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An SVM Classifier-based Speed Control and Soft Starting Method for a Three-Phase Induction Motor

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Abstract

Three-phase induction motors are extremely popular and almost ubiquitous in industrial applications. Issues related to starting and speed control of these motors are of great importance in performance determination. This paper presents the speed control of a 3-phase induction motor using a Support Vector Machine (SVM) based classifier. A thyristorised voltage controller regulates the motor speed by utilizing the speed-voltage proportionality. Input to the controller is a multiclass SVM classifier that has been trained to estimate the appropriate firing angle '‘α'’ for the desired torque-speed combination. A soft starter is also included in the model and, as demonstrated, gives a proper time variation to '‘α'’. The simulation findings show that the soft starter's progressive increase in the motor supply voltage significantly reduces the amplitude and the pulsating nature of the starting current and Torque of the motor. The performance of the SVM controller and the soft starter at various torque speed combinations are evaluated on the model and found to be satisfactory.

Keywords: Support vector machine; Three-phase induction motor; Soft starting.

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1. Introduction

Industrial and domestic applications both frequently use induction motors. One of the issues concerning these motors is the large current and Torque, often pulsating in nature, witnessed during the time of starting [1]. The high pulsating starting torque can harm mechanical linkages and bearings, damage load couplings, or result in belt slippage. Similarly, the high starting current causes voltage dips that interfere with the operation of electric and electronic devices attached to the load busbar [2]. Hence, a soft starter is preferred for starting an induction motor whose main purpose is to reduce the voltage at the time of starting in a graded manner so that the current and Torque, which have a direct proportionality with the applied voltage, reduce as a consequence.

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A soft starter can be used to conserve energy when the load is low and assist in lowering the initial current/torque by giving a lower voltage during start-up [3]. In comparison to traditional starting techniques employed for induction motors, soft starters are thyristor/IGBT-based devices that are less expensive and offer a better modulation of the input voltage [4], and several novel algorithms aimed at implementing an efficient soft start have appeared in the literature of late [5-7]. This technique can also be used to regulate the motor's speed by applying voltage control. The thyristors' firing delay can be modified for a specific voltage matching to a specific desired speed [8,9]. Several have proven the soft starting efficiency.

A soft start technique supported by an SVM classifier for the speed control of a 3-ϕ asynchronous motor is provided in this research. SVMs, although relatively new, have attracted a lot of attention and have become quite popular for classification problems [10,11]. They have also been applied to numerous induction motor applications, such as failure diagnosis [12-15], classification of the status of voltage supply [16], and estimation of rotor resistance [17]. Very little evidence of SVM being investigated for motor speed control can be found in the literature, although the use of ANN or Fuzzy logic is well documented [18-20]. In the work presented here, the firing angle '‘α'’ required to meet a given torque-speed combination is optimally generated by the SVM and then given to the soft starter, which limits the starting current Torque and reduces the Torque's pulsations. In the sections that follow, the specifics of the circuit implemented in MATLAB / SIMULINK are covered.

2. Speed Control using SVM Classifier

2.1. *Training and test data*

An SVM classifier network is used in the initial section of the study to implement the induction motor's speed regulation. Initially, a MATLAB model, as illustrated in Fig. 1(a), is used to gather the data necessary for training the network. The squirrel cage induction motor used has the following parameters: Rated power = 3 hp, Rated voltage = 220V, No of poles = 4, Supply frequency = 50 Hz, Resistance of stator winding = 0.435 Ω / phase, Resistance of Rotor winding = 0.816 Ω / phase, Rotor inertia J = 0.089 Kg-m^2. A thyristor voltage regulator is coupled to a three-phase, 220V voltage supply, and the motor is excited using the controlled voltage. As shown in Fig. 1(b), the voltage regulator comprises six thyristors stacked in an anti-parallel configuration for each phase. The built-in MATLAB synchronized 6-pulse generator produces the firing pulses for the thyristors. The firing sequence for the various phases is maintained, as illustrated in Fig. 1(d), to ensure the correct operation of the three-phase voltage regulator. The firing pulses given to the corresponding thyristors of the 3 phases differ in phase by 120°, and those used for the thyristors of a particular phase differ by 180° in phase.

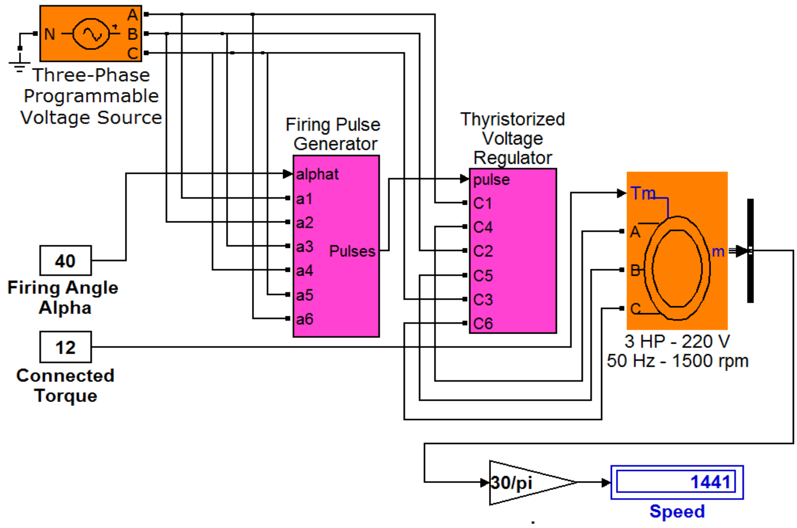


Fig. 1. (a) MATLAB model used for obtaining training data.

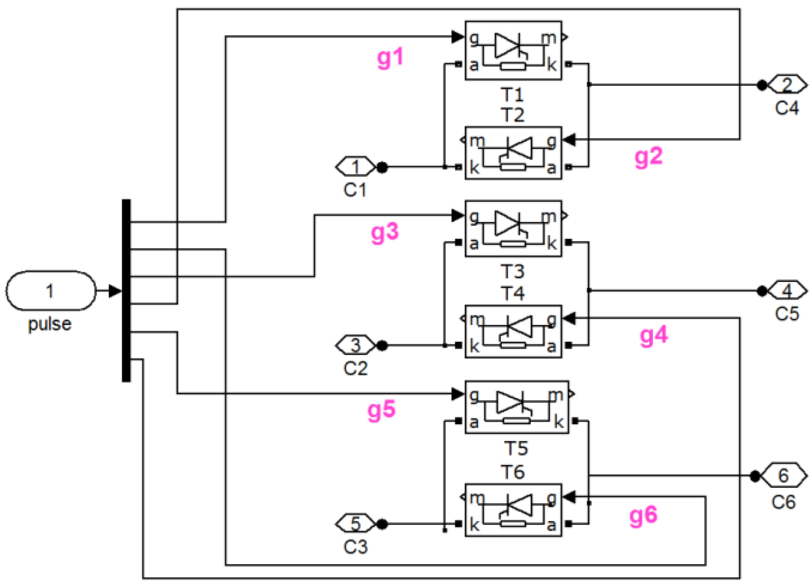


Fig. 1. (b) MATLAB model of the voltage regulator.

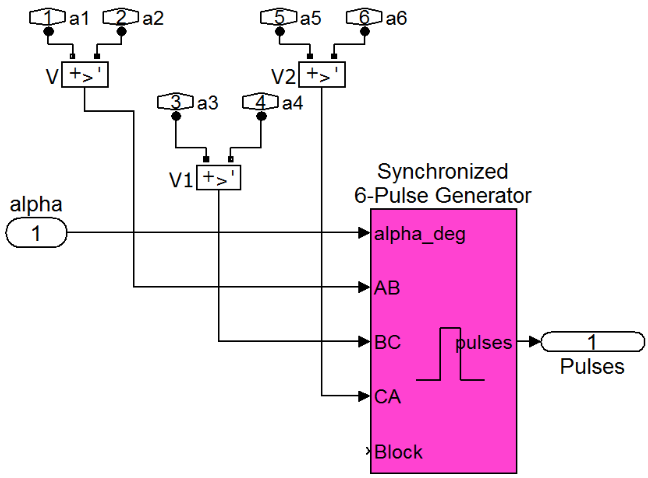


Fig. 1. (c) MATLAB model for firing pulses.

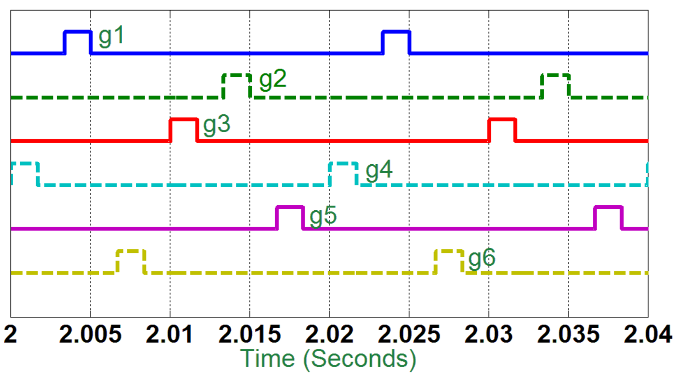


Fig. 1. (d) Firing delay sequence.

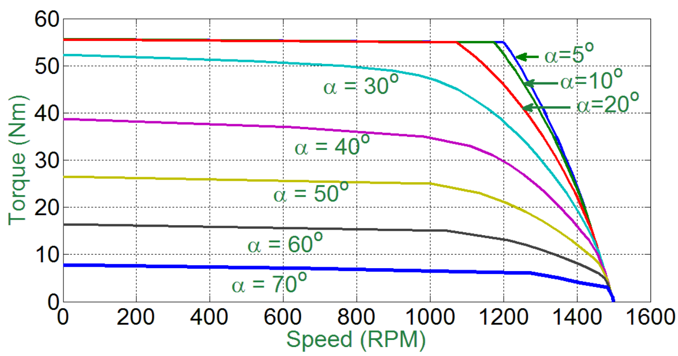


Fig. 2. Torque vs. speed and Torque vs. firing angle "α".

The firing delay given to the pulse generator is varied to control the induction motor's speed. An increase in the firing angle "α" reduces the regulator output voltage or the motor input voltage. Consequently, the motor speed (being proportional to the input voltage squared) reduces. The data required for training the A. I. model is obtained by changing the Torque for a given firing angle "α" and documenting the various speeds obtained. This information, shown in Fig. 2, depicts the typical induction motor speed torque characteristic for a specific firing angle (in its stable working range). A support vector machine-based classifier is used to implement automatic speed control of the induction motor. The classifier is trained by taking the different values of motor torque and speed as inputs and the required firing angle (α) as the output (label). Although determining the firing angle required to generate a specified voltage for the desired speed is a regression problem, multi-level classification has been attempted to achieve the objective.

2.2. *SVM classifier*

SVM, introduced by Vapnik [21], is a machine learning algorithm based on statistical learning and can be used for classification, regression, and ranking [22]. In its basic form, which solves the problem of binary classification, SVM classifies data by locating a hyperplane that maximizes the margin between data points of different classes. If the given input data is not linearly separable, i.e., a linear hyperplane cannot be found, then the data can be mapped from the input space to some feature space by means of a mapping function Φ and a suitable hyperplane can then be obtained [23]. However, mapping back the separation to input space makes the decision boundary non-linear. In practice, this process of transforming data to a higher dimensional space is simplified by using a kernel function that computes the dot product of input vectors. Some commonly used kernel functions are:

(i) Linear Kernel Function

$$K(x, y) = x^T y + c$$

(ii) Polynomial Kernel Function

$$K(x, y) = (\alpha x^T y + c)^d$$

(iii) Gaussian Kernel Function

$$K(x, y) = e^{-\left(\frac{||x-y||^2}{2\sigma^2}\right)}$$

(iv) RBF (Radial Basis Function) Kernel Function

$$K(x, y) = e^{-(\gamma ||x-y||^2)}$$

When SVMs are intended for multiclass classification, two approaches can be used. These are called the One vs One approach and the One vs All approach. In the One vs One method, for a n-class system, n(n–1)/2 number of classifiers are constructed. Each input instance is separately tested for two classes taken at a time, probabilities are added for each case, and a final classification decision is taken based on the maximum vote (or probability) obtained. In the One vs. All method, for an in-class system, n number of classifiers are required, and the training algorithm checks for the proximity of the input instance to a particular class as opposed to an in-class system, n number of classifiers are required and the training algorithm checks for the proximity of the input instance to a particular class as against all other classes. This method is reported to have performed poorly in cases where some of the classes were sparse [24].

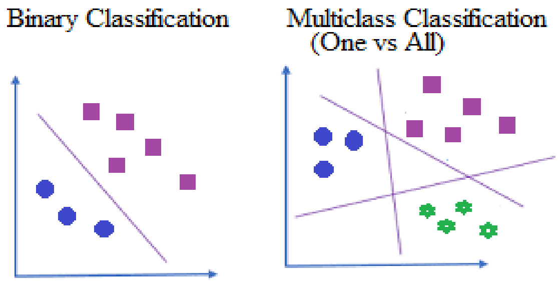
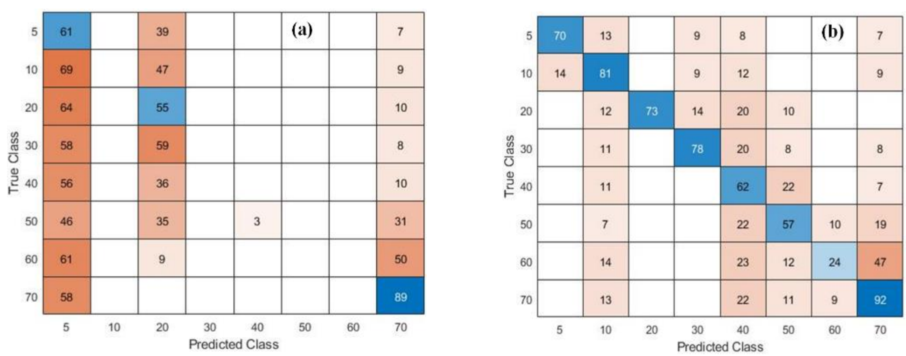


Fig. 3. Binary vs multiclass classification of SVM.

For the present study of the automatic speed control of an induction motor, SVM was implemented in its classification mode using the MATLAB toolbox, and the "One vs All" strategy was adopted. A sample size of 4,850 was used, which included some redundancy for better training. The input vector was of size (4850 x 2), indicating the two inputs (applied Torque and the desired speed), while the target vector (labels) was 8 in number, corresponding to eight different values of the firing angle, namely 5°, 10°, 20°, 30°, 40°, 50°, 60° and 70°. 20 % of the data was reserved for testing, while 80% was utilized for training. Different kernel functions were used for testing: linear, polynomial, gaussian, and rbf. A confusion chart was plotted for each of the kernel functions utilizing the results on the test samples (970). The results are shown in Fig. 4. The accuracy computed by dividing the trace of the matrix by total test samples is 0.2113 for linear, 0.553 for polynomial, 0.612 for Gaussian, and 0.6206 for rbf kernel functions. As the ''rbf'' kernel function has shown the best accuracy, it is selected for the final training and implementation in the speed control block.



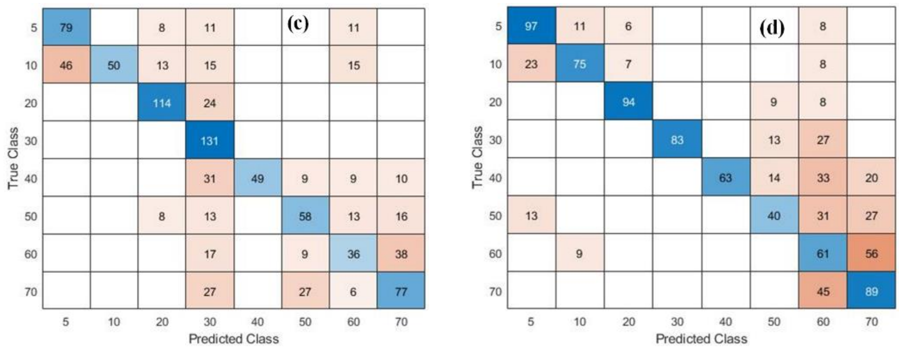


Fig. 4. Confusion Charts for different Kernel Functions studied: a) linear, b) polynomial, c) gaussian, and d) rbf.

3. Soft Starting

A soft starter is created in the work's second section to lessen the starting torque and current pulsations. Depending on the required speed and the load torque, the soft starter calculates and smoothly varies the firing delay. The value of α is changed from an initial high value (which is best picked to be 70°) to the necessary number. The high starting ''α'' results in a small starting voltage and reduced starting Torque. This high value of ' ''α'' is gradually decreased to the needed value. Through simulations, it was found that a value of ''α'' greater than 70^0 produces a voltage too small to start the motor or increase its speed (resulting in unstable operation). Equation (1) can be used to calculate the variance in ''α'' with regard to time. In this Equation, ''A'' is the pre-decided initial value of ''α'', t_R is the time given for ''α'' to reach its final value from the pre-decided high initial value, and ''p'' stands for the rate of change of alpha with respect to time during its transition. The MATLAB implementation of Equation (1) in the form of a block diagram is shown in Fig. (5). The time-varying α, or α(t), is the output of this soft starting block. The block also includes a selector switch for retaining the value of ''α'' after time t_R.

$$\alpha(t) = A + \frac{\alpha_f(t^p)}{{t_R}^p} - \frac{A(t^p)}{{t_R}^p} \quad ; \quad t < t_R \qquad \alpha(t) = \alpha_f \quad ; \quad t > t_R \tag{1}$$

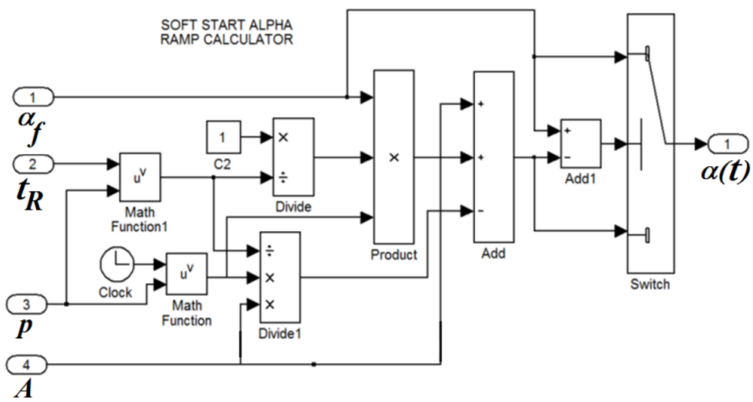


Fig. 5. Soft starting logic implemented in SIMULINK.

4. Simulation Results and Discussion

The complete model implementing the induction motor's soft starting and speed control is depicted in Fig. 6. A 3-ϕ thyristor-based voltage regulator feeds the induction motor. For a given speed-torque combination, the optimally trained SVM classifier block determines the appropriate firing delay "α" (final value) that is supplied to the soft starting block. The soft start block then generates the time varied "α" used in generating the firing pulses.

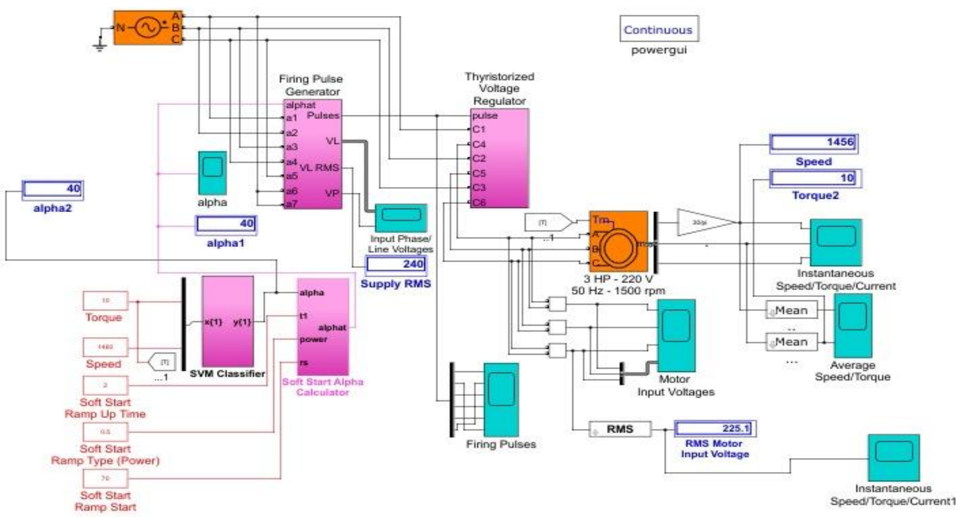


Fig. 6. Simulink Model for SVM-based induction motor starting.

The voltage regulator adjusts the motor input voltage in accordance with the variation in α, thereby regulating the variations in Torque, speed, and current. A number of measurement blocks are inserted to plot the speed, voltage, Torque, and current. The results of simulating the model for various torque-speed combinations are found to be satisfactory. The findings for the torque-speed pair (T = 10 Nm, N = 1456 RPM) are shown in Fig. 7, Figs. 8, and 9 as a sample case. In these Figs., a comparison is made between the performance obtained with soft starting and the performance obtained without its use. In the latter case, the voltage regulator receives the value of "α" determined by the SVM block without any modulation. In the former case, the time variation in "α" introduced by a soft starter is shown in Fig. 7a. For the given scenario, the value of "α" estimated by SVM is 40. By setting p = 0.5 in the block, a quadratic variation of α with time is selected. Fig. 7(b) illustrates the difference in the motor input (regulator output) voltage.

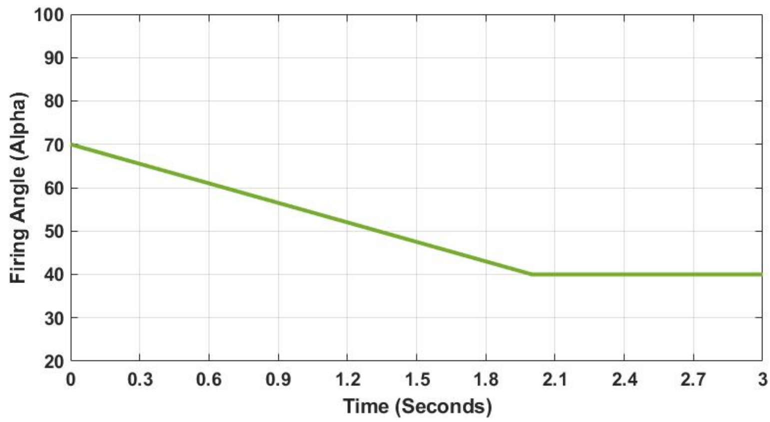


Fig. 7. (a) Firing delay profile – Soft Start.

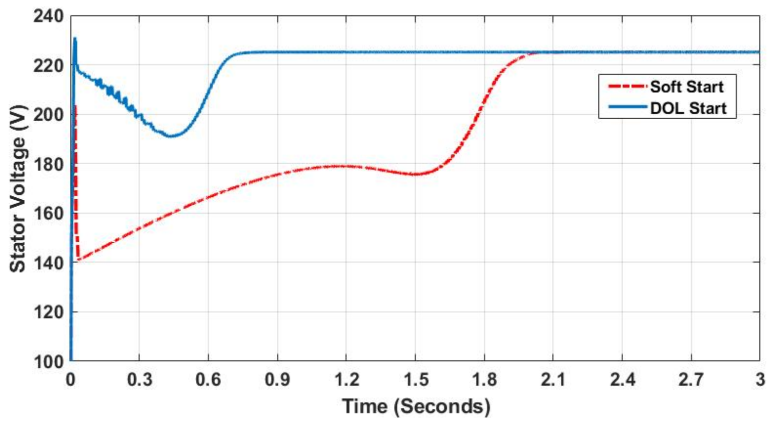


Fig. 7. (b) Motor input voltage profile – DOL start and soft start comparison.

From the voltage profile, it can be observed that when a DOL starter is used, the supply voltage is initially close to 220V, falls, and then gradually rises to 225V (equivalent to α = 40) over the course of around 0.6 seconds. When soft starting is used, the voltage increases over the course of roughly 2 seconds from a starting value of about 140V to the ultimate value of 225V. Once more, a slight decrease is visible at about 1.6 seconds. Next, in Fig. 8, variations in motor speed are shown. According to the speed characteristics, soft starting causes a time delay of around 1.2 seconds when compared to DOL starting before the final speed value (1456 RPM) is reached. In the majority of real-world applications, this delay may be acceptable.

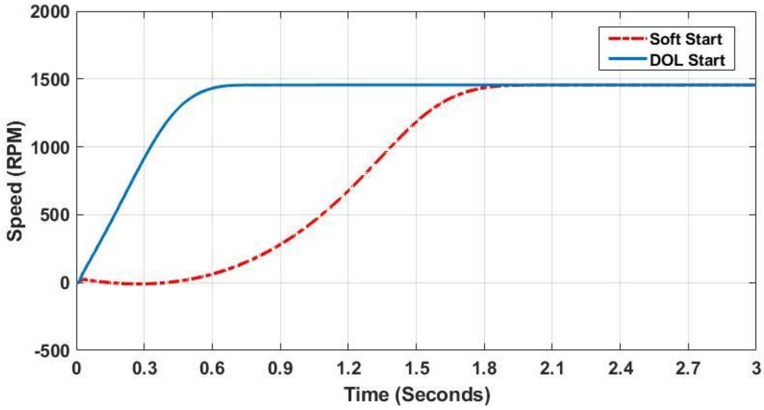


Fig. 8. Motor speed – DOL start and soft start comparison.

The torque and stator current changes displayed in Fig. 9 are the easiest to show the positive impacts of soft starting. Fig. 9(a) shows variations of the average Torque. In DOL start, the average Torque oscillates near 40 Nm during the first 0.25 seconds of the starting period before falling down. When soft starting is used, this high average torque drops to about 10 Nm during the same period. As shown in Fig. 9 (b), variations in instantaneous Torque make it simple to see how early torque pulsations have diminished in size. After a brief period of time, peaking at roughly 20 Nm in the case of soft starting, the motor torque eventually stabilizes at the predetermined level of 10 Nm. In soft starting, however, some additional time lag is seen before the Torque settles down (about 1.2 seconds). A comparison of starting current is made for the two cases in Fig. 9c. It illustrates the benefit of soft starting in decreasing starting current pulsations. When starting on a DOL, the stator current is close to 50A, but when starting softly, it is closer to 25A. In soft start, some increase in the current is observed at a later stage, but the amplitude (33A) is still less than that obtained with DOL. In Fig. 9 (d), the instantaneous currents are displayed. Thus, it is noticed that by using soft starting, current and starting torque pulsations can be minimized.

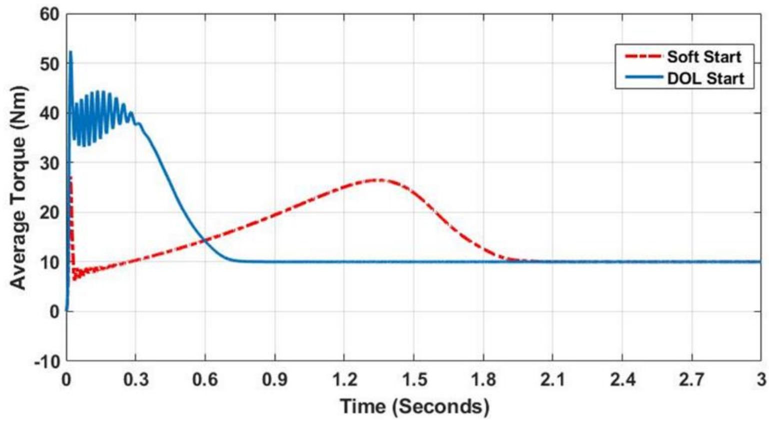


Fig. 9. (a) Average Torque – DOL start and soft start comparison.

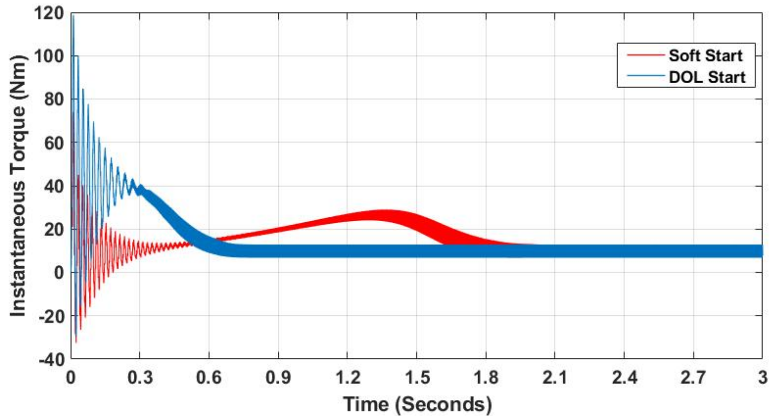


Fig. 9. (b) Instantaneous Torque – DOL start and soft start.

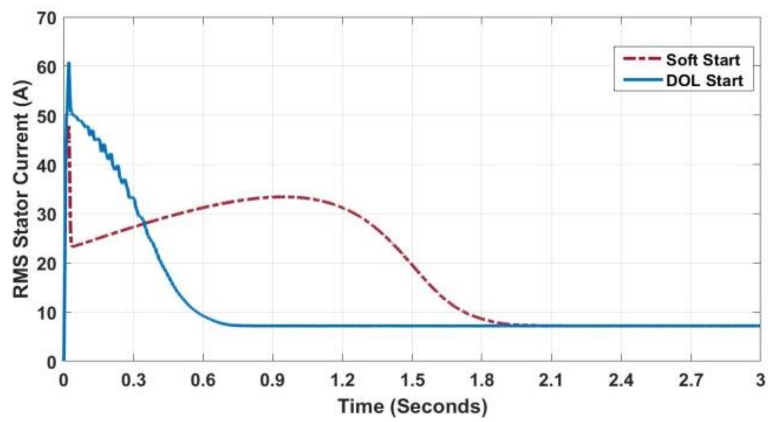


Fig. 9. (c) RMS stator current – DOL start and soft start.

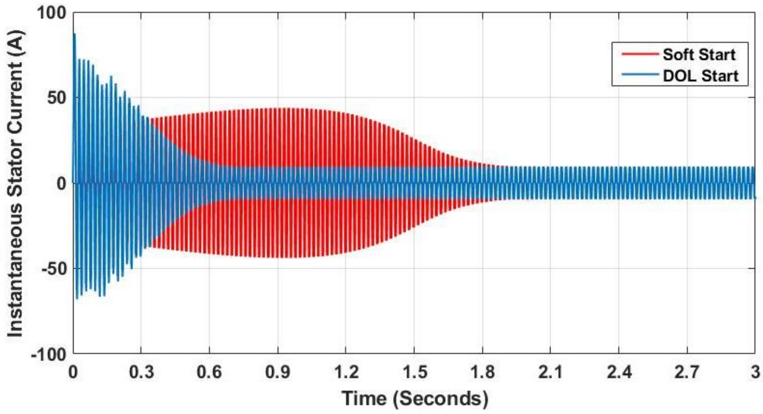


Fig. 9. (d) Instantaneous stator current – DOL start and soft start.

5. Conclusion

This work presents a soft starting method and uses an SVM classifier to control the speed of an induction motor. The SVM controller generates a firing angle appropriate for a given combination of Torque and speed and is initially trained using a variety of speed, Torque, and firing angle combinations. A modulated firing delay is inputted to the thyristorized voltage controller for soft start purposes to feed the motor. The initial Torque and current pulsations are decreased by progressively raising the motor supply voltage. The simulation results are determined to be adequate, and the circuits are implemented using MATLAB/SIMULINK.

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