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Online PI Controller Tuning for a Nonlinear Plant Using Genetic Algorithm

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***Abstract*— Proportional – Integral – Derivative (PID) controller performs well for linear systems. For systems with nonlinearity, controller parameters need to be tuned every time for new operating point to obtain 'local gain parameters'. These local gain parameters are not sufficient to get satisfactory performance at other operating points. In this paper a novel approach 'Aggregate Fitness Function' is presented to obtain the 'global gain parameters' that works satisfactorily at various operating points. Online optimization scheme with Genetic Algorithm (GA) is adopted to tune the Proportional-Integral (PI) controller parameters for setpoint tracking of DC Motor by minimizing Integral-Time-Absolute-Error (ITAE). Hardware validation of the results is presented and studied. The plant under study is DC Motor Control Module (MS15) from M/S LJ CREATE™. M/S National Instrument (NI) based software and hardware components i.e. LabVIEW™ and its add-ons toolkit and Data Acquisition (DAQ) Card has been utilized for online tuning and closed loop run time control. The simulation and run time results clearly show the efficiency of the proposed approach.**

Keywords—PI controller; online tuning; DC motor control; genetic algorithm; aggregate fitness function

I. INTRODUCTION

PID controller, since its origin and development, has been an important ingredient of process industries. PID has been termed as the 'Bread and Butter' of control engineering by K. J. Astrom [1]. PID controller has vital functionality of providing feedback; eliminating steady state offsets through integral action and anticipating the future through derivative action. According to the survey conducted by 'The Japan Electric Measuring Instrument Manufactures' Association in 1989, more than 90% of the control loops are of PID type [1]. Further, Audits of Paper Mills in Canada shows that a typical mill has more than 2000 control loops and that 90% use PI (Proportional-Integral) control. It has been found in literature that PID controllers are sufficient for control problems having benign process dynamics and modest performance requirements. But when we talk about process variability, PID controllers' performance depends largely on tuning of its gains parameters. Two classical methods for determining the parameters of PID controllers were presented by Zeigler and Nichols in their paper 'Optimum Settings for Automatic Controllers' in 1942 [2]. These tuning methods are very simple to use and require little process information and that's why still these methods are widely applied. But they suffer from many drawbacks. The fundamental drawback is the requirement of having closed loop system with quarter amplitude decay ratio which creates a very poorly damped closed loop system that has poor stability margin. Chien, Hrones and Reswick (CHR) suggested 'quickest response without overshoot' as design criteria and Cohen-Coon in 1953 proposed open loop tuning method for PID controller as modifications to traditional Ziegler-Nichols tuning formulae. Classical rules utilize control system information and a fixed performance index for implementation. This is the reason why Nature Inspired Optimization methods were being explored to tune the PID parameters. These techniques enjoy the benefits of customized performance index with very little process information. The aforementioned tuning rules perform well for a linear control system, but as nonlinearity or uncertainty increases in the system, trade-off between controller performance and controller design complexity has to be carried out. Model uncertainty can be seen as disturbance or other imperfections in model parameters. To deal with these uncertainties, various methods namely, frequency domain methods based on amplitude and phase margin, H_∞ and gain scheduling have been proposed in the literature [1]. It has been found that to deal with the model uncertainty and nonlinearity, the controller parameters have to be tuned at different operating point, means fresh tuning is required for every new operating point. So, the tuned parameters obtained are 'local gain parameters'.

In this paper, a novel approach namely 'Aggregate Fitness Function' is proposed to obtain the PI controller gain parameters which can give satisfactory results at all operating points i.e. to obtain 'global operating parameters'. Online tuning using GA is used to obtain the optimal gains of PI controller for DC motor speed control in run time. The hardware validation of the proposed scheme has been performed and presented in this work.

The rest of the paper is organized as follows: Section II describes the problem formulation part, PID controller and description of experimental setup; Section III discusses the plant nonlinearity and system identification part; Section IV proposes the novel approach and discusses controller tuning and GA; Section V discusses the simulation and experimental observations.

II. PROBLEM FORMULATION AND SYSTEM DESCRIPTION

It has been generally seen that when a PID controller is tuned at one operating point, it gives satisfactory performance only at that operating point. When the same PID controller with same tuned gains is used to operate at other operating points, satisfactory performance is not guaranteed. Fig.1shows DC motor response for two set-points i.e. 1V and 3V when PI controller gains tuned at 1V are used for both set-points. It can be clearly inferred from the figure that overshoot is increased up to 20% and settling time is increased up to 7 times when controller tuned at 1V is used for 3V. Though there are many methods available in literature to deal with the aforementioned problem such as gain scheduling, robust controller, adaptive controller etc. but these methods require a priori and exact information about the process and more sophisticated hardware implementation which ultimately increases system complexity and cost. Therefore, a methodology is needed to deal with the above said problem in simplest possible manner.

A. *PID Controller*

The PID controller is a vital part of almost every process industry from last several decades. The PID controller, in the form we know it today was emerged in the period of 1915 to 1940. The textbook version or the parallel form of PID controllers is given as,

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} + u_s \quad (1)$$

Where, $u(t)$ is controller output, $e(t)$ is error, u_s is the bias, K_p is proportional gain, K_i is integral gain and K_d is derivative gain.

The P-term known as Proportional term is responsible for controller action where the characteristic of controller is proportional to the control error. Proportional controllers were introduced as a remedy to the oscillations which occur in an On-Off controller. The main function of I-term i.e. the Integral term is to reduce the steady state offset which occurs in a proportional controller. In the integral action, the control signal, at any instant of time is the area under the actuating error signal curve up to that instant. So, even a small positive/negative error will give an increasing/decreasing control signal. The purpose of D-term i.e. Derivative term is to improve the closed loop stability by anticipating the actuating error and initiating an early corrective action. Derivative control action responds to rate of change of the actuating error and produces a significant correction before it becomes too large.

B. *System Description*

This section discusses the DC motor control module, DAQ card, and the experimental setup.

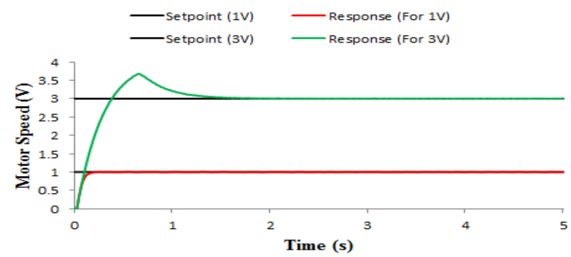

Fig.1. DC Motor Response for 1V and 3V with PI Controller Gains

1) *DC Motor Control Module*

The MS15 DC Motor Control Module [6] as shown in Fig. 2 enables the user to perform closed loop positional and speed control of DC motor. The speed and direction of the motor can be controlled by either an analog signal or a pulse width modulated digital signal. The motor take ±5 V as drive input which can run the motor up to a speed of 2500 RPM in either direction. The tachogenerator, used to convert motor speed to corresponding voltage, can give ±5 V at maximum speed in either direction. Disturbance can be introduced in the motor by an arrangement of 2 position eddy current brake. The module operates on two ranges of power supplies, ±5 V at approximately 400mA and ±12 V at approximately 0.5 to 0.9A respectively.

2) *DAQ Card Specifications*

NI PCI-6221 is used as DAQ card for data acquisition and control signal generation. It consists of 8/16 Differential/Single ended input channels and 2 output channels with input/output voltage range of ±10 V and is capable of acquiring data at maximum sampling rate of 250KS/s [7].

3) *Experimental Setup*

The scheme and snapshot of experimental setup is shown in Fig.3 and Fig.4. It consists of MS15 DC Motor Module connected to Intel Core 2 Duo, 1.99 GHz HP PC with Windows XP operating system via NI PCI-6221 DAQ card. The main application program and online tuning of PI parameters is done on LabVIEW™ environment. The run time data for speed of motor for setpoint tracking is acquired at sampling rate of 100S/s.

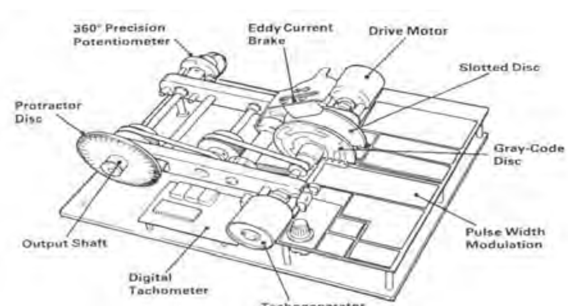

Fig.2. DC Motor Control Module Schematic Diagram[7]

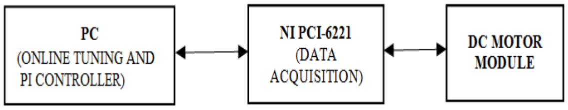

Fig.3. DC Motor Speed Control Scheme

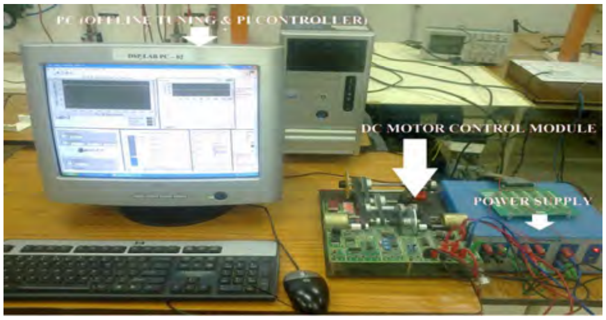

Fig.4. DC Motor Control Experimental Setup Snapshot [7]

III. SYSTEM MODELLING

This section discusses plant nonlinearity and system identification part.

A. Plant Nonlinearity

Fig.5 shows the plant's input-output characteristics for input voltage cycle 0V→5V→0V →-5V→0V. Nonlinearity in the form of dead zone can be clearly seen in the curve. When motor starts from zero voltage it requires more drive voltage to overcome the inertia, same phenomenon occurs when motor speed comes to zero and reverses its direction.

B. System Identification

In this paper, system identification is done on two different operating points. Firstly, the DC motor is excited with 1V and then with 3V in open loop respectively and transfer function on both operating points is estimated using system identification toolbox of LabVIEW™. The transfer function obtained for 1V as operating point and 3V as operating point is given by (2) and (3):

$$y(s) = \frac{0.713948}{1 + 0.29188\, s + 0.00416103\, s^2} u(s) \tag{2}$$

$$y(s) = \frac{0.807643}{1 + 0.274586\, s + 0.00473392\, s^2} u(s) \tag{3}$$

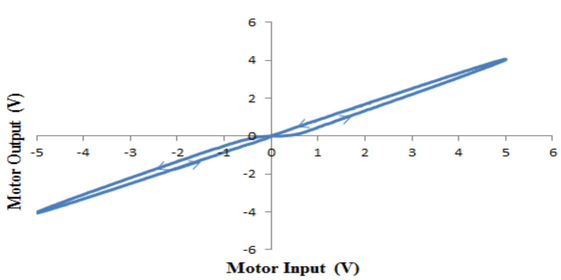

Fig.5. Motor Output(V) vs Motor Input (V)

Where, y(s) is DC motor speed scaled in voltage and u(s) is the excitation voltage. Parameter variation in the system can be inferred from (2) and (3) as 14% change in open-loop gain is seen in transfer functions obtained at 1V and 3V. For converting DC motor speed in RPM into corresponding voltage a tachogenerator integrated with the experimental setup is used. The tachogenerator is assumed to have zero order dynamics with a constant gain of 75.4248 RPM/V. Fig.6 and Fig.7 show open loop simulated and measured data for u=1V and 3V respectively. The curves clearly show the exactness of actual and estimated plant model. The closed loop simulated and run time curves for 1V and 3V operating points are shown in Fig.8 and Fig.9 respectively.

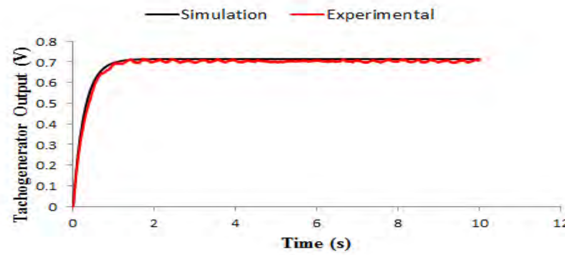

Fig.6. Open Loop Simulated and Experimental Data for 1V Input

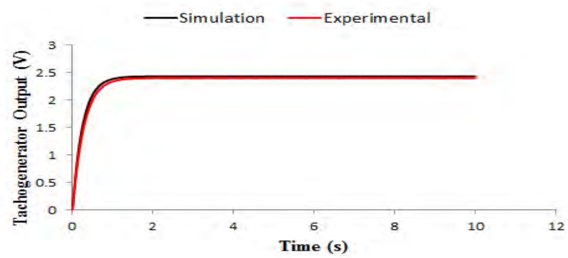

Fig.7. Open Loop Simulated and Experimental Data for 3V Input

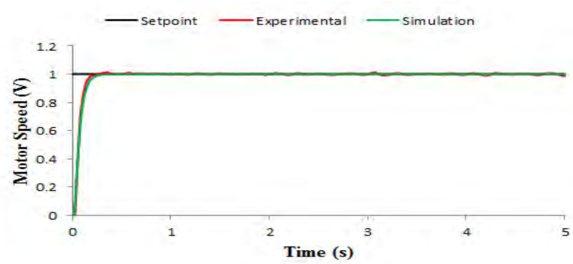

Fig.8. Closed Loop Simulated and Experimental Data for 1V Input

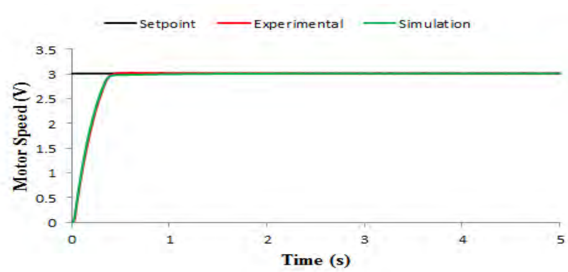

Fig.9. Closed Loop Simulated and Experimental Data for 3V Input

IV. PROPOSED APPROACH

This section discusses the proposed approach, controller tuning and GA.

A. Aggregate Fitness Function

In this approach, to deal with the system's parameter variation due to nonlinearity, a new fitness function is defined that has the equally weighted fitness function values obtained by tuning the controller at two different operating points (say at lower and higher operating point). The two operating points are chosen in such a way that the plant nonlinearity is incorporated in that. For simplicity let us assume 'A' be the case when PI controller is tuned for a setpoint of 1Vand has fitness function J_1, 'B', be the case when controller is tuned for a setpoint of 3V and has fitness function J_2 and 'A+B' be the case when controller is tuned for both cases A and B and has an Aggregate fitness function given by $0.5(J_1+J_2)$, where, J_1 and J_2 are ITAE for case A and B respectively. For simulation (offline tuning), the two fitness functions A and B are called in parallel while in run time (online tuning), A and B are cascaded as shown in the Fig. 10.

B. Controller Tuning

Offline [5] and online optimization utilizing GA has been adopted for PI controller tuning in simulation and run time as shown in Fig.12 and Fig.13. In online optimization technique the simulated plant model is replaced by the actual plant i.e. run time parameters' updating is achieved. The performance index taken for optimization is Integral-Time-Absolute-Error (ITAE) given by

$$ITAE = \int t\left|e(t)\right|dt \quad (4)$$

As discussed earlier online tuning is done for three cases namely for A, B and A+B. The optimization specifications and the values of Proportional gain K_p and Integral gain K_i (Experimental and Simulation) on above mentioned cases are tabulated in table I, table II and table III respectively. The fitness vs. Iteration curves for these cases are shown in Fig. 14, Fig.15 and Fig.16 respectively.

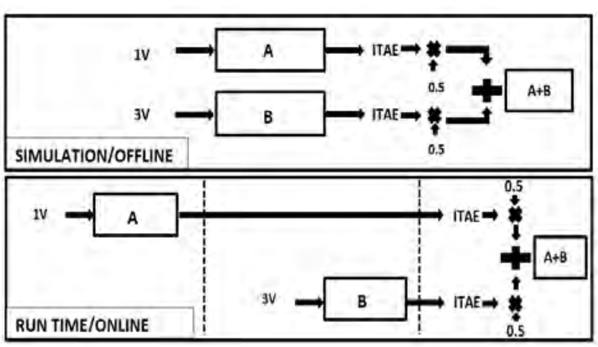

Fig.10.Aggregate Fitness Function Scheme for Simulation and Run-Time

C. Genetic Algorithm

GA originated by Goldberg in 1989 [3], is a probabilistic search algorithm based on 'Survival of the fittest' rule of well-known Darwin's Evolution theory. During last two decades, GA emerged out as an efficient nature inspired technique to solve optimization problem of PID controllers. GA starts with initial population of likely solutions of the optimization problems and further applications of three functions namely Reproduction, Crossover and Mutation in such a way to produce offspring that are superior to their parents. These off springs become the parents of next generation. As GA is multi-iteration process, the above operation is repeated until a required optimal solution is achieved or some pre-timed conditions are met [4].

Psedocode: Implementation of GA

Fitness function f(x), $x=(x_1\ldots\ldots\ldots x_n)^T$
Initialize a population of n solution vectors
While ($f(x) \geq$ desired fitness) or (stop criteria);
Calculate fitness F_i for each solution vector;
If ($F_i >$ selection parameter)
Select parent vector X_i;
Apply Crossover and Mutation Operation to generate offspring;
End
New solutions = offspring;
Repeat
End while
Post process results and visualization.

The flowchart of GA is shown in Fig.11.

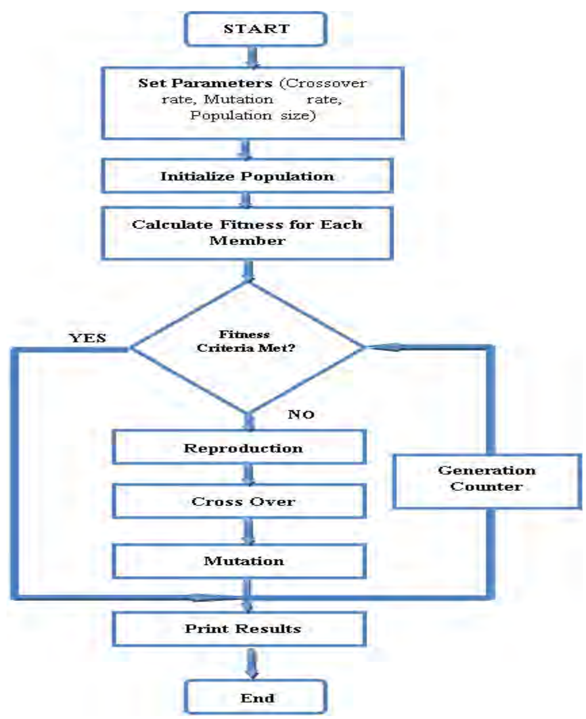

Fig.11. Flow Chart of GA

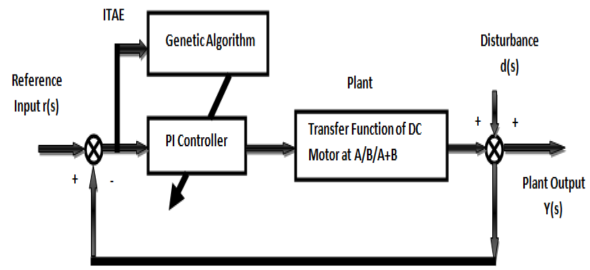

Fig.12. Tuning Scheme (Offline/Simulation)

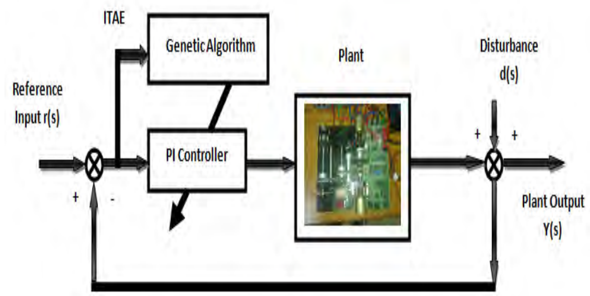

Fig.13. Tuning Scheme (Online/Experimental)

TABLE I. OPTIMIZATION SPECIFICATIONS

S.No.	Specification	Values
1.	No. of Iterations	30
2.	Dimension	2
3.	Initial Population	20

TABLE II. OPTIMIZED PI PARAMETERS (EXPERIMENTAL)

Case	PI Gains	
	Proportional Gain (K_p)	***Integral Gain (K_i)***
A	5.3773	19.7815
B	4.7493	7.4737
A+B	2.2981	7.4679

TABLE III. OPTIMIZED PI PARAMETERS (SIMULATION)

Case	PI Gains	
	Proportional Gain (K_p)	***Integral Gain (K_i)***
A	5.57398	19.6155
B	5.11192	7.99998
A+B	2.59999	9.40179

V. RESULTS AND DISCUSSION

Simulation and Run-Time performance of PI controller for setpoint tracking for different values of K_p and K_i obtained by offline and online tuning respectively for cases A, B and A+B for operating points 1V and 3V for 5 seconds are shown in Fig. 17 to Fig. 20 respectively.

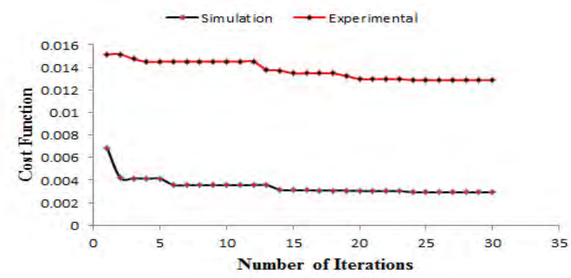

Fig.14. Fitness vs. Iteraration Curve for Case A

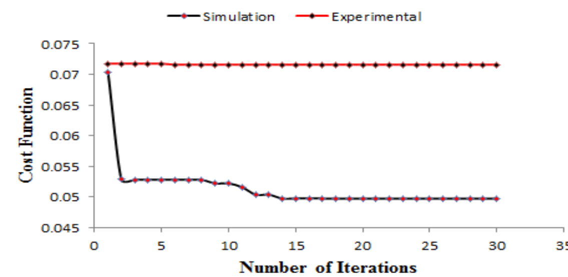

Fig.15. Fitness vs. Iteraration Curve for Case B

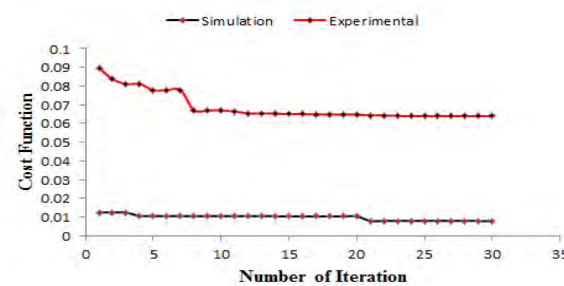

Fig.16. Fitness vs. Iteraration Curve for Case A+B

It can be clearly inferred from the curves that controller tuned by proposed approach performs well on both the operating points i.e. at 1V and 3V.

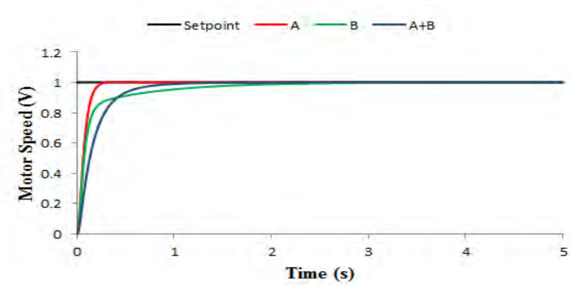

Fig.17. Simulated Setpoint Tracking at 1V

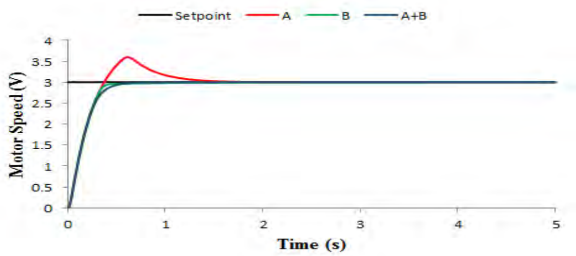

Fig.18. Simulated Setpoint Tracking at 3V

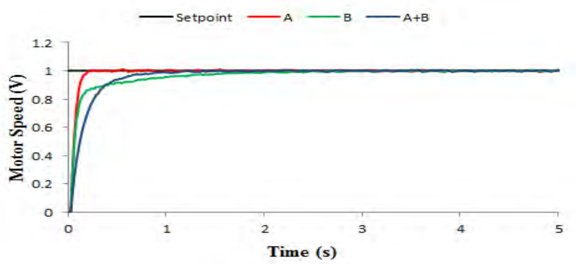

Fig.19. Run-Time Setpoint Tracking at 1V

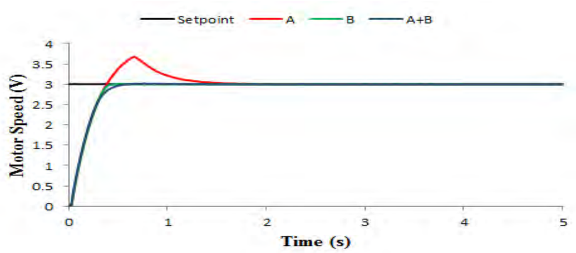

Fig.20. Run-Time Setpoint Tracking at 3V

Fig. 21 and Fig. 22 show the simulated and run time value of ITAE obtained when PI controller is tested for operating point 1V and 3V for different values of K_p and K_i obtained by considering cases A, B, and A+B respectively. The ITAE as tabulated in table IV for Aggregate Fitness Function (A+B) case is comparable at both the operating points indicating satisfactory performance on both operating points.

VI. CONCLUSION

In this paper, a novel approach for defining the 'Aggregate Fitness Function' to handle system nonlinearity and uncertainty has been proposed and evaluated. Using this scheme the PI controller was tuned using GA in simulation and run time for the DC motor speed control. The performance of the tuned controller was investigated on the two different operating points. The controller performed satisfactorily as compared to the other two studied cases thereby avoids fresh tuning of controller parameters at every new set point. An additional benefit of the proposed approach comes in the form of a simple solution to deal with parameter variation due to nonlinearity as other methods require complex hardware implementation instead of existing PID controller structure with increased cost whereas the proposed approach does not require replacement of commonly existing PID controller structure.

TABLE IV. ITAE

Case	ITAE			
	Simulation		*Experimental*	
	Operating Point 1V	*Operating Point 3V*	*Operating Point 1V*	*Operating Point 3V*
A	0.003926	0.26155	0.03941	0.33675
B	0.09046	0.050702	0.10919	0.10258
A+B	0.01991	0.10172	0.06924	0.1098

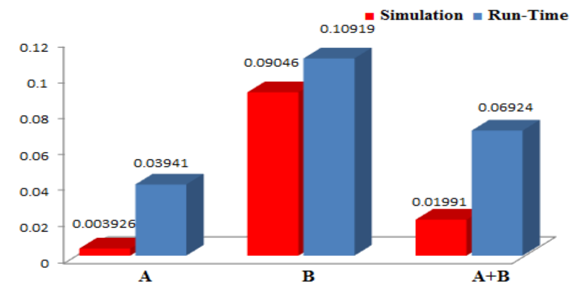

Fig.21. ITAE at Operating Point 1V

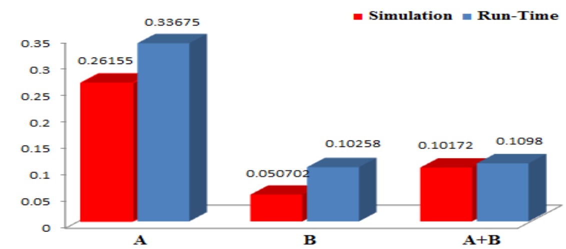

Fig.22. ITAE at Operating Point 3V

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