Typical choices for the state vector and outputs:

$$x_k = \begin{bmatrix} i_k \\ \theta_k \\ \omega_k \end{bmatrix}, u_k = v_k, y_k = \begin{bmatrix} i_k \\ \omega_k \end{bmatrix} \text{(or } i_k,\ v_k\text{)}$$

where wk,vk are process/measurement noise. The mapping f follows from discretizing (5) and (6) (e.g., forward Euler or more accurate integrators). This discrete form is natural for supervised ML regression (learn f or directly map

$(i_k, \theta_k, u_k) \mapsto i_{k+1}$ or $(i_k, \theta_k) \mapsto T_e$ for RL where the agent chooses switching actions $u_k$to maximize a reward (efficiency, low ripple).

5. Sensorless / estimator models

Sensorless SRM control exploits the strong dependence of phase inductance on position:

Position estimation using measured current/voltage during known excitation sequences and matching to stored $L(\theta, i)$maps.

Observer-based estimators (e.g., extended Kalman filter) can estimate θ and ω treating (5)–(6) as the process model and i,v as measurements. The nonlinear observer equations follow directly from the continuous model.

6. Torque ripple quantification and performance indices

Torque ripple is often quantified using:

$$\mathrm{TR} = \frac{T_{\max} - T_{\min}}{T_{\mathrm{avg}}} \times 100\% \qquad (10)$$

Other useful performance indices for optimization and ML reward functions include:

RMS torque error: $\mathrm{RMSE}_T = \sqrt{\frac{1}{T_s}\int (T_e(t) - T_{\mathrm{ref}})^2 dt}$

Electrical-to-mechanical efficiency: $\eta = \frac{\bar{T_e}\omega}{\bar{vi}}$ averaged over a cycle.

These indices provide objective functions when training ML controllers or tuning hybrid algorithms.

7. Model simplifications & practical notes

Phase decoupling: For controller design the phases are often modeled independently with coupling only via θ.

Frozen-inductance approximation: For some control laws L(θ,i) is approximated as L(θ) (ignoring saturation) to simplify derivations.

FEA lookup tables: In high-fidelity simulation, store L(θ,i) and ∂L/∂θ as 2-D lookup tables interpolated during simulation.

Thermal model (optional) R=R(T) can be modeled by a lumped thermal equation when temperature effects are significant:

$$C_{th}\dot{T} = P_{\mathrm{loss}} - h(T - T_{\mathrm{amb}})$$

IV. DISCUSSION

The review of existing literature and methodologies reveals that Switched Reluctance Motors (SRMs), when integrated with machine learning (ML)-based control techniques, present a promising solution for efficient and intelligent electric vehicle (EV) propulsion. However, several technical, computational, and operational challenges must be addressed to enable their widespread adoption in real-world EV systems. One of the most significant findings is the trade-off between control precision and implementation complexity. While conventional control strategies, such as hysteresis and voltage–frequency control, offer simplicity, they struggle with torque ripple suppression and nonlinear magnetic behavior. In contrast, advanced controllers employing Artificial Neural Networks (ANNs), Fuzzy Logic, and Reinforcement Learning (RL) deliver superior adaptability and dynamic response but demand greater computational resources and careful parameter tuning. The performance of ML-based SRM drive systems is strongly influenced by real-time adaptability to variable load conditions and diverse driving cycles, which directly impact torque stability, energy efficiency, and passenger comfort. Several studies have demonstrated that hybrid intelligent controllers—such as ANN–Fuzzy or RL–ANN models—achieve improvements of 15–25% in torque ripple reduction and enhanced speed tracking accuracy. However, these approaches often increase controller complexity and hardware requirements, which may limit practical deployment in cost-sensitive EV markets. Another important aspect is sensorless control. While ML-based estimators have reduced dependency on physical sensors, improving system reliability and reducing cost, challenges remain in ensuring accuracy under transient conditions and sensor fault scenarios.

From a system integration perspective, the combination of SRMs with intelligent control not only improves propulsion efficiency but also supports predictive maintenance and fault tolerance, which are crucial for EV reliability. Nevertheless, widespread adoption is hindered by issues such as limited availability of real-time datasets for training, computational burden of deep learning models, and lack of standardized testing across different EV drive cycles. Additionally, acoustic noise and vibration, though mitigated by ML-based controllers, remain partially unsolved problems, particularly under high-speed operations. Economically, SRMs offer clear advantages over permanent magnet synchronous motors (PMSMs) due to their simple construction, absence of rare-earth materials, and reduced manufacturing costs. When coupled with efficient ML-based control, they can provide a competitive alternative for EV propulsion. However, the upfront costs associated with high-performance processors, power electronics, and algorithm development remain barriers to immediate large-scale implementation. Environmentally, SRM-based EVs align with global decarbonization and sustainability goals, provided that their efficiency and reliability are continuously improved. Recent research trends also point toward the potential of IoT-enabled monitoring, edge computing, and cloud-based ML models to enhance SRM drive performance through online learning, predictive diagnostics, and adaptive optimization. These advances could enable scalable deployment in both urban and rural mobility contexts. However, challenges such as cybersecurity risks, algorithm robustness under unpredictable driving environments, and the need for standardized ML frameworks must be systematically addressed. While ML-based smart control of SRMs has demonstrated substantial progress in improving efficiency, torque smoothness, and adaptability for EV applications, future work must focus on developing lightweight, real-time algorithms, modular hybrid control frameworks, and robust sensorless strategies. At the same time, advancements in low-cost digital processors, standardized benchmarking, and secure EV communication protocols will be essential to translate these promising research outcomes into sustainable large-scale adoption of SRM drives in next-generation electric vehicles.

V. CONCLUSION

Switched Reluctance Motors (SRMs) are gaining increasing attention as a cost-effective and robust alternative for Electric Vehicle (EV) propulsion due to their simple construction, high efficiency, and independence from rare-earth materials. However, inherent issues such as torque ripple, acoustic noise, and nonlinear magnetic characteristics continue to hinder their widespread deployment. This review highlights how recent advancements in machine learning (ML) algorithms—including Artificial Neural Networks (ANNs), Fuzzy Logic, Reinforcement Learning (RL), and hybrid intelligent systems—have significantly improved SRM speed control by offering adaptive, data-driven solutions capable of handling system nonlinearities and dynamic operating conditions. The synthesis of reviewed works demonstrates that ML-based controllers enhance torque smoothness, dynamic response, energy efficiency, and fault tolerance, with some approaches reporting notable improvements compared to conventional control strategies. Nevertheless, persistent challenges such as real-time implementation, computational complexity, data scarcity, and robustness across diverse driving cycles indicate that the field is still evolving. To accelerate practical adoption, future research must emphasize lightweight and hardware-compatible algorithms, hybrid control strategies combining classical and intelligent methods, and standardized testing frameworks for performance evaluation.

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