Overload Protection using Artificial Intelligence for DC Motors

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Abstract— *This paper describes the design and implementation of overload protection for DC motor speed control application based on Artificial Intelligence (AI). A replica of DC motor hardware was modeled for simulation. Two neural network models were designed under no load and rated torque conditions to predict the output voltage to be applied for the given DC motor to achieve desired setpoint speed. From the output of a Proportional-Integral (PI) controller the Neural network model will predict the voltage to be applied and a comparator will determine whether the voltage that has to be applied for the current load exceeds than that for the rated torque of the DC motor. The outcome from the comparison is the safety for the equipment by not exceeding rated current value and thereby reduce the thermal degradation of motor windings. A PI controller with delimiter can limit the output of the PI controller and thereby protect the motor windings from higher voltages, still, the windings get degraded when the motor run under overload conditions with lower setpoint speed for longer period. Simulation and real-time experiments along with the results are presented to demonstrate the reliability of the proposed control method over the traditional PI controller in DC motor speed control applications.*

Keywords— *Overload protection, Artificial intelligence, PI controller, DC motor, speed control.*

I. INTRODUCTION

DC motors are used in various control applications including valve actuators, drives for centrifugal pumps, belt driven applications and disk drives because of the features such as high torque, adaptability to various types of control methods and better speed control performance over a wide range resulting in a high level of flexibility for solving complex drive problems [1], [2], [3]. Even though there are several factors that contribute to damage to motor windings such as mechanical damage and high temperature, the prime factor which all the various factors lead to, is the thermal degradation of insulation. The lifespan of insulation is reduced to half for each 10°C increase in winding temperature [4]. The research on the application of Artificial Intelligence (AI) in the field of control system engineering has enjoyed much attention over the past few decades and the credits for this goes to the advancement in computing capability and deep learning algorithms. The power of AI in areas such as auto-tuning of Proportional-Integral-Derivative (PID) controller parameters [5], wind energy [6drainage system monitoring and control [7] provides a strong evidence for the rapid growth and promising future for intelligent control. In this paper, the feasibility of using a combination of AI and PI controller for DC motor speed control and overload monitoring is studied and the controller performance is compared with the classical PI controller in real-time.

The subsequent sections of this paper are organized as follows: the background and methodology for the research are presented under Section II and Section III. Section IV details about the experimental setup and modelling of the DC motor hardware followed by a description about the proposed idea in Section V. The experiments conducted, and result analysis are demonstrated in Section VI. Section VII outlines a conclusion.

II. BACKGROUND

The two essential facts that dictate the speed control for a DC motor are as follows. When the speed of the rotor is regulated, the armature current is determined by the load torque while the rotor speed is determined by load torque under armature current regulation. The relationship between load torque and rotor speed is inversely proportional and the rotor speed reaches zero at stall torque. The rotor speed reaches its maximum value and consumes less current at no load torque condition. On the other hand, at rated torque value, the speed of the rotor decreases and more current flows through the armature coil. The increase in load or moment of inertia will cause the high motor currents followed by thermal degradation of the motor windings from I^2R (I-Current, R-Resistance) heating. The change in load will vary depending on applications. For example, in motor operated valves, if the valve is not operated for a certain period the valve torque increases due to the deposit of particles in between the valve seating area which in turn increases the moment of inertia of the rotor. Various devices and circuits are used along with the motor control circuitry to monitor fault conditions. Such devices include ground fault relays, transient voltage protectors, harmonic filters and thermal overload relays. The thermal overload relays function as overload protector for electric motors and are widely used in the industry [8]. The question arises with these techniques is that what happens to the motor winding when the hardware fails. To vanquish the above problems, we have introduced the overload protection technique at software level using the AI.

A PID controller is a closed loop control mechanism consisting three basic coefficients which are varied to achieve optimal response for a control system and is commonly used in process industries. The purpose of this research is to study how to eliminate the overvoltage signal from the controller without affecting the controller performance under high load condition for a DC motor speed control application. Another serious issue for using a conventional PID controller is that the change in nominal inertia affects the motion control system stability [9]. Even though various tuning methods are existing for the PID controllers, the proper tuning of controllers is still a serious issue for many control applications. A comparison study on the performance of Artificial Neural Networks (ANN) and fuzzy logic control techniques over conventional control techniques for DC motor speed control was conducted by Mo-yuven Chow and Alberico Menozzi [10]. The study states the classical PI controller is more constrained and less flexible compared to that of a fuzzy logic controller. The emerging techniques in controller design improve the performance and stability of the control system compared to that of the conventional controller designs [11], [12].

III. METHODOLOGY

Quantitative approach has been exercised in this thesis as research methodology. The quantitative methodology applied to this thesis has been organized as follows:

Initially, this research performs the analysis of potential hazards and fault conditions for motor and motor protection methods. Also, a detailed study on the application of AI for sequential prediction and control systems were done. The above investigation shapes the problems and limitations with the existing techniques and formulates the problem definition. Modelling the hardware and designing the solution for the identified problems followed by implementation of the design in real-time is the next stage in this methodology. The DC motor model was modeled using real-time hardware-in-the-loop control platform for a DC motor hardware in Matlab/Simulink. The model was verified by simulating the same for no load and full load speed at rated voltage and comparing with the motor data sheet [13]. The derivative term of the PID controller for a DC motor speed control application will be zero due to the first order transfer function of a DC motor [15]. As a result, the PID controller turns to a PI controller. The conventional PI controller under variable load conditions was experimented to study the response from a speed control system for a DC motor. The responses for the mathematical model of DC motor were within the tolerance limit and the same model was used to generate the training data and testing data for designing neural network models for the proposed solution. Even though the speed of the motor measured in real time was within the tolerance limit, the slight noise in the measurement can be eliminated by the mathematical model due to its stable output. The prediction of the supply voltage to obtain corresponding speed was done by the neural network model designed using the neural network toolbox in Matlab/Simulink. The proposed

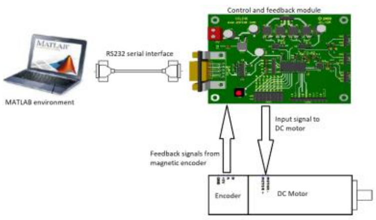

Fig. 1: Schematic representation of the system

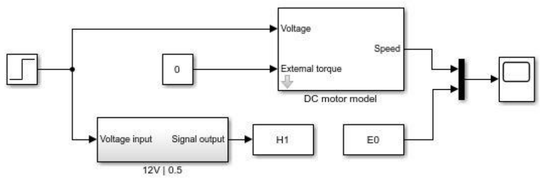

Fig. 3: Simulink model for system analysis

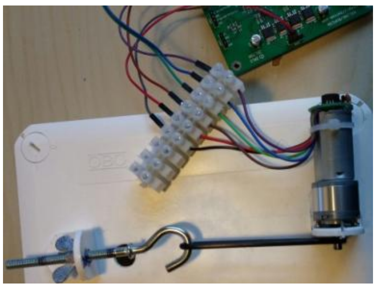

Fig. 2: Load test arrangement

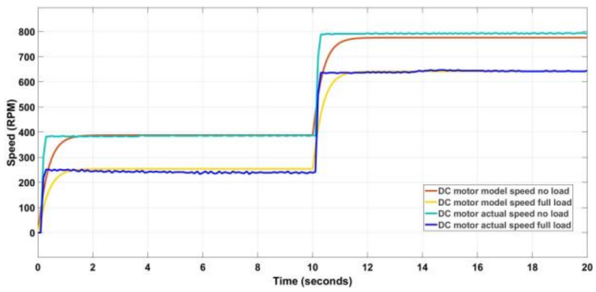

Fig. 4: Step input response for mathematical model and DC motor

solution was tested in real-time followed by comparing with the classical control methods comprises the evaluation of test results. Finally, the method ends with a conclusion that discusses the contribution of the work done. Fig. 1 shows the schematic representation of overall system and Fig. 2 shows the load test setup for the real-time experiments.

IV. DC MOTOR MODELLING

The DC motor is a power actuator device that delivers energy to a load by converting direct current electric energy into rotational mechanical energy. The dynamic equations for a DC motor are as follows:

$$d\omega/dt = 1/J\ (K_m - B.\omega - m) \quad (1)$$

$$di/dt = 1/L\ (V - R.i - K_e\omega) \quad (2)$$

Where, J is the moment of inertia of the rotor, K_m is motor torque constant, i is the armature current, B is motor viscous friction constant, m is the external disturbance/load torque, L is electric inductance, R is electric resistance, and K_e is electromotive force constant [16]. The values for above parameters for the given DC motor were calculated and shown in Table I from the motor response to various real-time experiments [13], [14].

TABLE I
DC MOTOR PARAMETERS

Parameters	Symbol	Value	Units
Motor torque constant	K_m	8.91×10^{-2}	N.m/A
Armature coil resistance	R	5.0	Ω
Moment of inertia of the rotor	J	9.52×10^{-5}	$Kg.m^2$
Viscous friction constant of the motor	B	1.28×10^{-4}	N.m/rad/s
Inductance of the armature coil	L	0.167	H
Electromotive force constant	K_e	8.28×10^{-3}	V/rad/s

Figure 3 shows the Simulink model designed for studying the behavior analysis between the DC motor hardware and the mathematical model. The 12V|0.5 block perform the scaling of the signal for the input to the control module. The H0 block applies the signal to the motor driver unit while, E0 block collects the feedback signals from the encoder and calculates the speed of the DC motor [14]. Figure 4 shows step input response of the system and the mathematical model under full load and no-load conditions. To test the accuracy of the model, the load torque was varied in mathematical model as well as in real time followed by comparing the measured speed from both, with the actual no-load speed (789 rpm) and rated speed (639 rpm) for the given DC motor. The speed tolerance for given DC motor is +/-15 rpm [13].

V. PROPOSED METHOD

The entire idea behind the method revolves around utilizing the controlling capability of a conventional PI controller along with the prediction capability of Artificial Intelligence. The setpoint speed is fed into the PI controller which calculates the corrected value of speed and delivered to the neural network model which predicts the voltage to the DC motor. The voltages from two different neural network models (one trained under the no-load condition and other trained under full load condition) are then compared to monitor the variation in voltage from the load variations and delivered to the DC motor. The block diagram representation of the proposed solution is shown in figure 5. The motor will be tripped at software level if an overload condition is detected while, the motor will run smoothly under normal load conditions. The maximum load condition was determined from the rated torque for the given DC motor i.e., 0.03 N-m [13].

A. Data Pre-processing

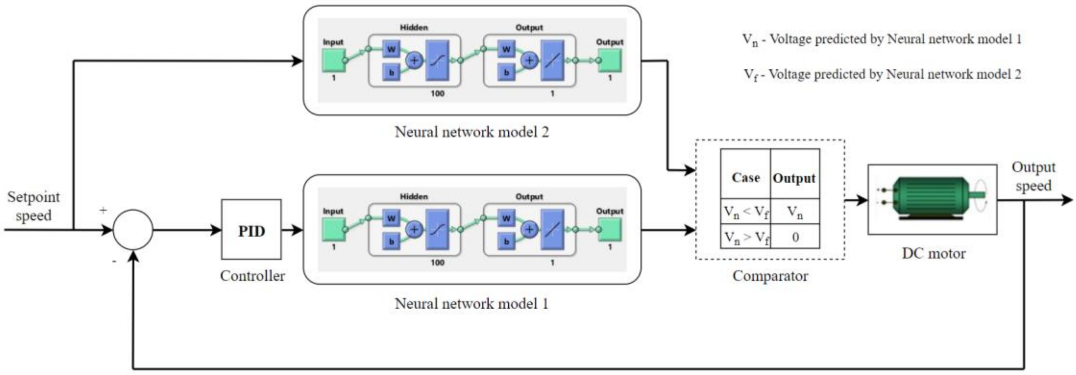

Fig. 5: Block diagram representation

The data consists of features which are the descriptive attributes and labels which are the outputs/predictions from the neural network. In this research, the setpoint i.e., the speed of the rotor at different voltages are the features and corresponding voltages are the labels. The rotor speed and corresponding voltage are collected by simulating the model using the plant identification tool from the neural network tool box in Matlab/Simulink. The sample data collected were loaded into the neural fitting tool in Matlab, in matrix column format followed by dividing the data sets into 70 percent for training, 15 percent for validation and 15 percent for testing. The validation data helps to stop training when the generalization is not further improving, by measuring the network generalization while the testing data helps to provide an independent measure of network performance. From the experiments conducted, it was observed that the prediction accuracy was less for 10,000 data samples. As a result, a total of 100,000 samples were collected, shuffled and divided into two sets in which one set consists 0f 70,000 data for training and the other set consisting of 30,000 data for testing and validation.

B. *Modelling and Training of Neural Network*

Recurrent Neural Networks (RNN) are the traditional neural network architecture that is used for the sequence to sequence prediction [17]. The Levenberg-Marquardt algorithm is used for training the neural network. Even though the algorithm consumes more memory, the processing time is very less and automatically stops when the generalization reaches a point at which there will be no further improvement [18]. The measure of generalization is calculated from the mean square error of validation samples. The network parameters consist of a single input layer, 100 hidden layers with sigmoid transfer function as activation and a single output layer with a linear transfer function as activation. Finally, the model has been tested for the test datasets.

C. *Implementation*

The PI controller regulates the input speed to neural network model based on the setpoint speed and the measured feedback. The controller gain values were identified using the PID tuner tool from control system toolbox in MATLAB. From the PI controller output one of the neural network model (trained under no-load condition) will predict the voltage input that has to be applied to DC motor. On the other hand, the other neural network model (trained under rated torque condition) will predict the voltage for monitoring the overload condition from the setpoint speed. A comparator along with a switch will route the safe voltage to the control system hardware. The final comparison was done to ensure that the armature current not exceeding the rated current of the motor and thereby ensure the equipment safety.

VI. EXPERIMENT AND RESULT ANALYSIS

A. *Test scheme*

For verifying the proposed method under normal load conditions, initially we deal with 50 percent of rated torque with a step input change from 300 rpm to a setpoint of 500 rpm. In the later experiment, the load torque was decreased to 75 percent followed by an increase of 110 percent of rated torque after 30 seconds to test the system response for overload conditions with the same step input as that of the first experiment. Finally, the experimentation was done at rated speed and overloaded condition, to study the controller response when, the system is unable to achieve the desired setpoint. For the above experiment, the step input changes from 300 rpm to a setpoint of 639 rpm instead of 500 rpm. The performance of a conventional PID controller and the proposed method was compared. The rated torque for the given DC motor is equal to 0.03 N-m [13].

B. *Test results*

In this section, results from various experiments are described. Figure 6 and Figure 9 shows the

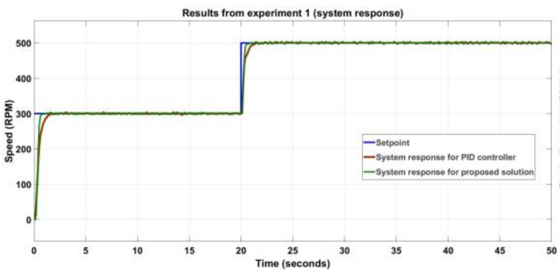

Fig. 6: System response – normal load conditions

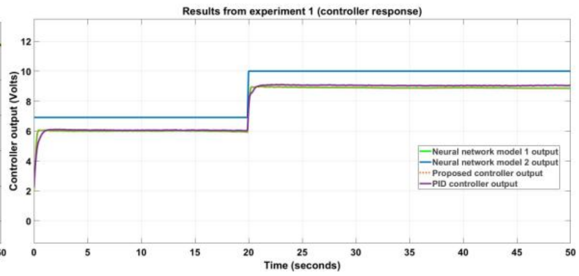

Fig. 9: Controller response – normal load conditions

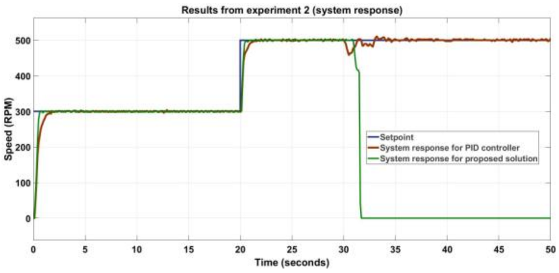

Fig. 7: System response – overload load conditions

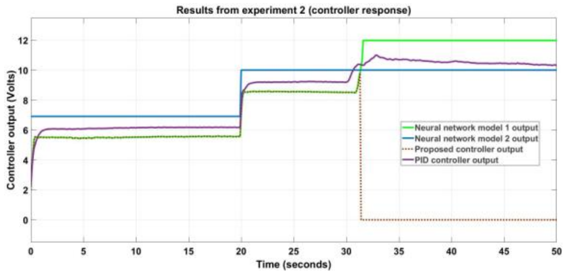

Fig. 10: Controller response – overload load conditions

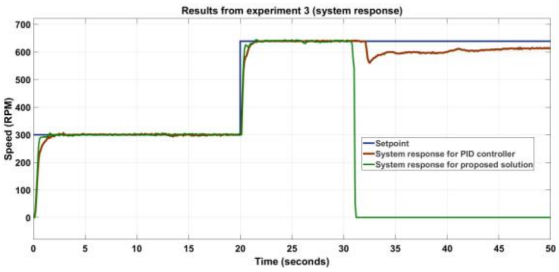

Fig. 8: System response – overload conditions at rated speed

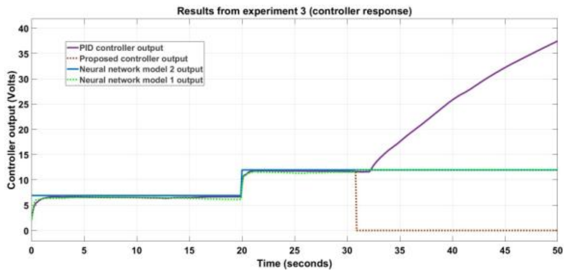

Fig. 11: Controller response – overload conditions at rated speed

system response and controller response for PI controller and proposed solution under normal load conditions. Figure 7 and Figure 10 shows system response and controller response for PI controller and proposed solution for overload conditions. The system response and controller response at overload condition and rated speed of DC motor for both control methods (PI controller and proposed solution) are shown in Figure 8 and Figure 11.

C. Evaluation

From Figure 9, it was observed that overall system stability for proposed solution and the traditional PI controller looks similar at normal load conditions while, with the proposed solution, controller achieves the stability bit faster than the conventional PI controller and is represented by the green line in Figure 10. At overload conditions the PI controller pushes the system to its extreme conditions to achieve the setpoint as shown in Figure 10. As a result, the system achieves the desired set point as shown in Figure 7 but, the system running under these conditions for the long-term will thermally degrade the motor windings and thereby damage the motor. On the other hand, the proposed solution will trip the DC motor to zero when an overload condition exists while the system is running at normal load conditions and the proposed controller response is represented by the brown dotted line shown in Figure 10 and the result is the safety of the equipment. The blue shaded line represents the output of neural network model trained under full load conditions which is same as the response of the given DC motor for the same setpoint at rated torque conditions. Figure 8 and Figure 11 details system response of both control strategies at overload conditions at rated speed conditions. The system will not be able to achieve rated speed of 639 rpm when load torque is greater than the rated torque of 0.03 N-m and it has been observed that the PI controller output will go on increasing at the above conditions while with the proposed control strategies the DC motor gets tripped.

VII. CONCLUSION

In this paper we designed and implemented an AI-based protection technique for overload conditions in DC motor speed control applications and examined the performance and reliability of the same with the classical PI controller in real-time.

From simulation results and evaluation, it was observed that, the system behavior for overload conditions is better in terms of equipment safety in comparison to its rival PI controller. Even though a delimiter along with a PI controller can limit the output of the PI controller for DC motor protection, from higher voltages, the probability for the occurrence of DC motor winding damage exists when the motor run under overload conditions with lower setpoint speed for a longer period. The proposed solution proves its feasibility by tripping the motor at the above conditions and thereby, ensure the safety of equipment in a long-term run.

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