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Induction Motor Speed Control Employing LM-NN Based Adaptive PI Controller

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Abstract. Induction motors are the widely adopted electrical machines that revolutionized the industrial process due to their versatility, simplicity, reliability, ruggedness, less maintenance, quiet operation, low cost, high performance, and longevity. This paper presents a Levenberg-Marquardt neural network (LM-NN) based adaptive proportional-integral (PI) control strategy for controlling the speed of three-phase induction motor. The adaptive PI controller adjusts the voltage and frequency of the voltage source inverter (VSI) to minimize the reference speed tracking error under abrupt change of mechanical torque. It develops and tests the proposed LM-NN based adaptive PI controller model in MATLAB/SIMULINK platform. Besides, it derives the control properties of volt/hertz technique from its rotor axis oriented mathematical model. Moreover, the output parameters of the LM-NN are tuned employing a heuristic optimization technique called the backtracking search algorithm (BSA) where the objective is to minimize the integral time squared-error (ITSE). The result shows improved transient and steady state performance for the LM-NN based adaptive PI controller over the conventional PI controller that validates the efficacy of the proposed technique.

Key words. Adaptive PI controller; Induction motor; Backtracking search algorithm; Integral time squared error; Levenberg-Marquardt neural network; Speed control.

1. Introduction

Owing to high efficiency, simple hardware structure, robust nature and low cost, induction motor becomes the backbone of the industry. Its application ranges from industrial drives (robotics and motion control),heating, ventilation, and air-conditioning (HVAC)to automatically controlled electric or hybrid vehicles[1]. Dramatic drop of prices of the high computing semiconductor devices make the semiconductor based advanced controller economically viable. It is desirable that the controller must track its reference trajectory regardless of load changes, parameter variation, and model uncertainties. Among different control technique, volt/hertz and vector control are the two most important type controller that have been widely used in the industrial applications[2], [3]. Vector controller can provide the performance same as the direct current (DC) motor [4]. However, parameter variation of the induction motor can reduce the high performance of field oriented or vector controller performance. Additionally, the sensor devices are expensive and prone to malfunction that degrades the reliability of the sensor-based vector controllers. On the other hand, sensor-less drives are also dependent on the parameter of the machines that could be changed with the passage of time. Conventional PI controller and proportional integral derivative (PID) controller can address the problem related to induction motor speed control. However, the dynamic performance of the fixed gain PI and PID controllers degrades over time due to parameter change of the induction machines. Besides, these type controllers do not cover wide range of operating point. Hence, its performance is good to some point but it does not perform well to wide range of other operating points. As a result, controller needs to be continuous adjusted upon deviation from its pre-specified value. Model reference adaptive technique (MRAT) [5] and sliding-mode control (SMC) [6] are few adaptive control techniques that can perform well over wide range of operation for induction machines. However, these techniques are very sensitive to true mathematical model of the system. Developing true mathematical model is difficult for several reasons including highly nonlinearity, temperature and load variation, and system disturbance. Fuzzy logic controller can perform well for the model-based controller, as the mathematical model is not required. Irrespective of the mathematical complexity of the system, its logic-based design can ensure the high performance of the induction motor drives. The practical oriented logic-based algorithm of fuzzy set theory has gradually found many applications in the industry [7]–[9]. However, it requires a large number of computations to process the error and change of error signal to produce meaningful output that requires powerful processor.

Conversely, the ANN is the faster processing network and works well in real life applications [10]. It includes the behavior of human being in its algorithm. Once it is trained, it could process the unknown input and capable of generating optimal output. Since, most of the real-life problems are nonlinear and complex, the ANN became very important due its self-adaptive learning and ability to model complex non-linear relationship. ANN is used in many applications like machine translation, computer vision, filtering social network, speech recognition, video games, image processing, weather forecasting and medical diagnosis etc. The performance of scaler controller can be improved using artificial neural network over wide operating point. Literatures in [11]–[15] have discussed the use of ANN in different type control of induction motor. The article in [16] has used ANN for scaler control of induction motor. However, data generation for ANN training is not based on heuristics technique like genetic algorithm, evolutionary algorithm, differential evolution algorithm, particle swarm optimization, backtracking search algorithm etc. The addition of ANN can improve the existing conventional PI model as it changes the value of K_P and K_I of PI controller due to command change. ANN needs the optimal data set for its training otherwise its performance may degrade.

In this paper, heuristics technique named backtracking search algorithm is used to find the optimum K_P and K_I data set by minimizing the objective function. This work uses the integral of time-multiplied squared-error (ITSE) as an objective function to reflect the weight of percentage of overshoot, rising time, steady state error and settling time. In addition, it applies the backtracking search algorithm to find the best Kp and Ki pair corresponding to minimum ITSE value for a certain operating point. Levenberg-Marquardt neural network is used to form the ANN network using the optimized Kp and Ki training data. To the best of the authors' knowledge, such approach has not been reported yet in the literature. Matlab Simulink platform is used to implement the mathematical model of the induction motor. The design based on ANN based adaptive PI control model is carried out in Simulink and tested its control dynamic on induction motor drive under speed reference change and abrupt load change. This work provides the comparative performance by considering the case of constant speed/constant torque, constant torque/variable speed, variable torque/constant speed and variable torque /variable speed.

2. Proposed controller design

The developed torque expression for constant airgap flux or voltage to frequency ratio is [17]

$$T_{em} = \frac{3p}{2e(\omega_e - \omega_r)} \frac{{E_{m\,rated}}^2}{(r_r' \frac{\omega_b}{\omega_e - \omega_r})^2 + (x_{lr}')^2} r_r' \quad (1)$$

Where, r_r', L_{lr}' are rotor resistance and inductance, p is the number of pole pairs, ω_e, ω_b, and ω_r are angular speed for frequency f_e, angular speed for base frequency f_b, rotor speed. From equation (1), torque can be kept constant over wide range of speed variation by maintaining constant air gap flux or volt/hertz ratio constant. Fig 1 shows the control properties of scaler or volt/hertz control. Artificial neural network based adaptive PI control and conventional PI-control for the speed control of three-phase induction motor is shown in Fig. 2. ANN based adaptive PI control or conventional PI-control process the speed error signal to generate the appropriate frequency for the V/f block, which produces the reference stator voltage for the voltage source converter that drives the three-phase induction motor. V/f block is a look up table, which stores the data corresponding to the Fig 1. Conventional PI control does not change Kp and Ki over its different operating point. However, ANN based adaptive PI control changes its Kp and Ki at different operating point to achieve the improved dynamic performance.

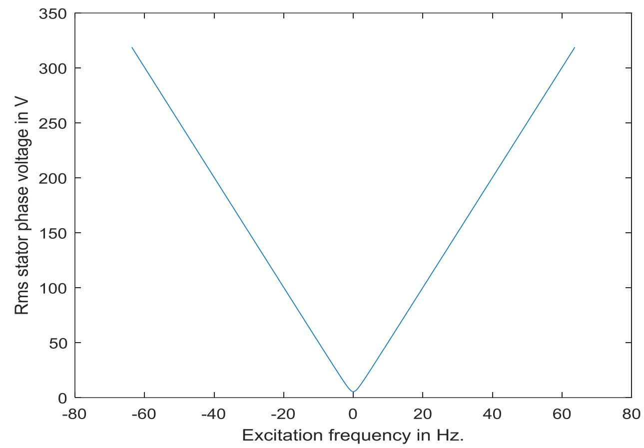

Fig. 1 Constant V/F or Scaler control.

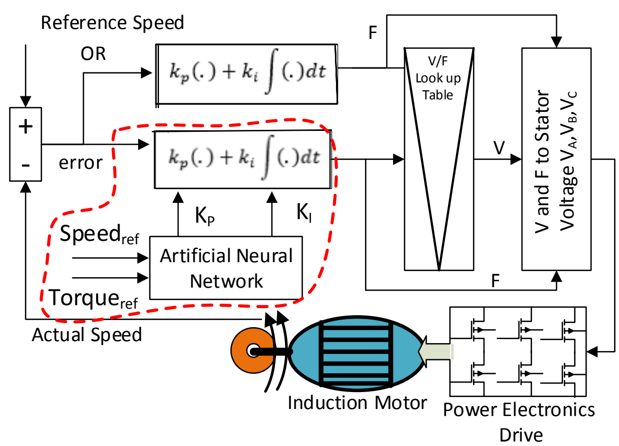

Fig.2 Speed Control system of three phase induction motor.

3. Artificial neural network training

A. Training data generation

Preparing data is the most important for the training, validating and testing the Levenberg-Marquardt neural network (LM-NN). Therefore, we must find out the best value for K_P and Ki at a certain torque and speed of the induction motor. The optimized value of K_P and Ki will ensure smaller steady state error and rise time, reduced percentage of overshot and settling time. However, tracking and measuring these four parameters are computationally expensive. Therefore, error performance indices can be used which yields a single positive number that includes a measure of steady state error, rise time, settling time and percentage of overshoot. Various error performance indices have been proposed in the literature[18]. The integral absolute error (IAE), integral time squared error (ITSE), integral time absolute error (ITAE), and integral squared error (ISE) are the most widely used error performance indices. These indices can be defined as

$$ISE = \int_0^{\tau} e^2 dt \quad (2)$$

$$ITSE = \int_0^{\tau} te^2 dt \quad (3)$$

$$IAE = \int_0^{\tau} |e| dt \quad (4)$$

$$ITAE = \int_0^{\tau} t|e| dt \quad (5)$$

Where, τ is time range.

This work selects ITSE as an objective function to find the best pair of K_P and Ki employing backtracking search algorithm (BSA) technique for different operating conditions. The objective function for BSA is formulated as

$$Minimize\ ITSE = \int_0^{\tau} te^2 dt \quad (6)$$

Subject to:

$$\begin{cases} K_{Pmin} \le K_P \le K_{Pmax} \\ K_{Imin} \le K_I \le K_{Imax} \end{cases} \quad (7)$$

A set of one thousand optimal parameters K_P and K_i for induction motor speed control using PI control are generated employing backtracking search algorithm where ITSE is used as an objective function. The generated data set is used to train the LM-NN network. The reference speed and torque are defined as inputs and the optimal K_P and Ki are defined as targets for the LM-NN network. The details explanation of BSA can be found in [19]–[21]. In brief, BSA comprises the steps of initial population generation, Selection-I, mutation and crossover, Selection-II and finally finding global best solution. Fig. 3 shows the flow chart of BSA optimization technique.

Initial random population is generated using equation (6). Equation (7) is used as fitness function evaluation. Old or historical population is used for finding the search track which is generated through ‘if then’ random condition in stage Selection-I. Old population is further reshuffled using permutation function. Mutation and crossover are performed on the reshuffled old population, which creates trial population. Fitness function is evaluated for this trial population and compared against the initial population fitness function in the step Selection-II to update the initial population. Finally, global best solution is updated if the later trial population fitness function is found better than the former initial population fitness function.

B. Levenberg-Marquardt neural network

Artificial neural network (ANN) mimics the behavior of human being and has the ability of solving difficult problem in efficient way. It became very popular due to its quicker adaptiveness to external disturbances and capabilities of parallel calculation. Multilayer perceptron neural network (MLP-NN) is one of the widely used feed-forward network,

which determines the optimized parameter of PI controller. Among different second order training algorithms, the derivative form of Newton Method named Levenberg–Marquardt (LM) training algorithm is a widely used efficient algorithm [22]. Fig. 4 illustrates the process from generation of optimized data employing BSA to LM-ANN network training. Out of one thousand optimized data set generated by BSA optimization technique, randomly selected 75% data is used for training the ANN and the rest is used for testing.

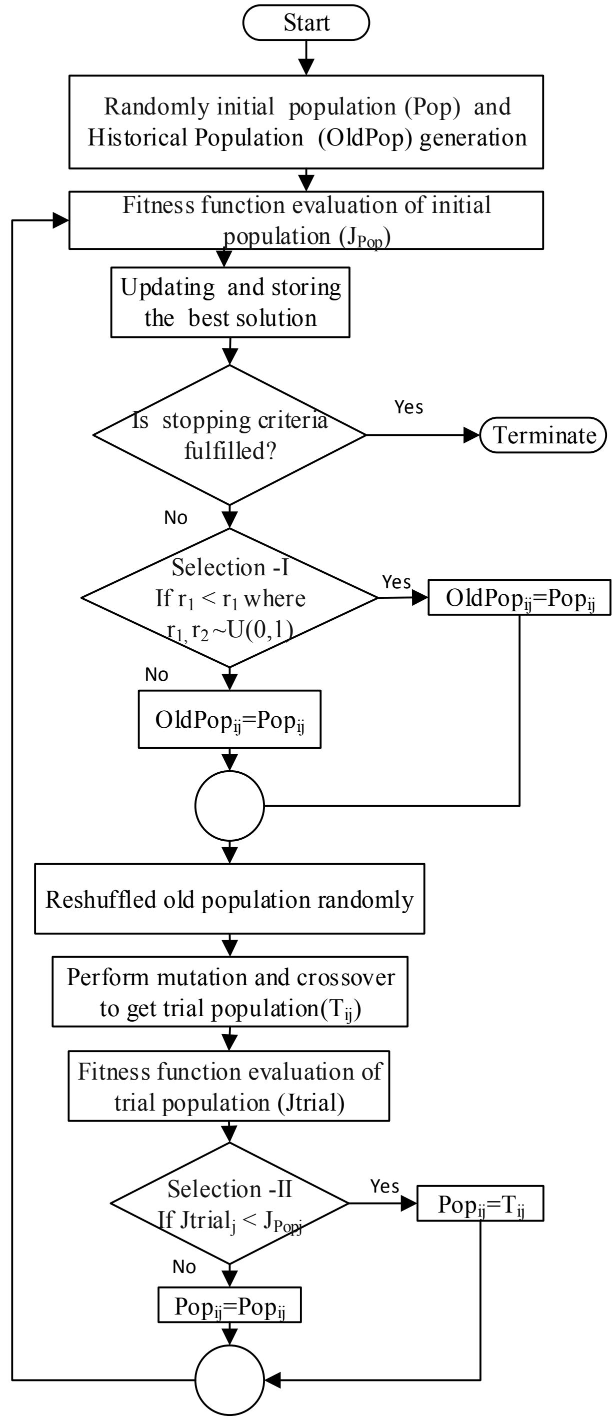

Fig 3 Flowchart of BSA

Testing and training process are continued until its statistical measures become acceptable. Finally, it generates the ANN network for the adaptive PI controller.

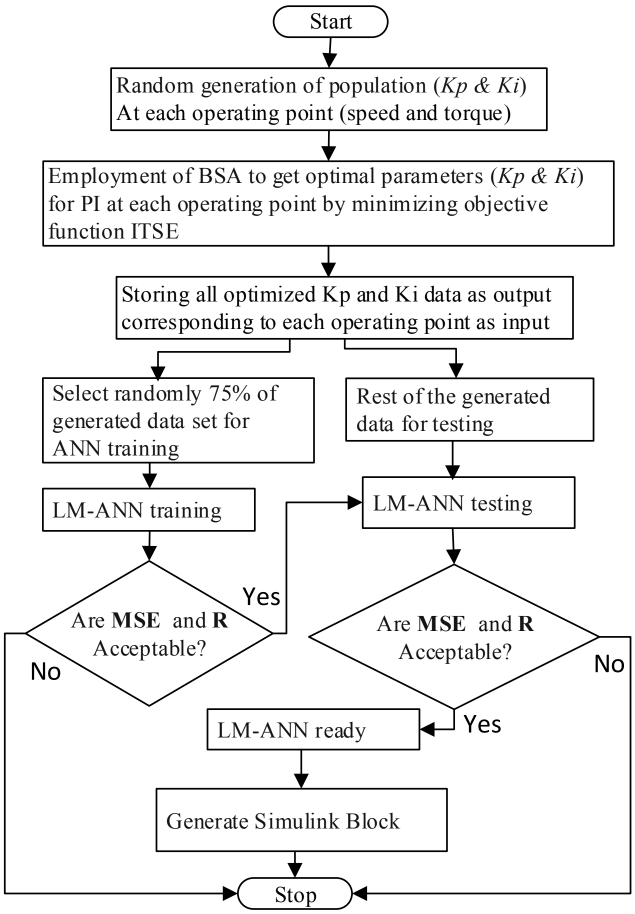

Fig. 4 Optimized LM-ANN network flowchart for adaptive tuning of PI controller

4. Simulation and discussion

This research modeled the LM-NN based adaptive PI and conventional PI controllers for the speed control of a three phase 20hp induction motor in MATLAB/SIMULINK platform. Table I presents the nameplate data of the induction machine used in this study. It is worth mentioning that this research varied the speed and the torque within the tolerable limit of the machine. In addition, the selection of Kp and Ki parameters for conventional PI controller are based on trial and error method. This research estimated the parameters (Kp and Ki) of the adaptive PI controller employing LM-NN based on operating conditions (reference speed and torque) of the machine. The regression (R) and mean squared error (MSE) are determined to evaluate the performance of LM-NN in estimating K_P and Ki. The average squared difference between output and target is called MSE and the correlation between outputs and targets is defined by regression R. Lower value of MSE indicate better train network whereas higher value of R points closer relationship.

TABLE I Induction machine data

Items	Specifications
Rated power	20 hp
System frequency	60 Hz
Rated voltage	220 V
Number of poles	4
Stator resistance	0.1062 Ω
Stator reactance	0.2145 Ω
Rotor resistance	0.0764 Ω
Rotor reactance	0.2145 Ω
Mutual reactance	5.834 Ω

Smaller value of MSE and higher value of R from the Table II presents improved correlation between ANN network based Kp and Ki values and BSA generated optimized Kp and Ki values. Four cases have been considered for the performance evaluation of the ANN based adaptive controller. Fig. 5 presents the performance of speed control for the constant speed and constant torque reference. After 0.5s the speed reference is set at 0.8pu and torque at -0.5pu. Negative sign is used to fit in the figure; however, it operates in the first quadrant. In both cases, actual speed follows the reference speed. However, the zoom view of selected part in Fig. 5 reveals that the conventional PI controller produces 2% overshoot, small steady state error, and large settling time for the actual speed. In contrary, the ANN based adaptive PI controller gives small percentage of overshoot, almost zero steady state error and small settling time. In the second case as shown in Fig. 6, torque is changed while speed remains constant. Conventional PI controller results in higher overshoot at each transition point while it is smaller for the ANN based adaptive PI controller. There is steady state error for the conventional PI controller due to swept change in the torque reference. In the third and fourth case, variable speed/constant torque and variable speed/variable torque have been considered which is depicted in Fig. 7 and Fig. 8 respectively. In both cases, Conventional PI controller produces oscillation around the reference value. However, the dynamic performance of ANN based adaptive PI controller is superior comparing to Conventional PI controller in terms of reducing percentage of overshoot, steady state error and settling time.

Table II Statistical measures of LM-NN technique

Kp and Ki parameters	MSE	R
Training	0.02316	0.95607
Testing	0.04605	0.96055

In summary from Fig. 5 to Fig. 8, ANN based adaptive PI control for the speed control of three-phase induction motor under abrupt load change and reference speed change provides superior dynamic tracking performance over conventional PI control system. The developed electrical torque for the different mechanical reference torque set point for both controller is depicted in Fig. 9. Conventional PI controller provides sustained oscillation in few operating points due to swept change of torque reference point. However, for longer duration of reference torque, oscillation decreases to zero as shown in Fig. 9. For ANN based adaptive PI controller in Fig. 9, it produces high percentage of overshoot at the transient point which quickly decreases and settles to steady state within small time.

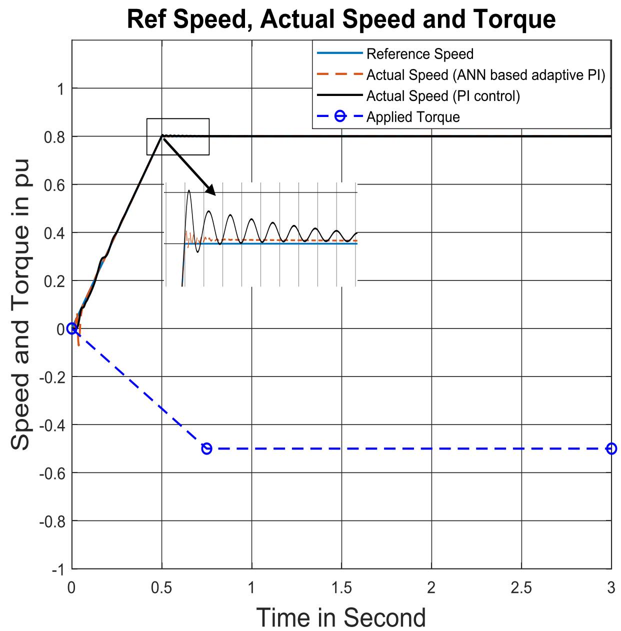

Fig 5. Performance at Constant Speed and Constant Load torque with zoomed view of selected portion

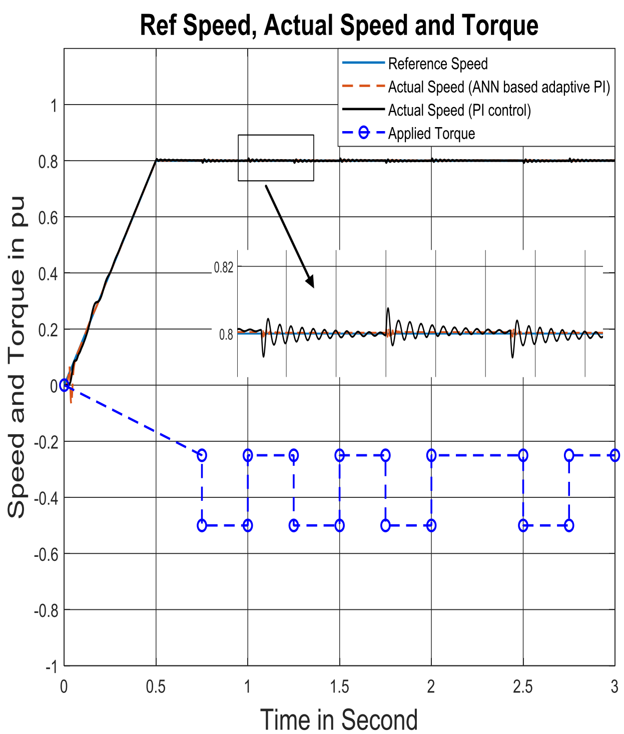

Fig 6. Performance at Constant Speed and Variable Load torque with zoomed view of selected portion

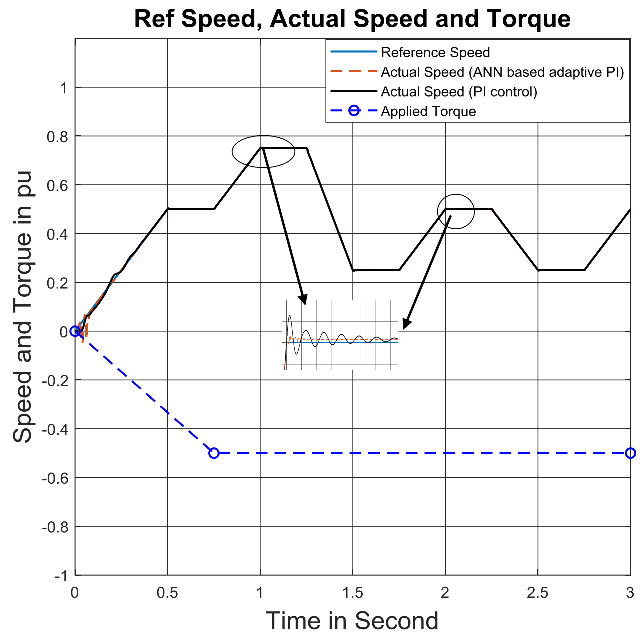

Fig 7. Performance at Variable Speed and Constant Load torque with zoomed view of selected portion

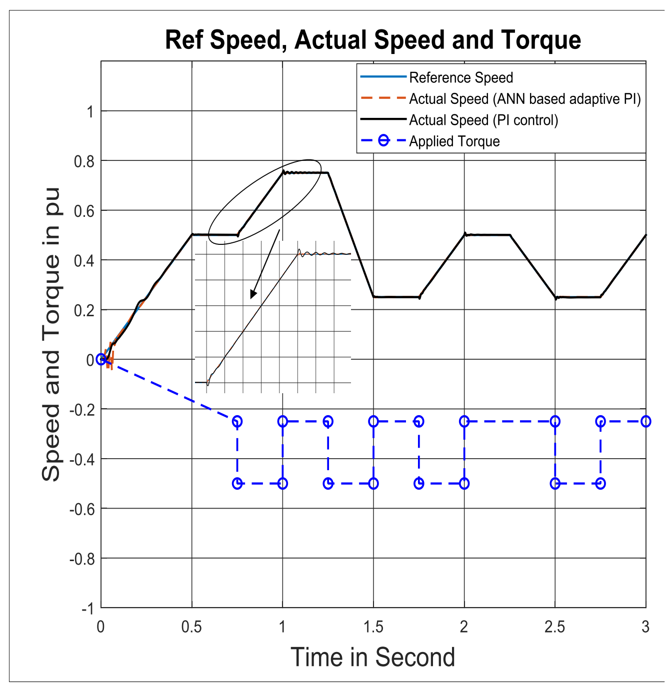

Fig 8. Performance at Variable Speed and Variable Load Torque with zoomed view of selected portion

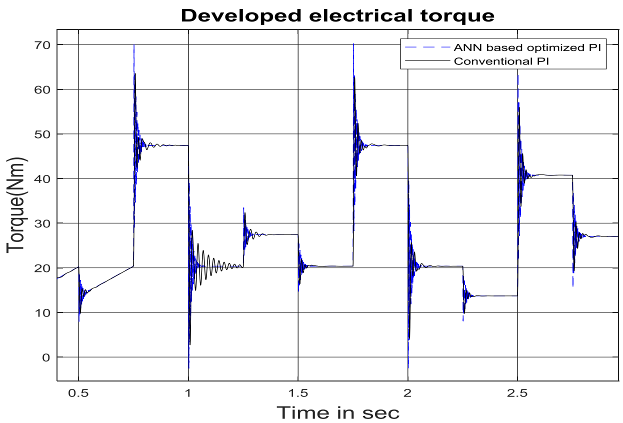

Fig 9. Electrical torque during variable speed and variable torque operation

5. Conclusion

This research developed an ANN based adaptive PI controller for the speed control of three-phase induction motor. It employed a heuristic optimization technique called the BSA to tune the PI controller parameters for a specified range of operating conditions. During the training and testing processes, this paper used the optimized PI parameters as the outputs and the operating conditions as the inputs to the LM-NN. Matlab Simulink platform has been used to test the proposed controller. The result from ANN based adaptive PI controller shows improved performance in reference speed tracking under abrupt mechanical load variation. It investigated the efficacy of the developed controller under different conditions including the constant speed-constant torque, constant speed-variable torque, variable speed-constant torque, and variable speed-variable torque. Simulation results of the proposed controller showed superior performance over the conventional PI controller under abrupt load variation in tracking the reference speed. The controller confirmed its effectiveness in terms of overall steady state error, percentage of overshoot, and settling time compared to the conventional PI controller. As an extension of this work, the proposed method needs to be tested in actual hardware platform.

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