A Review on Machine Learning Based Approaches For Speed Control in Induction Motors

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Abstract- *Speed control of induction motor drives remains a key area of research due to the affordability, simplicity, and durability, induction motorswhich find extensive use in a variety of industrial settings. Because of their nonlinear features and the impact of different uncertainties, precisely controlling the speed of these motors is still a tough challenge. When faced with unpredictable conditions, traditional control approaches frequently fail to deliver the expected performance. Machine learning (ML) models have shown great promise in this regard, providing adaptability and enhanced accuracy, to improve the speed control of induction motor drives. This paper presents the basics of speed control of induction motor drives along with evolutionary algorithms which are used for their speed control. This paper presents a systematic review of the fundamentals as well as the salient points pertaining to machine learning models employed for the speed control mechanism for induction motors and induction motor drives.*

Keywords- Induction motor drives, speed control, machine learning, evaluation metrics, overshoot.

I. INTRODUCTION

As mechanical loads in the industrial business can exhibit continuously variable behavior, necessitating continuously variable torque from the motor. As a result, IM calls for two modes of operation: one that runs straight from the mains and another that uses changeable frequency drives [1]. Due to its easy speed control, DC motors were popular in the early years of the industrial revolution for applications with changing loads. The system becomes much more cumbersome due to the need for an extra corrected assembly in such a system. A DC motor's carbon brushes also cause sparks to fly and necessitate regular servicing. Because of this, variable speed IM drives were developed, and they have now supplanted DC motor drives entirely [2].Electrical drives consist of a power source (the electrical machine) and a control system (the means of regulating electrical parameters) that work together to transform electrical energy into mechanical energy. The two primary functions of an electric motor drive are controlling the beginning speed and applying the brakes. This whole enterprise is just a temporary one. Both open and closed loop control may operate electric drives, although close loop control is more commonly used because of its many benefits and shortcomings. The fundamental control mechanisms namely current limiting, torque limiting and closed loop speed control mechanisms are presented next [3]-[4]

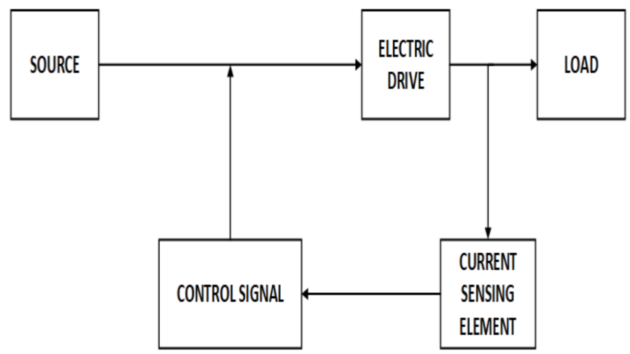

Figure 1: Current Limiting Mechanism

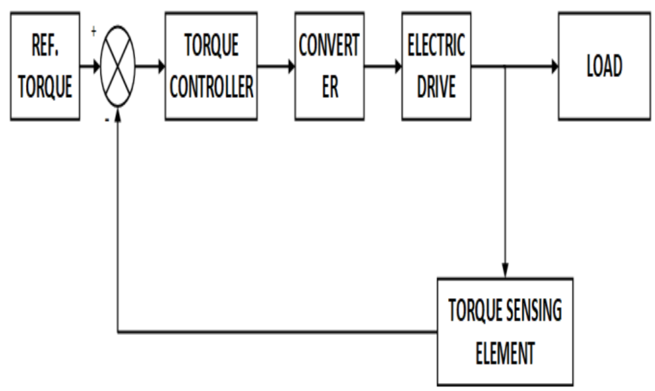

Figure 2: Torque Limiting Mechanism

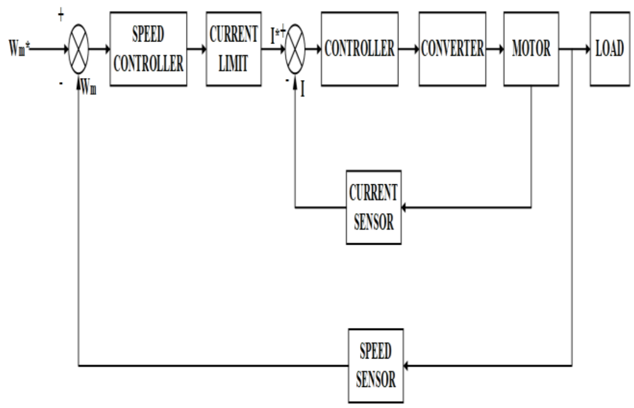

Figure 3: Closed Loop Speed Control Mechanism

The energy that the motor can run on is represented by the source block, which can be either AC or DC. The power modulator receives this signal and uses it to regulate the system. A power modulator (PM) allows the motor to respond to changes in speed and torque by adjusting the supply. A motor block can be any device that converts electricity into mechanical motion. The 3ϕ motor is being used in this project. Mechanical torque demanding tasks, such as load blocks, require maximum efficiency in the application of motor output torque. In order to provide a better speed-torque relationship, the sensing unit measures the output speed or motor current and feeds that data back to the input supply side [5].

The major working block whose output signal to PM provides the intended outcomes is the control unit, which receives its input signal from the sensing unit and compares it with its own output signal to determine the right control action to signal to the power modulator. The input command block stores the predefined action that provides the system with information about the controller command. Out of the multiple speed control mechanisms, the V/f method happens to be one of the most commonly used mechanisms [6]Changing the frequency is the key to this method's IM drive speed control. The aforementioned formulae for rotor speed allow for easy tuning of synchronous speed by changing frequency. The rotor speed can be altered in response to changes in the synchronous speed. Below, we'll go over why we're using the V/f approach. The induced emf can be expressed as V = 4.44kTfϕ.

V, k, and T are constants in the previous equation. So, ϕ reduces as the frequency increases and vice versa. Magnetic saturation occurs very rapidly in the machine's core as ϕ rises. Another way to express ϕ is as:

$$\phi = \frac{1}{4.44kT}\left(\frac{V}{f}\right) \quad (1)$$

Instead than just changing the frequency value to control the value of ϕ, the value of V is additionally modified so that (V/f) remains constant, which means that the value of ϕ remains constant. Now, controlling V/f requires the ability to vary V/f.

II. MACHINE LEARNING MODELS FOR SPEED CONTROL

Nonlinear systems, such as induction motors, are well-suited for control by machine learning models like neural networks, support vector machines, and fuzzy logic systems because of their ability to learn complicated patterns and correlations from data. Because these models don't necessitate explicit mathematical representations, control design becomes more easier, and the system becomes more adaptable to new circumstances [7]. Motor speed regulation performance can be enhanced with the use of ML models trained on historical data, which can forecast the ideal control action [8]s.

When it comes to controlling the speed of an induction motor, one of the most common ML strategies is the use of neural networks. They are great at capturing the motor's dynamics and can approximate any nonlinear function. Various types of neural networks, including feedforward, recurrent, and convolutional, have been used for this task. These networks can accurately change the motor speed in the presence of disturbances and parameter variations by training on the input-output data of the motor system [9]-[10].

Another machine learning method used for speed control is support vector machines (SVMs). In order to regress or classify data, support vector machines (SVMs) search for the best hyperplane that either fits the data points or divides the data into several classes. Training support vector machines (SVMs) to correlate motor operating circumstances with control actions is a common practice in motor speed control. Their extensive speed control capabilities in induction motors are a result of their capacity to manage high-dimensional areas and prevent overfitting.

Induction motor control is a perfect application for fuzzy logic systems since they use human-like reasoning to deal with uncertainties and imprecise data. In order to determine the control actions depending on the motor's present state, fuzzy controllers use a set of language rules. In addition to being easily interpretable, these systems can be fine-tuned to operate as needed. To further improve the motor's speed control capabilities, fuzzy logic systems can be integrated with machine learning algorithms to dynamically adjust their rules. [11]

Combinations of Methods

Improving speed control is a promising area for hybrid systems that incorporate different machine learning techniques. In order to take advantage of both the learning power and the interpretability of neural networks and fuzzy logic, neuro-fuzzy systems combine the two. A similar effect can be seen when SVMs and neural networks are combined to improve the control system's accuracy and robustness. Because they take advantage of the best features of both methods, hybrid models can outperform their solo counterparts [12]-[13].

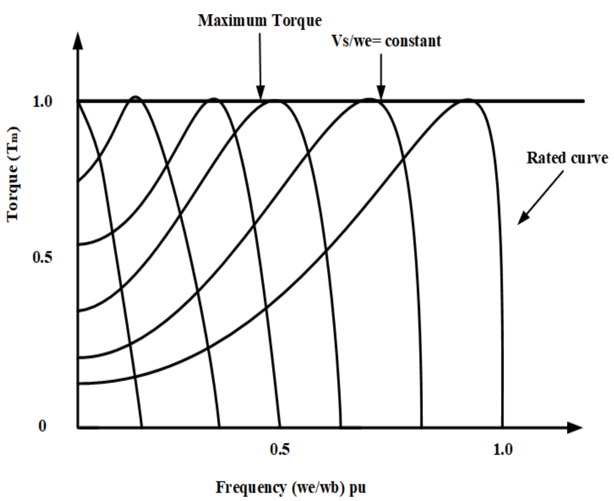

Figure 4: Frequency-Torque Curve

Figure 4 depicts the frequency torque curve for induction motors.With its minimal beginning current and mechanical stress, the V/f speed control technique requires less maintenance.

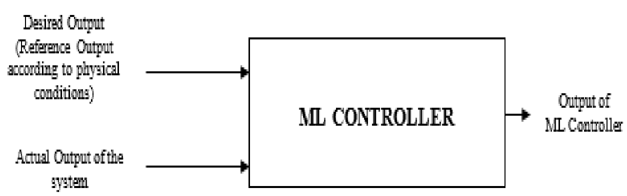

Figure 5: Mechanism of working for ML based controller

In the current physical state, the ML-based controller calculates the difference (error) between the expected output and the actual output. It then generates an output with the goal of reducing the difference (error) as a function of the difference [14]This is depicted in figure 6.

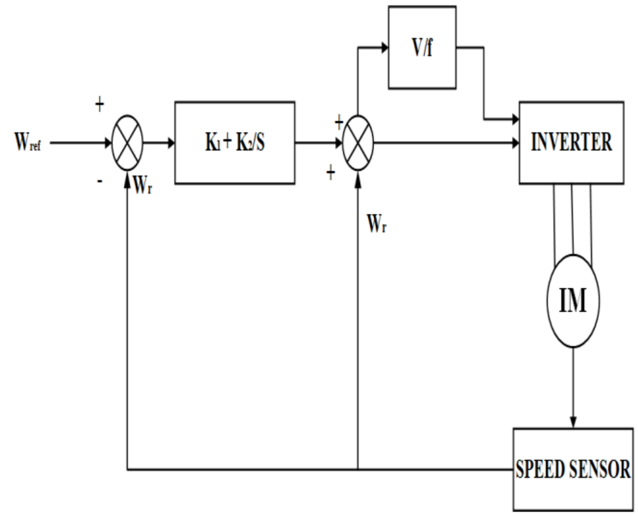

Figure 6: The Typical V/f controlling mechanism

The evaluation metrics for the method are [15]:

$t_{rise} = t_{Y=100\%} - t_{Y=0\%}; underdampled\ systems$ (1)

And

$t_{rise} = t_{Y=90\%} - t_{Y=10\%}; over - dampled\ systems$ (2)

The training algorithm for the machine learning model is given by:

The training algorithm adopted in this work is given by:

Step.1: Initialize weights (w) randomly.

Step.2: Fix the maximum number of iterations (n) and compute $\rho = \frac{k_1}{k_2}$

Step.3: Update weights using gradient descent with an aim to minimize the objective function J given by:

$J = \frac{1}{m}\sum_{i=1}^{m}(v_i - v'_i)^2$ (3)

Step.4: Compute the Jacobian Matrix J given by:

$$J = \begin{bmatrix} \frac{\partial^2 e_1}{\partial w_1^2} & \cdots & \frac{\partial^2 e_1}{\partial w_m^2} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 e_n}{\partial w_1^2} & \cdots & \frac{\partial^2 e_n}{\partial w_m^2} \end{bmatrix} \quad (4)$$

Here,

The error for iteration ‘i’ designated by e_i is computed as:

$e_i = (y_i - y'_i)$ (5)

Here

y_i is the actual value

y'_i is the predicted value

Step.5: Iterate steps (1-4) till the cost function J stabilizes or the maximum number of iterations set in step 2 are reached, whichever occurs earlier.

It is desirable to attain least amount of steady state error at least number of iterations.

III. PREVIOUS WORK

This section presents the summary of previous work in the domain:

Savarapu et al. proposed the Modified Brain Emotional Controller (MBEC) method. Variations in torque and flux ripples make IM highly sensitive in low-speed operation. The IM drive's performance is negatively impacted by these changes in stator currents, which inertly produce low-order harmonics. By incorporating a controller that enhances the drive's performance while simultaneously reducing harmonic presence, the drive's overall efficiency can be enhanced. To get better performance out of the drive, this research suggests a biologically inspired intelligent speed controller, MBEC. A discrepancy between the reference speed and the motor's actual speed, as determined by the Model Reference Adaptive System (MRAS), is fed into the MBEC as input. The inverter was built using a support vector machine (SVM) based topology, and the sensorless DTC technique is used to operate the IM. This research presents a stability analysis of an IM drive that is based on MBEC in order to demonstrate its usefulness. We use Opal-RT OP5600 for real-time experiments to verify the proposed control setup under varying operating conditions and confirm the findings. We compare the suggested control algorithm's performance under various operating situations to that of the BEC and PI methods to ensure its efficacy in preventing torque ripples and low flux ripples.

Stender et al. proposed that one must prioritize developing induction motors with high torque estimation accuracy for torque-controlled applications, such as electric automobiles. The accuracy of the measured magnetic flux has traditionally been a key component of torque estimate, but this has proven to be a difficult task owing to a number of less-than-ideal effects, such as skin effect influences, iron losses, and magnetic saturation. The alternative is a hybrid machine learning observer that estimates torque and stator flux simultaneously; in other words, it combines the two tasks into one. The utilization of physically-inspired architectures grounded in expert knowledge (hybrid modeling) allows for both small model size and excellent estimation accuracy, as opposed to arbitrary neural network topologies. The key benefit of this approach is that not only are extra flux measurements not needed, but the training of the enclosed neural networks is also dependent on recorded torque data. This method achieves a root-mean-square inaccuracy of just 1.0% with respect to nominal torque across the whole operational range.

Verma et al. presented the challenge of calculating induction motor torque and speed from measured voltages and currents. When evaluated using conventional measures from a machine learning standpoint, neural networks demonstrate respectable performance on this problem. But we prove that there are certain restrictions on analyzing a neural network model with machine learning metrics for induction motor issues. The validation of neural network performance from an electrical engineering perspective is necessary due to the mission-critical nature of induction motor operations. In order to achieve this goal, we use electrical engineering criteria to assess several state-of-the-art and more conventional neural network designs on both static and dynamic benchmarks.

Ali et al. proposed a failure diagnostics of induction motors that is based on machine learning. Two identical induction motors are subjected to a variety of single- and multi-electrical and mechanical failures in laboratory testing. In order to create the fault diagnosis method, experiments are conducted in which the motors' stator currents and vibration signals are recorded simultaneously. For feature extraction, two signal processing techniques—discrete wavelet transform and matching pursuit—are selected. To assess the efficacy and appropriateness of various classifiers for induction motor fault diagnosis, the study employs three classification algorithms—ensemble, support vector machine (SVM), and K-nearest neighbors (KNN). A total of seventeen classifiers from the MATLAB Classification Learner toolbox are utilized in the evaluation process. Out of the twelve classifiers tested, only five—fine Gaussian SVM, fine KNN, weighted KNN, bagged trees, and subspace KNN—achieved near-perfect classification accuracy for all motor errors. When testing motors for defects, a new curve fitting method is created to determine characteristics that are not evaluated for, such as stator currents or vibration signals under specific loads. Induction motors with one or more electrical or mechanical failures can be precisely located using the suggested fault diagnosis procedure.

Talla et al. proposed the construction of an adaptive controller for speed control of induction motor (IM) drives that use erroneous models. To be more precise, we presuppose that the drive's state-space model has constantly changing errors in all of its equations. An adaptive feedforward control term ensures system stability and accounts for nonlinear and uncertain aspects in the proposed controller. The other part of the controller is a feedback control term. The suggested method ensures quick and accurate speed tracking while also being straightforward to implement. By applying the Lyapunov theorem and a related lemma, we can verify that the suggested speed controller is stable. We evaluate the proposed control method in comparison to three different types of controllers: adaptive backstepping sliding mode control (ABSMC), conventional field oriented control (FOC), and nonadaptive feedback linearization control (FLC). Experiments conducted on a 4 kW IM drive prototype show that the controller outperforms the competition in terms of control performance, particularly in situations where there is a large parameter mismatch between the actual drive and the model used to design it. This includes better robustness, smaller mean square, and maximum absolute errors (MAEs).

Conventional methods for controlling the speed of induction motors, such as scalar control (V/f control), vector control (field-oriented control), and direct torque control, have limitations. These methods rely heavily on accurate mathematical models of the motor, which can be difficult to obtain and maintain due to parameter variations and external disturbances [16]. Furthermore, these traditional controllers may not adapt well to changes in operating conditions, leading to suboptimal performance. This underscores the need for more flexible and robust control strategies.All conventional control methods, including scalar control, vector control, and DTC, are highly sensitive to motor parameter variations. Parameters such as rotor resistance, stator resistance, and inductances can change due to temperature fluctuations, aging, and load conditions. These variations can lead to degraded performance and reduced accuracy in speed control. Traditional controllers often struggle to adapt to these changes, resulting in suboptimal performance and inefficiencies [17]. Moreover, Conventional control approaches typically rely on fixed control laws and parameters, which are designed based on a specific set of operating conditions. However, induction motors often operate in dynamic environments where load conditions, supply voltages, and operating requirements can vary significantly. The lack of adaptability in traditional control methods makes it difficult to maintain optimal performance across a wide range of operating conditions. This limitation can lead to increased energy consumption, reduced lifespan of motor components, and higher maintenance costs [18].While advanced methods like vector control and DTC offer better performance than scalar control, they involve complex mathematical calculations and require high computational power [19]. This complexity can be a significant barrier for implementation in cost-sensitive applications or systems with limited computational resources. The need for real-time processing and fast response times further exacerbates this challenge, making it difficult to achieve the desired performance without significant investment in hardware and software resources [20].Hence machine learning models are superior.

IV. CONCLUSION

This paper presents the need and importance of machine learning based models for speed control of induction motor drives. Due to the dynamics is complex and conventional methods have their limits, speed control of induction motor drives must rely on optimization algorithms and machine learning. Optimization methods provide effective parameter adjustment, whereas ML algorithms provide adaptability, resilience, and flexibility. When used in tandem, these cutting-edge technologies boost motor control systems' accuracy, dependability, and efficiency. Improvements in performance and widespread industrial use are anticipated outcomes of applying these technologies to induction motor drives as they progress. A fundamental analysis of control mechanism along with salient noteworthy contribution in the filed of study has bene presented.

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