A Contemporary Approach for an Efficient Controller Design Using Optimization Techniques

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Abstract

The work presented here describes how an efficient controller can be effectively designed by optimizing performance subject to robustness constraints of the system. The optimization problem is solved using PSO, ABC and ACO techniques. These methods present a general process description in terms of processed data and it can cope with many different parameters. Here in the presented work process is effectively explained with the help of examples and some pitfalls in optimization are discussed.

Keywords: **PSO, ACO, ABO.**

1. Introduction

Controller design is a very good problem because it requires the in-depth calculations of many factors related to performance and robustness [1]. Many features can be captured by formulating the design problem as a constrained optimization problem [2], [3].

PID controllers have been designed using optimization earlier with similar problem formulations [6], [7], [8]. The method proposed here is similar to M-constrained Integral Gain Optimization, MIGO [9] but it shows more flexible constraints and the computations are so simple as compare to previous one. Similar approaches using linear programming can be found in [10], and [11] for MIMO systems.

The most used type of closed-loop controller architecture and the one that is employed in this work is PID. PID controllers, if tuned correctly, can increase the stability of the system, reduce the response time needed to reach the reference value and reduce the steady state error to zero. A PID controller can be tuned using 3 variables Proportional (P), Integral (I) and Derivative (D). These three values are then added to provide the process input. Figure 4.2 shows the structure of a PID controller.

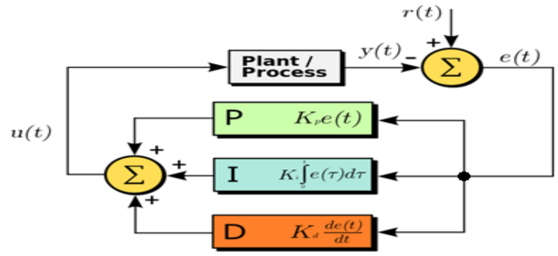

Figure 4.2, PID control scheme, r(t) is the reference value at time t, e(t) is the error value at time t, u(t) is the output of the controller (input of the process) at time t and y(t) is the output of the system at time t, from ref [6]

The P value compensates for the present error and is just a multiplication of the proportional gain Kp multiplied by e(t) (error on time t). The I value compensates for the errors in the past, is calculated by multiplying the internal gain Ki and the integration of e(t). The D value is a prediction for errors in the future, based on the current rate of errors and is calculated by multiplying the derivative gain Kd and the differentiation of e(t).

2. Design Methodology

2.1 Dynamic Particle Swarm Optimization

A dynamic particle swarm optimization (PSO) algorithm [15] is based on time-varying cognitive (c1) and the social component (c2) with or without varying inertia weight. It is desirable to encourage searching the solution through the entire search space without trapping around local solution as well as making particle convergence towards the global solution.

Proper control of c1 and c2 in addition to inertia weight w, will help to reach the optimal solution in an efficient way in PSO [5] with varying inertia weight. It may be possible for individuals not get trapped in local minima at an early stage and converge towards the global solution at the latter stage using the iterative cognitive, social parameters with constant or varying inertia weight.

2.2 Artificial Bee Colony Optimization

In 2013, El Telbany [8] has developed an artificial bee colony (ABC) algorithm, a population-based search technique from scrounging behavior of bees for solving optimization problems. In ABC algorithm, the bees are divided as employed bees, onlooker bees, and scout bees.

The employed bees find the food sources position and share the information to onlooker bees at the hive. On the other hand, onlooker bees select the high-quality food sources based on nectar information and search further around the selected food sources.

The ABC algorithm begins with the initial population of food source positions (Sp). The ith food source is defined with the d-dimensional vector Pi = [pi1, pi2… pid] for i = 1,2,…….,Sp. Each food source position/solution is generated using equation (1).

$$p_{ij} = p_{\min,j} + \mathrm{rand}(0,1)(p_{\max,j} - p_{\min,j} \quad (1)$$

where j = 1,2,……..,d.

In ABC algorithm, each food source position corresponds to six PMDC motor parameters to be estimated. The position of the food sources is limited using equation (1). After initialization, all employed bees search for the food sources and generate candidate food source position/solution using equation (2).

$$v_{ij} = p_{ij} + \emptyset_{ij}(p_{ij} - p_{gj}) \quad (2)$$

where $g = 1,2, \dots\dots\dots, S_p$ and $\emptyset_{ij}$ is a random value in the range $[-1,1]$.

After generation of new food source position, the fitness of the new food source position is evaluated. The employed bees would replace the previous food sources position with new one; if the fitness value of the new food sources is better otherwise the employed bees retain the previous food source position. The employed bees share food source position and nectar information to onlooker bees.

An onlooker bees select the food sources depending on the probability value estimated using equation (3).

$$pr_i = \frac{fit_i}{\sum_{j=1}^{S_p} fit_i} \quad (3)$$

Where fiti is the fitness value of ith food source position which depends on food source position. The number of food source position Sp is equal to the number of employed bees/onlooker bees.

The food source position is abandoned in case no improvement in the food source position is observed for predetermined number of cycles. Subsequently, scout bees discover the new food source position using equation (2). The new food source discovered by the scout bees will replace the abandoned one. This process of identification of best food source position is continued until the termination criteria are reached or the maximum number of iteration is reached.

2.3 Ant Colony Optimization

The Dorigo [13] [14] has proposed ant colony optimization (ACO) from the inspiration of ant, to find an optimal path between food and nest. The optimal solution is found via the amount of pheromone on the ground. The parameters are limited in the range and are given by equation (4). Each parameter is the vector corresponds to a layer/level. The upper and lower limits of the parameter depend on the user experience and divided into q number of nodes with possible values.

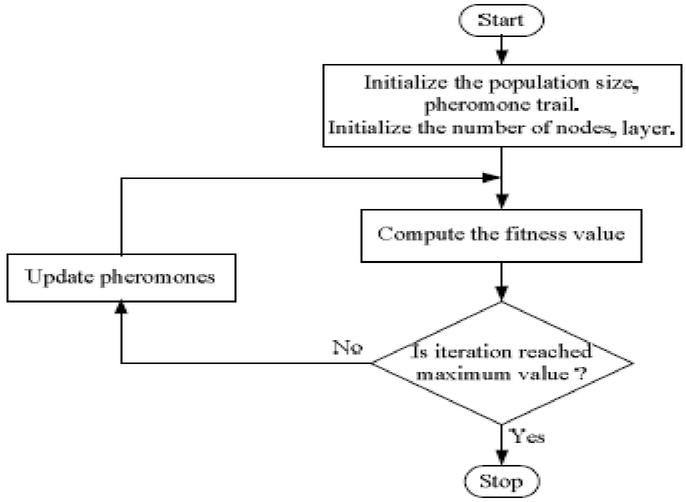

FIGURE 5. Flowchart of the ACO algorithm.

Ant colony optimization algorithm begins with initialization of ants and equal amounts of pheromone trail. The number of layers is six, constituting a motor parameter in each layer. Each layer consists of q nodes with permissible values assigned to each node using equation (4).

At each iteration, ant assumes the path using equation (4) to construct the probabilistic state transition rule for a complete solution. The state transition rule is mainly based on the state of pheromone.

$$p_{qs} = \frac{\tau_{qs}^{\alpha}}{\sum_{q=1}^{d} \tau_{qs}^{\alpha}} \qquad (4)$$

The objective function is evaluated corresponding to the complete path to determine best and worst path of H ants. Subsequently, the optimal solution is obtained when all the ants follow the same best path.

If optimal solution is not obtained, the pheromone information is updated using equation (5).

$$\tau_{qs} = (1 - \rho)\tau_{qs} + \frac{Q}{f_{best}} \qquad (5)$$

III. Results and Discussion

The dynamic PSO optimization algorithm needs a less number of iterations compared to other methods.

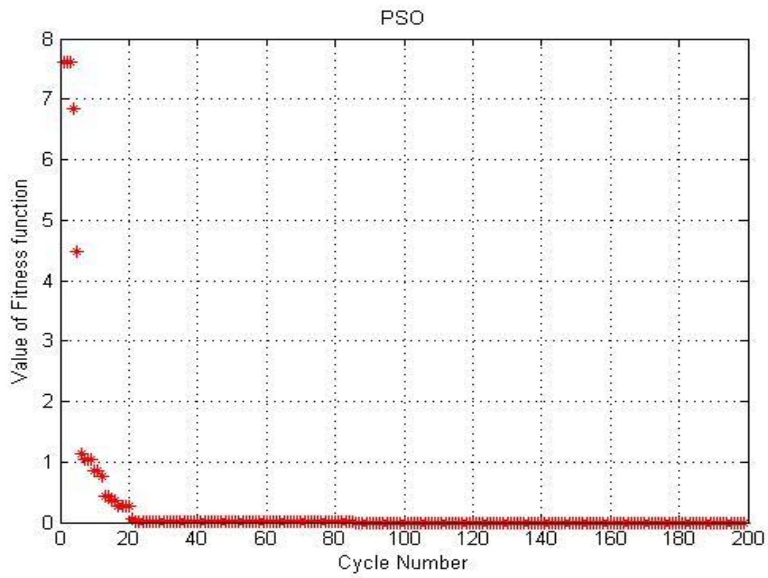

FIGURE 7. Fitness Function of Dynamic PSO

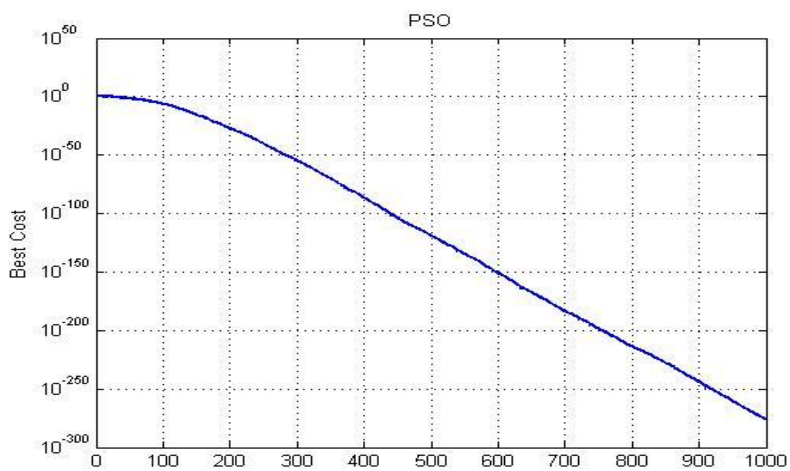

FIGURE 8. Fitness Function of PSO

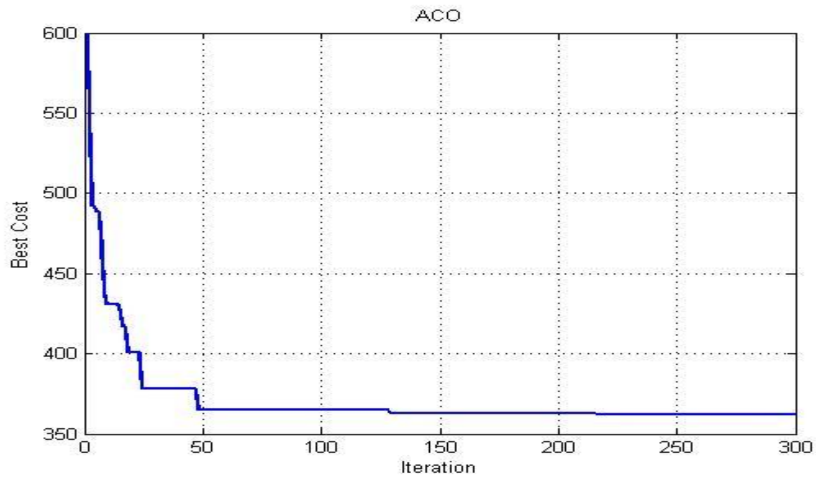

FIGURE 9. Fitness Function of ACO

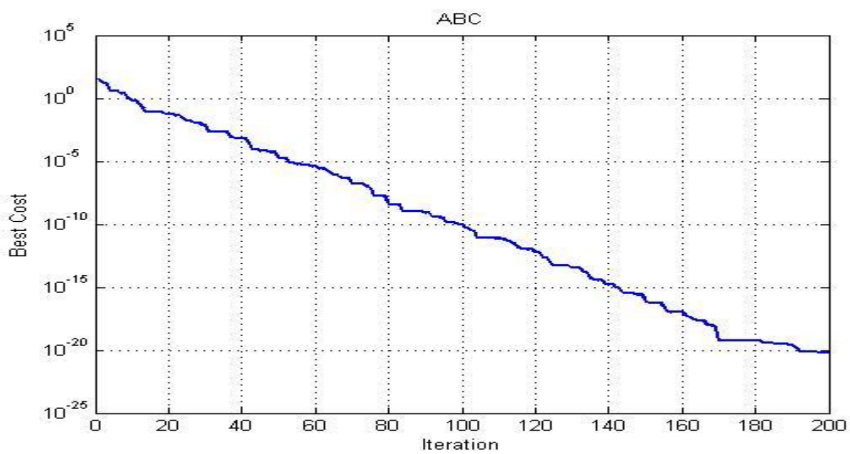

FIGURE 10. Fitness Function of ABC

Ant colony optimization with constant inertia weight as well as standard PSO takes a number of iterations for convergence. However, dynamic PSO with varying inertia weight needs less iteration compared to other techniques considered. Further, it is clear that dynamic PSO algorithms takes less number of iteration for convergence and performance is significantly closed to dynamic PSO with varying inertia weight algorithms. Therefore, dynamic PSO algorithm may be considered for less computation and less error in the estimation of motor parameter.

IV. Conclusion

In this paper, applications of the convex-concave algorithm, dynamic PSO with constant inertia weight and dynamic PSO with varying inertia weight algorithms, ABC, and ACO algorithms have been studied for parameter estimation of a motor along with experimental tests. The dynamic PSO algorithm a variant of standard PSO, modifying parameter iteratively improves the parameter estimation accuracy. It is evident that the dynamic PSO with varying inertia and artificial bee colony algorithms may be used to obtain motor parameter with more accuracy without being trapped in local minima. The artificial bee colony algorithm may be preferred for estimation of motor parameters due to faster convergence as well as relatively less current error except for dynamic PSO with varying inertia. The dynamic PSO with varying inertia weight may be used for more accurate motor parameter estimation.

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