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Neural Network based Soft Starting Technique for Squirrel Cage Induction Motor

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Abstract

The soft start of squirrel cage induction motors is highly imperative in order to avoid any excessive currents, torque pulses, and mechanical stresses. As a matter of fact, traditional Direct on Line (DOL) techniques of motor starting involve heavy current transients and torque pulses that tend to shorten the life of the motors and destabilize system performance. In this regard, this paper presents a soft starting scheme for a three-phase squirrel cage induction motor using an artificial neural network (ANN) based on a thyristor-controlled AC voltage controller. The proposed feed-forward multilayer perceptron (MLP) ANN model incorporates various motor operating parameters including motor current, speed, electromagnetic torque, and loading condition to provide optimal firing angles of the thyristors. The induction motor is represented in dq-coordinates while the MLP ANN is trained by means of backpropagation algorithm with the performance index being Mean Squared Error (MSE). From the MATLAB simulations, the results indicate that the proposed ANN model can significantly decrease the starting current from 90A to 30A and starting torque from 125N-m to 40N-m compared to the traditional DOL scheme.

Keywords: Artificial Neural Network (ANN), Soft Starting, Squirrel Cage Induction Motor, Starting Current, Torque Ripple, Motor Control.

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1. Introduction

Induction motors are widely employed in industries as well as at homes due to their unique features like sturdy build-up, economical nature, dependability, etc. Of all the induction motors available, the squirrel cage induction motors are widely used owing to their simplicity and rugged operation. However, despite all its positive attributes, one important drawback of an induction motor is that of its operation. When the induction motor is started directly on line, there is an enormous rise in the value of starting current which is almost six to eight times greater than the normal value, causing great voltage fluctuations and putting tremendous thermal and mechanical stress on the motor [5]. These effects not only lowers the life span of the motor but also affects the stability and efficiency of the entire electrical system that is connected to the motor. In order to overcome this, various types of soft start methods have been introduced which include star delta starters, auto transformer starters, and phase angle controllers. The objective of this method is to lower the starting current through lowering the voltage used for starting. Though these methods are quite efficient to some extent, yet there are certain shortcomings associated with these methods. The disadvantages include step-by-step change in voltage, un-adaptability to changing loads, and high torque ripple [6].

The development of intelligent control methods in the past few years has provided opportunities to improve the efficiency of the induction motor drive systems. The AI-based technique has received much focus owing to its proficiency in modeling nonlinear processes and learning from experience [1]. The ANN-based controller makes it possible to tune the controller parameters based on analysis of the actual working condition of the motor system, thus optimizing the control action. This is responsible for offering good dynamic response, minimum overshoot, and better stability [3].

The proposed techniques provide enhanced flexibility, uncertainty management capability, and accurate control of the nonlinear systems [4]. Control methods using ANN technology have been proven highly effective in minimizing transients, torque pulsations, and achieving improved efficiency [2]. In addition, recent research has been centered on developing simplified, low-cost, and efficient soft starting schemes suitable for real time applications [7]. Moreover, the literature suggests that soft starters designed through ANN technology greatly excel in comparison to the traditional approaches in terms of reducing starting currents, torque ripples, and improving energy efficiency [8]. Consequently, an approach based on ANN technology is suggested to be adopted for implementing soft starting scheme of squirrel cage induction motor drives to address the shortcomings of the existing approaches.

2. Methodology

The designed system involves the use of the three-phase squirrel cage induction motor which is powered by the use of the soft starter which comprises thyristors along with the ANN based intelligent control strategy. The primary aim of the design of the above said system is to provide the desired control action for the motor during the starting process through varying stator voltage supplied to the induction motor in order to limit the magnitude of in-rush currents and minimize the torque ripple. In the above mentioned system, the ANN plays the role of controller while other elements include the induction motor and the soft starter made up of thyristors. The ANN continuously analyzes motor parameters such as current, speed, and electromagnetic torque among other parameters that affect the motor in order to derive the optimal firing angle (α) of the thyristor switches.

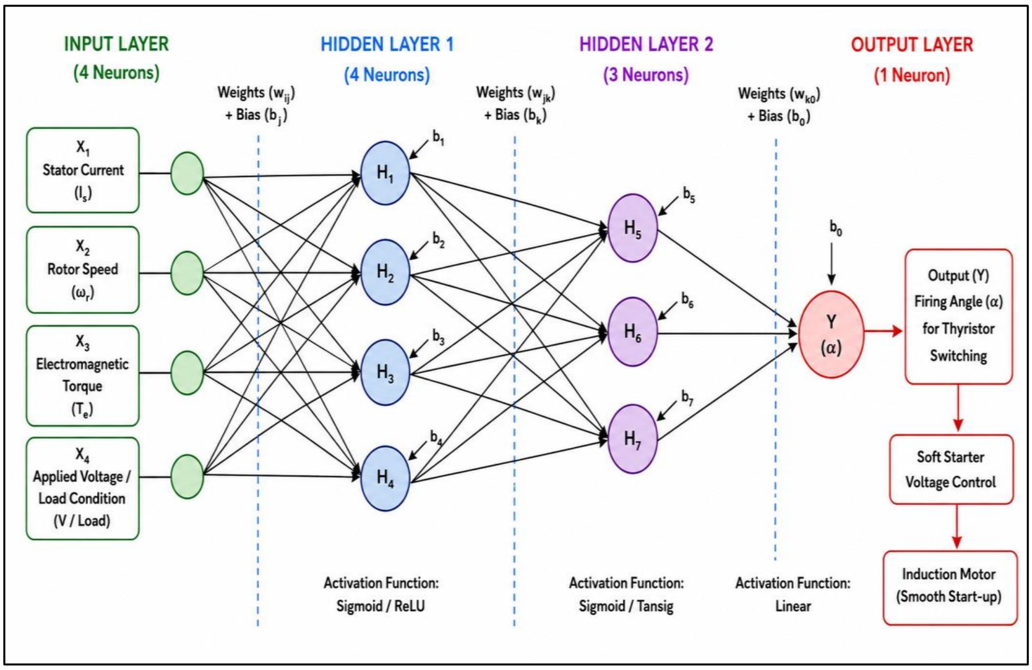

Figure 1. Proposed ANN Architecture for Soft Starter Control of Induction Motor

The proposed ANN architecture consists of an input layer, two hidden layers, and an output layer, as illustrated in figure 1. The input layer receives four normalized motor parameters denoted as X_1, X_2, X_3, and X_4, corresponding to stator current (I_s), rotor speed (ω_r), electromagnetic torque (T_e), and applied voltage/load condition (V/ Load), respectively. They are processed in the hidden layers using the weights and biases. The nonlinear functions of Sigmoid and ReLU are used in order to capture the nonlinearity of the induction motor system. The output layer generates the firing angle (α), which controls the conduction period of the thyristor-based soft starter and regulates the applied stator voltage during startup.

To study the dynamic performance of the induction motor, the machine equations are formulated within the dq-reference frame of the machine. The stator voltage equation can be written as:

$$V_{ds} = R_s i_{ds} + \frac{d\lambda_{ds}}{dt} - \omega_e \lambda_{qs} \tag{1}$$

$$V_{qs} = R_s i_{qs} + \frac{d\lambda_{qs}}{dt} + \omega_e \lambda_{ds} \tag{2}$$

Similarly, the rotor voltage equations are given by:

$$V_{dr} = R_r i_{dr} + \frac{d\lambda_{dr}}{dt} - (\omega_e - \omega_r)\lambda_{qr} \tag{3}$$

$$V_{qr} = R_r i_{qr} + \frac{d\lambda_{qr}}{dt} + (\omega_e - \omega_r)\lambda_{dr} \tag{4}$$

where V_{ds}, V_{qs} are stator voltages, V_{dr}, V_{qr} are rotor voltages, R_s and R_r are stator and rotor resistances, $i_{ds}, i_{qs}, i_{dr}, i_{qr}$ are current components, and ω_e and ω_r represent synchronous and rotor angular speeds, respectively.

The corresponding flux linkage equations are represented as:

$$\lambda_{ds} = L_s i_{ds} + L_m i_{dr} \tag{5}$$

$$\lambda_{qs} = L_s i_{qs} + L_m i_{qr} \tag{6}$$

$$\lambda_{dr} = L_r i_{dr} + L_m i_{ds} \tag{7}$$

where L_s, L_r, and L_m denote stator inductance, rotor inductance, and mutual inductance, respectively.

The electromagnetic torque developed by the induction motor is calculated using the dq-axis current components and flux interactions as follows:

$$T_e = \frac{3}{2}\frac{P}{2} L_m \left(i_{qs} i_{dr} - i_{ds} i_{qr}\right) \tag{8}$$

where T_e represents electromagnetic torque, P denotes the number of poles, and L_m is the mutual inductance. The calculated electromagnetic torque (T_e) is continuously fed into the ANN controller as one of the input parameters (X_3) to ensure adaptive and smooth control during the starting process.

The ANN used in this study is a Multi-Layer Perceptron (MLP) architecture having feed-forward characteristics, enabling it to model a nonlinear system. Every neuron calculates the weighted sum of input values together with a bias term and applies a nonlinear activation function to it. The mathematical expression for neuron output can be given as:

$$Y = f(\sum_{i=1}^{n} w_i X_i + b) \tag{9}$$

where X_i denotes the input parameters, w_i represents connection weights, b is the bias term, and $f($. represents the activation function. The final ANN output corresponds to the firing angle (α) required for controlling the thyristor switching operation:

$$\alpha = f(X_1, X_2, X_3, X_4) \tag{10}$$

ANN regulates the angle of firing based on the operation mode of the motor, thus making the rise in voltage progressive.

ANN is then trained using the dataset that is generated through simulation under various modes of operation characterized by changes in the supply voltage, load torque, etc. Before being subjected to the training process, the parameters are first normalized in order to increase the training speed, as shown below:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{11}$$

The training process uses supervised learning with the backpropagation algorithm to update network weights iteratively. The Mean Squared Error (MSE) is employed as the performance index to minimize the error between the target output and predicted ANN output:

$$MSE = \frac{1}{N} \sum_{k=1}^{N} \left(\alpha_{\text{target}} - \alpha_{ANN}\right)^2 \tag{12}$$

The weight updating rule during backpropagation is given by:

$$w_{new} = w_{old} - \eta \frac{\partial E}{\partial w} \tag{13}$$

where w_{new} and w_{old} are the updated and previous weights, η is the learning rate, and E represents the error function. The training process continues iteratively until the error converges to a minimum value, resulting in accurate prediction of the firing angle for different motor operating conditions.

During operation, the measured motor parameters X_1, X_2, X_3, and X_4 are continuously fed into the trained ANN controller. Based on these real-time inputs, the ANN generates the optimal firing angle (α) for the thyristor-based soft starter. The generated firing angle controls the conduction period of the thyristor switches, thereby regulating the applied stator voltage supplied to the induction motor.

Unlike traditional soft starters which use a fixed voltage profile for ramping, the ANN-based intelligent control scheme proposed here is able to adapt dynamically to changing operating conditions. With an intelligent and adaptive control method of operation, the starting current is reduced, torque pulsations are reduced, and acceleration becomes smooth. The result is an improved performance of the motor driven by the ANN-based soft starter.

3. Result and Discussion

Performance of the ANN-based soft starting system is studied by comparing with that of the traditional DOL starting system with respect to starting current, speed, electromagnetic torque and characteristics of ANN convergence.

Table 1 presents the simulation parameters used for validating the proposed ANN-based soft starter.

Table 1. Simulation Parameters of the Proposed ANN Model

Parameters	Values
Supply Voltage	415 V
Supply Frequency	50 Hz
Motor Type	Three-phase squirrel cage induction motor
Motor Rating	5 HP
Method	Direct on Line (DOL), ANN-based soft starter
Number of Poles	4

Stator Resistance (R_s)	1.405 Ω
Rotor Resistance (R_r)	1.395 Ω
Stator Inductance (L_s)	0.0058 H
Rotor Inductance (L_r)	0.0058 H
Mutual Inductance (L_m)	0.1722 H
Hidden Layer Configuration	4–3 neurons
Learning Rate	0.01
Performance Function	Mean Squared Error (MSE)
Simulation Time	0.5 s
Software Tool	MATLAB

The proposed ANN based controller adjusts the firing angle of the thyristor based soft starter depending on the real-time working condition of the motor, so that efficient startup is achieved.

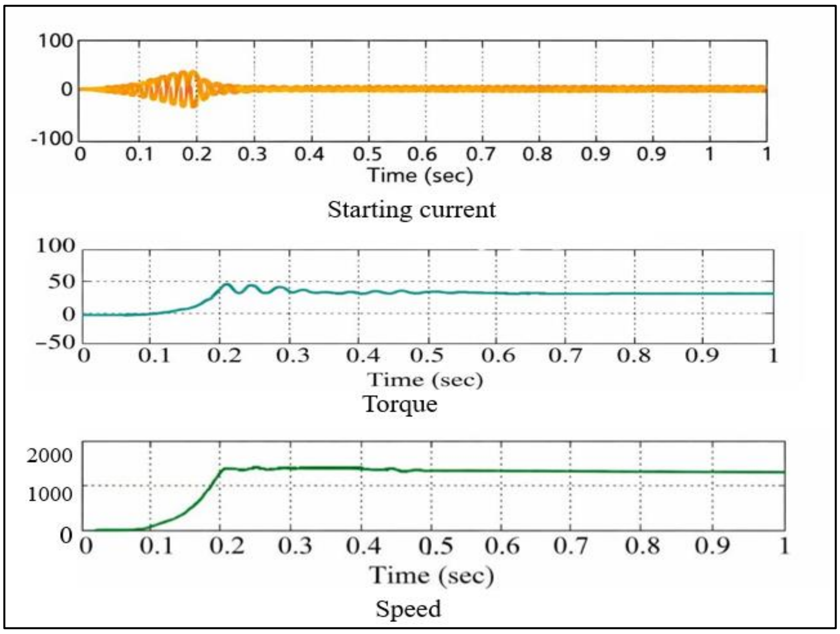

Figure 2. Dynamic Response of ANN-Based Soft Starter

Figure 2 depicts the complete dynamic behavior of the suggested ANN controlled soft starter, which comprises the starting current, electromagnetic torque, speed variation, and total harmonic distortion (THD). In terms of the starting current variation, it can be observed that there is an increase in starting current, and its magnitude is very low in comparison to the traditional techniques employed for motor startup. Torque variation curve indicates smooth torque production and less torque ripple with no transients, resulting in lower mechanical strain on the motor shaft. Also, similar to the starting current variation curve, the speed variation graph indicates smooth speed variation towards rated speed without any transients.

Apart from that, the convergence behavior of ANN in the training process was analyzed. In order to analyze the convergence of ANN, the backpropagation method was adopted and various input data sets were used after normalization on the basis of different operating conditions. The performance criterion for the network is Mean Squared Error (MSE), which reflects the learning capabilities of the network.

The following Figure 3 describes the converging nature of the ANN developed for the application. Initially, the network has a comparatively higher error value. However, the mean squared error starts decreasing steadily with the progress of training iterations. There is no significant oscillation or divergence of network parameters, thus indicating good convergence behavior.

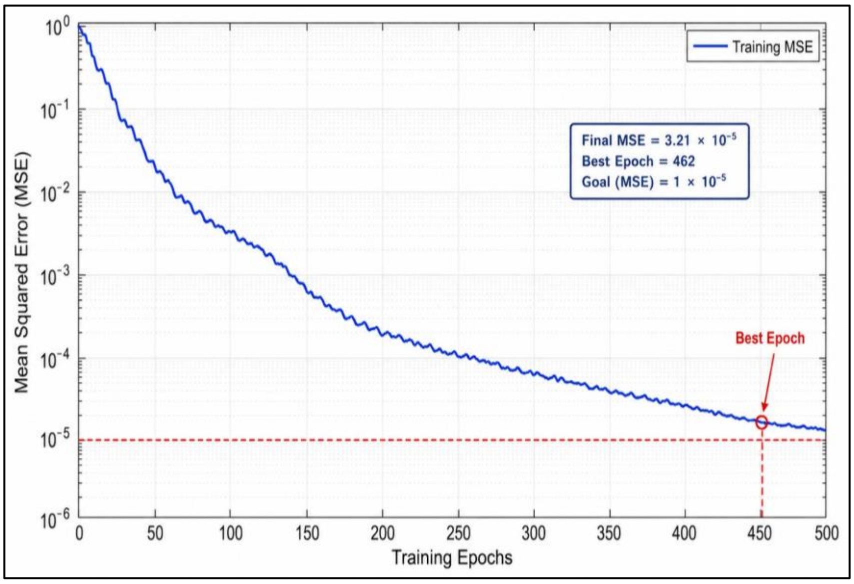

Figure 3. ANN Convergence Curve Showing MSE Versus Epochs

The decrease in loss value implies that the ANN has successfully learned the non-linear mapping function from the motor working parameter (X_1,X_2,X_3,X_4) and the firing angle (α). The final converging MSE value indicates the capability of the ANN in making predictions accurately. Convergence characteristics imply the feasibility of the suggested ANN structure and suitability of its use for induction motor soft starters. Convergence characteristics of ANN have an important role to play in improving the accuracy, adaptability, and generating firing angles for the soft starter.

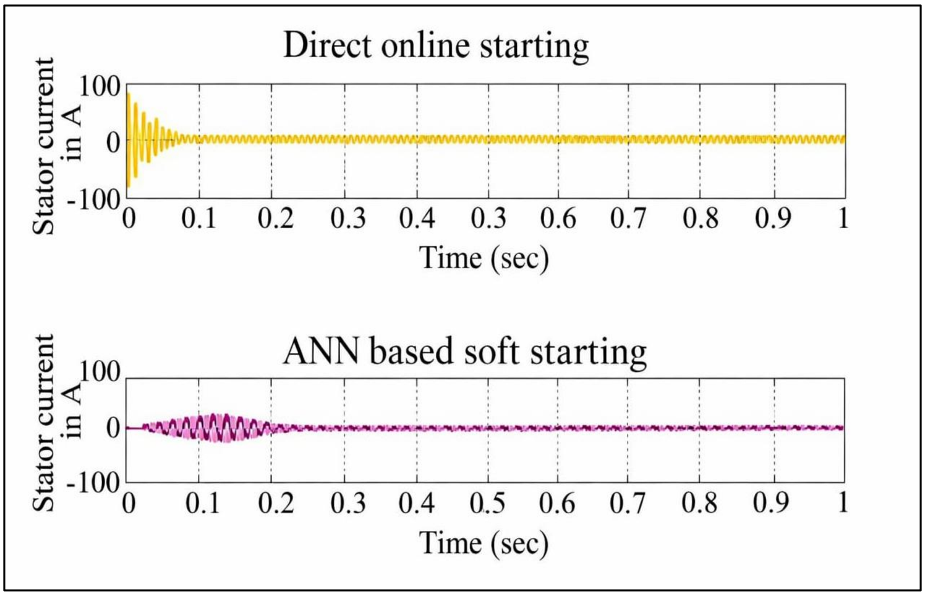

Figure 4. Starting Stator Current Comparison of DOL and ANN

Figure 4 depicts the performance comparison of stator current during motor starting using the conventional DOL method and the ANN-based soft start method. The figure clearly indicates that during the initial stage of the DOL method, a very high inrush current occurs which rises to several times of rated current with high fluctuations.

In this regard, the ANN controller based soft starter is effective in regulating the starting current by limiting the value of applied stator voltage due to adaptive firing angle adjustment. The resulting waveform of current is relatively smooth, with reduced magnitude and oscillation level. This shows the effectiveness of the ANN controller in controlling the starting current of the motor.

Figure 5 below shows the speed profiles for both DOL and ANN controlled soft starter. For DOL, the motor accelerates to its rated speed in a relatively short period; although, during such acceleration, there are transient disturbances. This may be attributed to high level of fluctuations that occur in the process, leading to the risk of stressing the motor shaft. For the proposed ANN control system, the speed of the motor increases relatively slowly in a smooth manner. The speed response of the motor converges to steady state in a gradual and smooth manner without any significant oscillation and overshoot. Although the time required to reach steady state is relatively longer than that of DOL, ANN is better for industrial use.

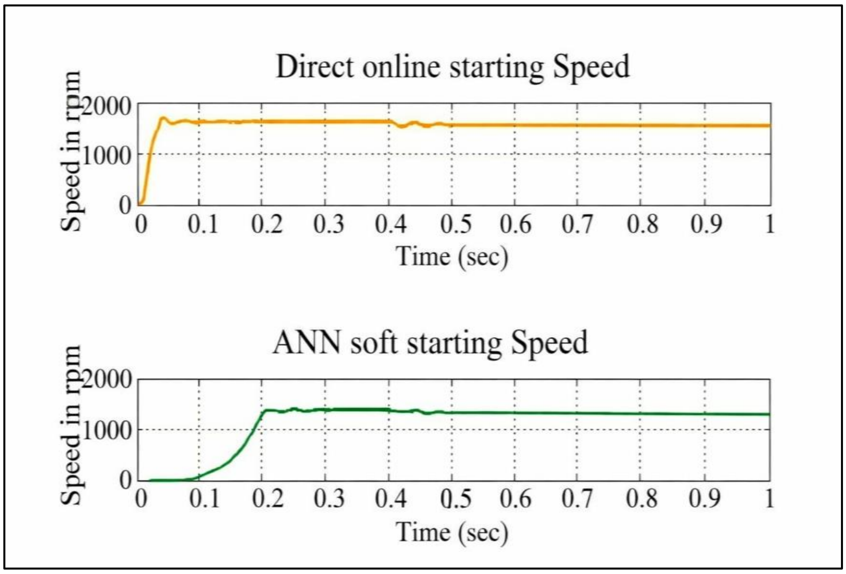

Figure 5. Speed Response Comparison of DOL and ANN

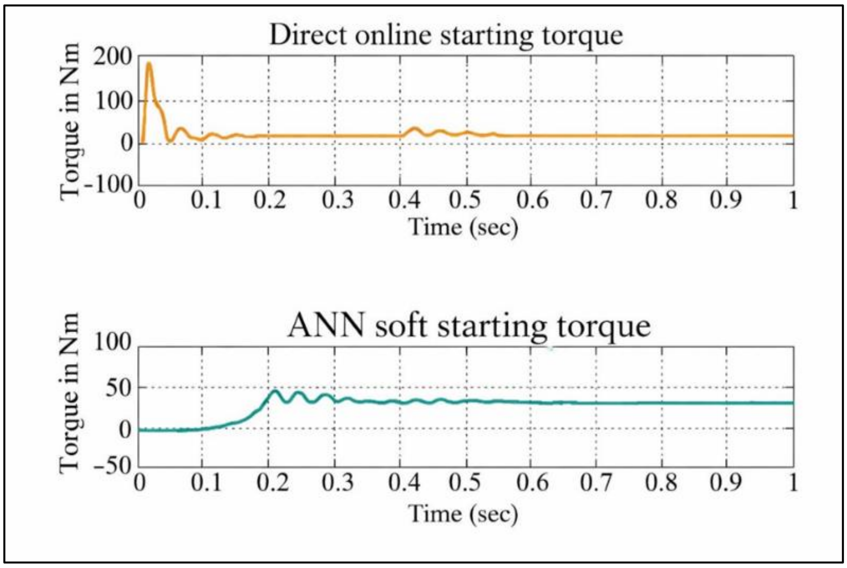

Figure 6. Electromagnetic Torque Comparison of DOL and ANN

Figure 6 illustrates the performance of the electromagnetic torque in relation to the starting procedure using both of the control techniques. In the case of DOL, there is a large rise in the torque at the beginning of the process, which leads to severe torque oscillations before settling down to the steady state. On the other hand, it is seen that the use of the artificial neural network soft starter has led to a much smaller torque rise during startup, together with very low torque oscillations during the whole process. It shows a gradual torque rise to a steady state, which suggests better control of the electromagnetic nature of the induction motor.

A comparative evaluation of the conventional DOL starter and the ANN based soft starter is provided in Table 2.

Table 2. Performance Comparison of DOL and ANN Soft Starting

Parameters	DOL Starting	ANN based soft starting
Initial Current	90A	30A
Time taken to reach steady state	0.05s	0.25s
Starting torque	125 N-m	40N-m

It is observed that the initial current under DOL starting conditions amounts to around 90 A while the ANN based soft starter successfully controls the current to about 30 A levels. This helps reduce the electrical load exerted on the motor as well as the power supply. While the conventional DOL approach attains steady state quickly, it generates very high transient disturbances. However, the ANN based approach ensures smooth acceleration with low starting torques. Overall, the simulation results clear that the dynamic performance of the proposed soft starter based on artificial neural network (ANN) is much better than that of conventional direct online starting.

4. Conclusion

In this work, a novel ANN-based soft starting strategy has been proposed for the three-phase squirrel cage induction motor in order to address the challenges involved in traditional Direct-On-Line (DOL) starting approaches. In this context, the ANN controller has been applied along with a thyristor-based soft starter in order to ensure an adaptive intelligent control scheme. In this context, the ANN has been designed in such a way that the firing angle could be computed based on continuous monitoring of parameters including stator current, rotor speed, electromechanical torque, etc., and consequently ensures a stable voltage regulation mechanism during starting. Moreover, it has been demonstrated through simulation that the proposed ANN-based soft starter ensures a better reduction of the inrush current and minimizes torque ripple in comparison to the conventional DOL method. Besides, the convergence analysis along with ANN loss analysis confirms the success of the proposed ANN by achieving better MSE reduction. Overall, the proposed intelligent technique is found to improve transient behavior, reduces electrical/mechanical stress, and also improves system efficiency.

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