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NSGA-II Based Multiobjective Pid Controller Tuning for Speed Control of DC Motor Drives

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Abstract: In this study, a control scheme based on multi-objective Non-Dominated sorting genetic Algorithms NSGA-II is proposed which is able to tune the PID controller parameters simultaneously in order to find the set of trade-off optimal solutions. Single-objective population based methods such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have only one solution in a single run. Unlike single objective methods, multi-objective optimization can find different solutions in a single run. This study deals with four conflicting objective functions. In the proposed method, conflicting objectives considered are maximum overshoot, rise time and settling time for multi-objective optimization. The proposed method is used for designing of PID parameters for speed control of dc motor drives.

Key words: Multi-objective PID controller, speed control, DC motor, NSGA-II, pareto optimal front, scheme

INTRODUCTION

DC motors have long been the primary means of electrical traction. DC motor has at torque/speed characteristics compatible with most mechanical loads. The speed control methods of a dc motor are simpler and less expensive than those of A.C Motors and speed control over a large range both below and above rated speed can be easily achieved (Yu and Hwang, 2004).

In a typical electric drive controller, there are usually several nested control loops for the control of current/torque, speed and position each of which may use a separate Proportional Integral Derivative (PID) controller. Although many alternative control structures have been proposed for this application, the PI controller continues to be the most popular controllers used in industrial processes (Visioli, 1999).

The most advantage of this kind of controller is its simplicity to implement. In spite of the fact that the effect acquired as a result of disturbances and environmental conditions on the structure of the system (Montiel *et al*., 2007) adding complexity to the controller's design, it is not easy to find another controller with such a simple structure to be comparable in performance.

A very important step in the use of controllers is the controller parameters tuning process. In a PID controller, each mode (proportional, integral and derivative mode) has a gain to be tuned giving as a result three variables involved in the tuning process. There have been a lot of approaches to search the parameters of PID controllers including time response tuning (Hang *et al*., 1991), time domain optimization (Zhuang and Atherton, 1994), frequency domain shaping (Voda and Landaq, 1995) and genetic algorithms (Chun-Liang *et al*., 2003).

The speed response of the drive with PID controllers designed with the above techniques may be satisfactory but not necessarily be the best, since they do not pose any constraint on settling time, overshoot/undershoot etc.

In any classical PID control problem, the required controller parameters should be optimally designed. Despite the method of Zeigler-Nichols (ZN) ultimate cycle tuning scheme, these parameters can be optimally obtained via Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).

The optimal design of the PID controller is a complex and challenging problem since it often involves various conflicting objectives and goals. So the selection of an optimal solution can be stated as a nonlinear programming problem. This problem may be solved using suitable numerical optimization technique (Wang, 2004; Cupertino *et al*., 2002).

Many real world control problems track several objectives simultaneously. The objectives under consideration conflict with each other and optimizing a particular solution with respect to single objective will

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result in unacceptable results with respect to other objective. Competing goals of real world problems gives rise to a set of compromise solutions called as pareto ptimal solutions. A reasonable solution to a multiobjective problem is to investigate a set of solutions each of which satisfies all the objectives at an acceptable level without being dominated by any other solution. Thus the solution to any Multiobjective problem is a family of points known as non-dominated solutions or pareto optimal points and the curve that joins all pareto optimal points are called Pareto optimal front. If all the objective functions of a solution cannot be improved simultaneously, then that solution is said to have a non dominated character.

Classical Proportional and Integral (PI) or Proportional and Derivative (PD) is used not only for their simplicities but also due to its success in a large number of industrial applications. These controllers are tuned based on trial-error approaches, there for have large frequency deviations. A number of state feedback controllers based on linear optimal control theory have been proposed to achieve better performance (Astrom and Wittenmark, 1996).

In this study multi-objective Non-Dominated Sorting Genetic Algorithm (NSGA-II) is usedinter for tuning of non-linear PID controller parameters for speed control of dc motor drives. There is no constraint in the searching space of the optimal PID parameters. The new PID tuning algorithm is applied to the speed control of DC motors. The performance measure to be minimized contains the objectives of the PID controller.

Unlike classical methods such as Ziegler-Nichols and Cohen-Coon (Montiel *et al*., 2007) and single objective optimization methods such as binary coded GA, multi-objective optimization can minimize some important aspect of a system such as overshoot/undershoot and settling time simultaneously so that various solutions with different overshoot/undershoot and settling time are obtained. From these different PID Parameters, one can select a single solution based on system constraints, reliability and etc. For example in such cases overshoot/undershoot has more importance than setting time and vice versa.

DC MOTOR MODELING

The motor torque, T is related to the armature current, i by a constant factor K_t: $T = K_t I_a$. For the separately excited DC motor, the back emf, e is related to the rotational velocity by: $e = K_b u_T$, In SI units K_t (armature constant) is equal to K_b (motor constant) (Fig. 1).

V = input voltage (V), R = nominal resistance (Ω), L = nominal inductance (H), J = Inertial load (kg*m^2/s^2),

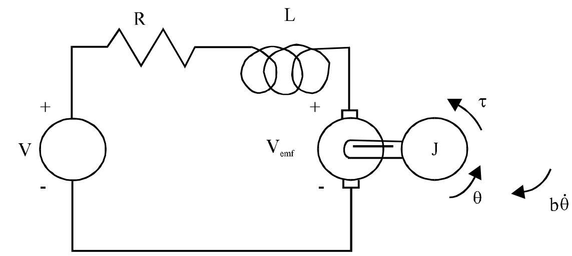

Fig. 1: Electro-mechanical mode of a DC motor

V_{emf} = back emf voltage (V), b = damping constant (Nm.S), τ = motor output torque (Nm), θ = motor shaft angle (rad). The DC motor equations based on Newton's law combined with Kirchhoff's law:

$$J\frac{d\omega}{dt} + B\omega = K_t i_a - T_L \tag{1}$$

$$L_a\frac{di_a}{dt} + R_a i_a = V_a - K_b\omega_r \tag{2}$$

Where:

J = The moment of inertia
B = Damping ratio of the mechanical system
R_a = The electrical resistance of the armature circuit
L_a = The electrical inductance of the armature circuit

In the state-space form, the equations above can be expressed by choosing the rotational speed and electric current as the state variables and the voltage as an input. The output is chosen to be the rotational speed.

$$\frac{d}{dt}\begin{bmatrix}\omega_T\\ i_a\end{bmatrix} = \begin{pmatrix}\frac{-B}{J} & \frac{K}{J}\\ -\frac{K}{L_a} & \frac{-R_a}{L_a}\end{pmatrix}\begin{pmatrix}\omega_T\\ i_a\end{pmatrix} + \begin{pmatrix}0\\ \frac{1}{L_a}\end{pmatrix}V_a \tag{3}$$

$$\omega_T = \begin{pmatrix}1 & 0\end{pmatrix}\begin{pmatrix}\omega_T\\ i_a\end{pmatrix} \tag{4}$$

MULTI-OBJECTIVE OPTIMIZATION OF PID BASED ON NSGA-II ALGORITHM

Multi-objective genetic algorithm belongs to an evolutionary algorithm for solving multi-objective optimization problem. Its core is to coordinate the relationship between the objective functions to find the optimal solution forcing them to approach to maximum or minimum.

NSGA is a new type of multi-objective genetic algorithm. High efficiency of NSGA algorithm lies in using a non-dominant classification procedure tosimplify the multiobjective into a way of fitness function by which the method can solve any number of objectives and to seek its maximum and minimum. In Deb *et al.* (2002) presented improved NSGA, i.e., NSGA-II, a quick non-inferiority sorting method, the key techniques of NSGA-II algorithm as the following:

Fast non-dominated sorting: Before selecting computation, classify all individuals of non-inferior solution in current population into Level 1.

Then remove the individuals out from the population and find a new non-inferior solution in the rest of individuals. Set it into Level 2. Repeat above process until all individuals in the population have been set into corresponding levels.

Virtual fitness: In order to maintain the diversity of individuals to prevent local accumulation, NSGA-II algorithm first proposed the concept of virtual fitness. It means the local crowding distance between every point and another adjacent to it in the same objective space. For example, the crowding distance of point i in objective space is equal to the sum of two side lengths in a rectangular composed of adjacent points i-1 and i+1 as shown in Fig. 2. This can be adjusted so that calculation results in the objective space are spread more evenly and with better robustness.

The selection for calculations: Let the selection process towards Pareto optimal solution direction and spread the solutions evenly. After sorting and crowding distance calculation, each individual in same group gets two attributes: non-domination order i_{rank} and crowding distance i_d. When $i_{rank}<j_{rank}$ or $i_{rank} = j_{rank}$ and $_{id}>j_d$, it refers to that individual i is superior to individual j. It means that if the non-dominated orders of two individuals being different, select the individual with lower order; if two individuals lie in the same level, select the individual with less crowded around it.

The elite strategy: The elite strategy in the study implies that superior individual in parent generation will be retained and transfer into children generation directly. Combine all individuals from to parent generation Pt and children generation Q_t into as a population $R_t = P_t\, Q_t$, with individual number 2N; Make the population R_t rapid non-dominated sorting and calculate the local crowded distance, select the individuals in turn according to their orders from high to low, until the individual number equals to N, form a new parent population P_{t+1}.

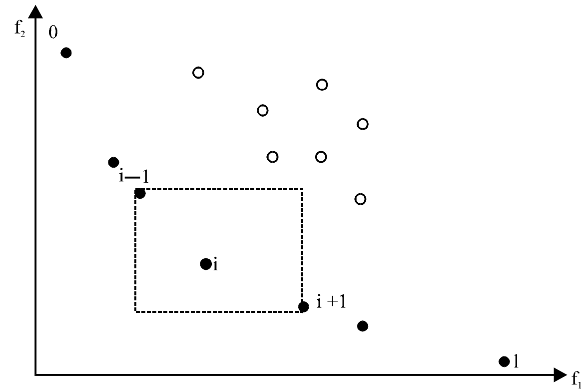

Fig. 2: Crowding distance calculation

FITNESS FUNCTIONS EMPLOYED IN MULTIOBJECTIVE DESIGN

In the general control problem, the optimization of different number of systems performances is desired. The following simultaneous performance specifications (the objectives) are adopted:

- Overshoot/Undershoot minimization:

$$f_1\ (K_I, K_P, K_D) = \max\left(\frac{1}{1+OU}\right) \tag{5}$$

- Settling time minimization:

$$f_2\ (K_I, K_P, K_D)\ = \max\left(\frac{1}{1+T_N}\right) \tag{6}$$

- Rise time minimization:

$$f_2\ (K_I, K_P, K_D)\ = \max\left(\frac{1}{1+T_R}\right) \tag{7}$$

Where OU denotes overshoot, T_N denotes total settling time and T_R denotes rise time. These objectives are being simultaneously optimized and results are obtained.

SIMULATION AND RESULTS

The specifications of the DC motor are given below: Armature circuit Resistance (R_a) = 7.56 Ω, Armature circuit inductance (L_a) = 0.055 H, Moment of inertia (J) = 0.068 Kg m^2, Coefficient of friction (B) = 0.03475 N.m.sec rad^{-1}, Torque constant (K_T) 3.475V. Sec rad^{-1}, Back-Emf constant (K_b) = 3.475 V.sec rad^{-1}.

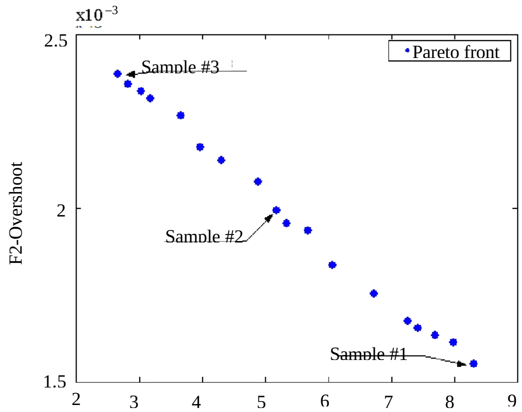

Fig. 3: Pareto optimal front with settling time and overshoot as objectives

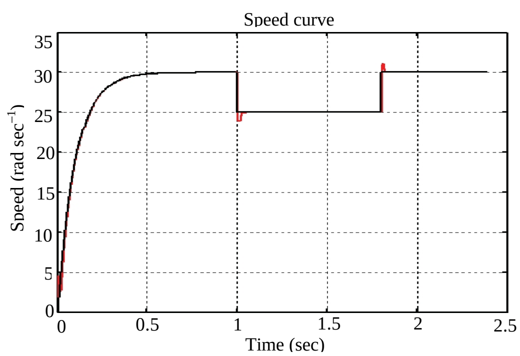

Fig. 4: Speed track response based on settling time minimization

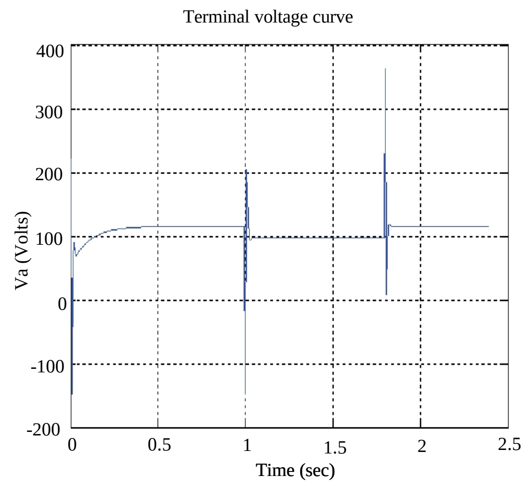

Fig. 5: Armature voltage based on settling time minimization

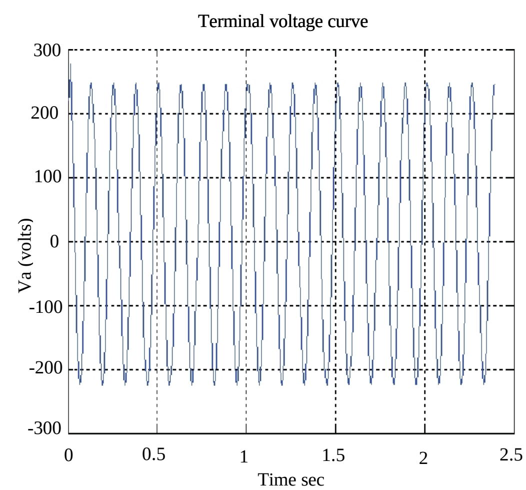

Fig. 6: Armature voltage based on settling time minimization for sine input

The multi-objective PID controller can coordinate various performance indices of the system and provide an effective tool for trade-off analysis among speediness, stability and robustness.

The decision-maker can choose the PID parameter needed from the Pareto solutions according to the requirement of actual system.

The multi-objective PID controller using the design method presented has good control quality which provides an effective approach for optimal design of PID controller and can be widely used for practical PID control.

Figure 3 shows the Pareto optimal front with settling time and overshoot as objective functions. From the Pareto optimal front, three samples are taken. From these samples, corresponding Kp, Ki and Kd values are obtained as per the requirements of the user. The following results are shown based on a selected point from the optimal Pareto front of the controller parameters (the set of acceptable (trade-off) optimal solutions) for compromising of different objective functions: settling time, maximum overshoot, rise time, steady state error and speed track error. The selected values of the PID controller are: $K_p = 29.1$; $K_i = 8.23$; $K_d = 15.26$.

The values of K_p, K_d and K_i are selected from the Pareto front and used in the block diagram shown in reference speed as a first track and the second track is assumed as a sinusoidal track.

The response of the first speed track (step change) is shown in Fig. 4-6 shows the system response of the second speed track (sinusoidal Track).

Figure 7 shows the response of the control system for load torque disturbance based on settling time minimization.

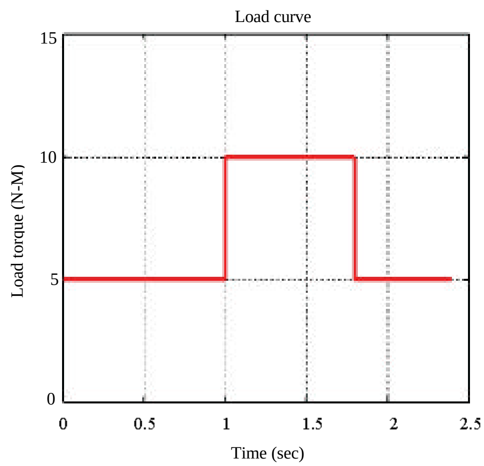

Fig. 7: Shows the response of the control system for load torque disturbance

CONCLUSION

This study has explained application of Multi-objective NSGA-II for the optimal PID controller design of an electro-mechanical DC motor drive. The main objective functions to be minimized are maximum overshoot, rise time and settling time. The optimization solution results are a set of near optimal trade-off values which are called the Pareto front or optimality surfaces. Pareto front enables the operator to choose the best compromise or near optimal solution that reflects a trade-off between key objectives. The iterative simulation results show the effectiveness of the multi-objective Non Dominated Sorting Approach NSGA-II since it allows the operator to find a near optimal good compromise among the proposed goals which is the best trade-off low cost PID controller design. The computer simulation results show that an optimized speed response is obtained always with load torque disturbance and change reference speed and demonstrates the excellent performance of PID controller.

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