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Control System Model Reduction using Hybrid Optimization Approach

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ABSTRACT

The foraging behavior of E. Coli is used for optimization problems. This paper is based on a hybrid method that combines particle swarm optimization and bacterial foraging (BF) algorithm for solution of optimization results. We applied this proposed algorithm on different closed loop transfer functions and the performance of the system using time response for the optimum value of PID parameters and order reduction is studied with incorporating PSO method on mutation, crossover, step sizes, and chemotactic of the bacteria during the foraging. The bacterial foraging particle swarm optimization (BFPSO) algorithm is applied to tune the PID controller of reduced type 2, 3 and 4 order systems with consideration of minimum peak overshoot and steady state error objective function. The performance of the time response is evaluated for the designed PID controller reduced order syatem as the integral of time weighted squared error. The results illustrate that the proposed approach is more efficient and provides better results as compared to the conventional PSO algorithm.

Key words: BFPSO, BSO, PSO, and PID.

1. INTRODUCTION

Evolutionary computation, offers practical advantages to the researcher facing difficult optimization problems. These advantages are multifold, including the simplicity of the approach, its robust response to changing circumstance, its flexibility, and many other facets. The evolutionary algorithm can be applied to problems where heuristic solutions are not available or generally lead to unsatisfactory results. As a result, evolutionary algorithms have recently received increased interest, particularly with regard to the manner in which they may be applied for practical problem solving. Usually grouped under the term evolutionary computation or evolutionary algorithms, we find the domains of genetic algorithms [2], evolution strategies [6], [7], evolutionary programming [1], and genetic programming [3]. They all share a common conceptual base of simulating the evolution of individual structures via processes of selection, mutation, and reproduction. The processes depend on the perceived performance of the individual structures as defined by the problem. Compared to other global optimization techniques, evolutionary algorithms (EA) are easy to implement and very often they provide adequate solutions. The flow chart of an EA is illustrated in Fig. 1. A population of candidate solutions (for the optimization task to be solved) is initialized. New solutions are created by applying reproduction operators (mutation and/or crossover). The fitness (how good the solutions are) of the resulting solutions are evaluated and suitable selection strategy is then applied to determine which solutions are to be maintained into the next generation. The procedure is then iterated.

For several problems a simple Evolutionary algorithm might be good enough to find the desired solution. As reported in the literature, there are several types of problems where a direct evolutionary algorithm could fail to obtain a convenient (optimal) solution [4, 5, 9, 10].This clearly paves way to the need for hybridization of evolutionary algorithms with other optimization algorithms, machine learning techniques, heuristics etc. Some of the possible reasons for hybridization are as follows [8]:

1. To improve the performance of the evolutionary algorithm (example: speed of convergence)
2. To improve the quality of the solutions obtained by the evolutionary algorithm
3. To incorporate the evolutionary algorithm as part of a larger system

In 1995, Wolpert and Macready [11] illustrated that all algorithms that search for an extremum of a cost function perform exactly the same, when averaged over all possible cost functions. According to the authors, if algorithm A outperforms algorithm B on some cost functions, then loosely speaking there must exist exactly as many other functions where B outperforms A. Hence, from a problem solving perspective it is difficult to formulate a universal optimization algorithm that could solve all the problems. Hybridization may be the key to solve practical problems. To illustrate the popularity of hybrid approaches, we searched the number of publications appearing in some of the popular scientific databases namely Science Direct [12], IEEE-Xplore [14], and Springer Link [13] using the keywords “hybrid evolutionary” and “hybrid genetic” and the query results are tabulated below. Since no filtering was used in the query, the number of relevant papers might be lower than the figure 1 mentioned.

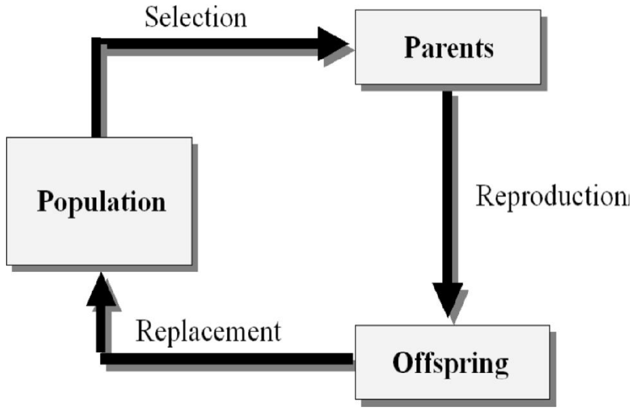

Figure 1: Flowchart of an evolutionary algorithm

Figure 2 illustrates some possibilities for hybridization. From initialization of population to the generation of offsprings, there are lots of opportunities to incorporate other techniques/algorithms etc. Population may be initialized by incorporating known solutions or by using heuristics, local search etc. Local search methods may be incorporated within the initial population members or among the offsprings. Evolutionary algorithms may be hybridized by using operators from other algorithms (or algorithms themselves) or by incorporating domain-specific knowledge. Evolutionary algorithm behavior is determined by the exploitation and exploration relationship kept throughout the run. Adaptive evolutionary algorithms have been built for inducing exploitation/exploration relationships that avoid the premature convergence problem and optimize the final results. The performances of the evolutionary algorithm can be improved by combining problem-specific knowledge for particular problems.

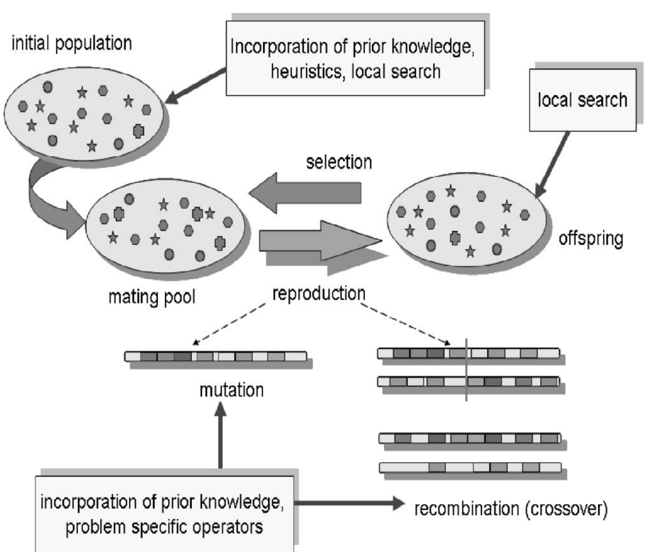

Figure 2: Hybridization prospectives in an evolutionary algorithm

2. RELATED WORK

In this work Licio Hernanes Bezerra et. Al., (2017), [1], provide a brand new brief evidence of the local quadratic convergence of the Dominant Pole Spectrum Eigensolver (DPSE). Also we introduce right here the Diagonal Dominant Pole Spectrum Eigensolver (DDPSE), another fixedpoint method that computes numerous eigenvalues of a matrix at a time, which additionally has nearby quadratic convergence. From effects of a few experiments with a huge strength machine version, it is proven that DDPSE also can be used in small-signal balance studies to compute dominant poles of a transfer function of the sort cT (A−sI)1b, where b and c are vectors, by its personal or combined with DPSE. Besides DDPSE is also effective in finding low damped modes of a huge scale strength system model.

Girish Parmar et. Al., (2018) [2], offered work deled with the software of evolutionary computation in approximation and manipulate of linear time invariant (LTI) structures. Stochastic fractal search set of rules (SFS) has been proposed to achieve low order gadget (LOS) from LTI better order machine (HOS) as well as in velocity control of DC motor with PID controller. SFS is quite easy to apply on top of things system and employs the diffusion property present in random fractals to find out the search space. In approximation of LTI systems, the essential rectangular errors (ISE) even as in control of DC motor [15], the essential of time accelerated absolute mistakes has been taken as an goal/health capabilities. In system's approximation, the effects show that the proposed SFS primarily based LOS preserves both the transient and steady state residences of authentic HOS. The simulation effects have also been compared in phrases of; ISE, crucial absolute errors and impulse response strength with widely recognized acquainted and currently posted works in the literature which shows the superiority of SFS set of rules. In manage of DC motor, the received consequences are great having no overshoot and much less upward push and settling instances in assessment to existing techniques.

The provided work offers with software of SFS algorithm in approximation and control of LTI structures. In gadget's approximation, the SFS has been used to limit the ISE in between the transient responses of HOS and LOS a good way to get all of the unknown parameters of LOS. The systems available within the literature had been taken as take a look at/ simulation examples. The step and frequency responses of HOS and LOS were compared with each other in conjunction with the currently posted strategies in the literature. Also, in simulation examples, comparisons of ISE, IAE and IRE have been proven with existing techniques to expose the effectiveness of SFS set of rules. The obtained ISE and IAE values by means of SFS algorithm are very low and the IRE fee of SFS primarily based LOS could be very close to HOS while in comparison with present strategies [18]. The temporary reaction's parameters of HOS and LOS by way of SFS and other existing strategies have also been as compared. The utility of SFS set of rules in control of LTI gadget has also been shown wherein general DC motor is used as check device. The ITAE has been taken as an objective/health characteristic. Comparison of proposed SFS/ PID approach has additionally been proven with other existing techniques; which includes IWO/PID and PSO/PID. The simulation effects screen that SFS/PID scheme with ITAE as an objective characteristic offers no overshoot and different parameters which includes; settling and upward thrust times also are similar with current techniques.

Zimmerling et. Al., (2018) [3], have advanced numerous Krylov projection-primarily based model-order reduction strategies to simulate electromagnetic wave propagation and diffusion in unbounded domain names. Such strategies may be used to successfully approximate transfer characteristic discipline responses among a given set of sources and receivers and permit for immediate and memoryefficient computation of Jacobians, thereby reducing the computational burden related to inverse scattering issues. We discovered how standard wavefield ideas inclusive of reciprocity, passivity, and the Schwarz reflection precept translate from the analytical to the numerical area and evolved polynomial, prolonged, and rational Krylov model-order discount strategies that keep these systems. Furthermore, we observed that the symmetry of the Maxwell equations permits for projection onto polynomial and prolonged Krylov subspaces without saving a entire basis. In particular, quick-time period recurrence members of the family can be used to assemble decreased-order models which might be as memory green as time-stepping algorithms. In addition, we evaluated the differences among Krylov reduced-order techniques for the overall wave and diffusive Maxwell equations and we evolved numerical examples to highlight the blessings and downsides of the discussed strategies.

A parametric decreased order model based totally on right orthogonal decomposition with Galerkin projection has been advanced and carried out by using Sokratia Georgaka et. Al. (2019) [4], for the modeling of heat delivery in T-junction pipes that are extensively discovered in nuclear energy reactor cooling structures. Thermal blending of different temperature coolants in T-junction pipes leads to temperature uctuations and this can probably reason thermal fatigue inside the pipe walls. The novelty of this paper is the development of a parametric ROM considering the 3 dimensional, incompressible, unsteady Navier-Stokes equations coupled with the warmth shipping equation in a finite quantity regime. Two one of a kind parametric cases are supplied in this paper: parametrization of the inlet temperatures and parametrization of the kinematic viscosity. Different training spaces are considered and the outcomes are as compared in opposition to the whole order version. The first take a look at case results to a computational velocity-up factor of 374 at the same time as the second check case to one in every of 211.

In Igor Maia et. Al. (2019) [5], work they investigated using multiple-input, a couple of-output (MIMO) transfer capabilities received empirically from a huge-eddy simulation of a turbulent jet. We evaluate the MIMO overall performance with single-enter-single-output (SISO) switch features used in preceding studies. The desire of sensor placement has been made based on effects of linear stability evaluation from the literature. The outcomes display that MIMO switch functions improve on SISO results wherein both single- and two-factor information are concerned. It is also determined that the quantity of sensors important to converge the estimates relies upon strongly on Strouhal quantity.

3. METHODOLOGY

In 2001, Prof. K. M. Passino proposed an optimization technique known as Bacterial Foraging Optimization Algorithm (BFOA) based on the foraging strategies of the E. Coli bacterium cells. Until date there have been a few successful applications of the said algorithm in optimal control engineering, harmonic estimation [13], transmission loss reduction [14], machine learning and so on. Experimentation with several benchmark functions reveal that BFOA possesses a poor convergence behavior over multi-modal and rough fitness landscapes as compared to other naturally inspired optimization techniques like the Genetic Algorithm (GA) [6] Particle Swarm Optimization (PSO) [7] and Differential Evolution (DE) [8]. Its performance is also heavily affected with the growth of search space dimensionality. In 2007, Kim et al. proposed a hybrid approach involving GA and BFOA for function optimization [9]. The proposed algorithm outperformed both GA and BFOA over a few numerical benchmarks and a practical PID tuner design problem.

In this article we come up with a hybrid optimization technique, which synergistically couples the BFOA with the PSO. The later is a very popular optimization algorithm these days and it draws inspiration from the group behavior of a bird flock or school of fish etc. The proposed algorithm performs local search through the chemotactic movement operation of BFOA whereas the global search over the entire search space is accomplished by a PSO operator. In this way it balances between exploration and exploitation enjoying best of both the worlds. The proposed algorithm, referred to as Bacterial Swarm Optimization (BSO) has been extensively compared with the classical PSO, a state-of- the-art variant of PSO and the original BFOA over a test suit of five well-known benchmark functions and also on a practical optimization problem of spread spectrum radar poly-phase code design [40]. The following performance metrics were used in the comparative study (i) quality of the final solution, (ii) convergence speed, (iii) robustness and (iv) scalability. Such comparison reflects the superiority of the proposed approach.

Architectures of Hybrid Evolutionary Algorithms

As reported in the literature, several techniques and heuristics/metaheuristics have been used to improve the general efficiency of the evolutionary algorithm. Some of most used hybrid architectures are summarized as follows [16]:

1. Hybridization between an evolutionary algorithm and another evolutionary algorithm (example: a genetic programming technique is used to improve the performance of a genetic algorithm)
2. Neural network assisted evolutionary algorithms
3. Fuzzy logic assisted evolutionary algorithm

4. Particle swarm optimization (PSO) assisted evolutionary algorithm
5. Ant colony optimization (ACO) assisted evolutionary algorithm
6. Bacterial foraging optimization assisted evolutionary algorithm
7. Hybridization between evolutionary algorithm and other heuristics (such as local search, tabu search, simulated annealing, hill climbing, dynamic programming, greedy random adaptive search procedure, etc)

In the following sections, we will briefly review some of the architectures depicted above. Figure 3 illustrates some of the generic architectures for the various types of hybridization. By problem, we refer to any optimization or even function approximation type problem and intelligent paradigm refers to any computational intelligence technique, local search, optimization algorithms etc.

Fig 3a,b represents a concurrent architecture where all the components are required for the proper functioning of the model. As depicted in Fig. 3a, evolutionary algorithm acts as a preprocessor and the intelligent paradigm is used to fine tune the solutions formulated by the evolutionary algorithm. In Fig. 3b, intelligent paradigm acts as a preprocessor and the evolutionary algorithm is used to fine tune the solutions formulated by the intelligent paradigm. Figure 3c, represents a transformational hybrid system in which the evolutionary algorithm is used to fine tune the performance of the intelligent paradigm and at the same time, the intelligent paradigm is used to optimize the performance of the evolutionary algorithm. Required information is exchanged between the two techniques during the search (problem solving) process. In a cooperative model the intelligent paradigm is used only for initialization or for determining some parameters of the evolutionary algorithm. As depicted in Fig. 3d, thereafter, the intelligent paradigm is not required for the proper functioning of the system. Also, there are several ways to hybridize two or more techniques.

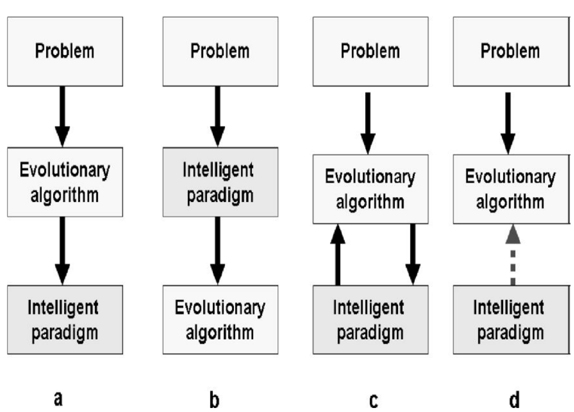

Figure 3: Hybrid evolutionary algorithm generic architectures

4. RESULT AND DISCUSSION

In this work our objective was to check the performance of Bacterial Foraging behavior base PSO technique for finding an optimum value of Kp, Ki, and Kd gains for a PID controller with reduced order model system. This objective is achieved by finding global minimum error in the step response of different types of transfer functions. Two kinds of transfer functions are considered Type0 and Type1. In the Type1 transfer functions no integral gain (Ki) is required to find because they already have low steady state error in step response. Hence for Type1 cases we have determine only Kp and Kd gains and for Type0 system we have determined all Kp, Kd and Ki gains.

The performance of developed Bacterial Foraging PSO algorithm (BSO) and basic PSO is tested for a system transfer function of different order. We have considered different transfer functions named as TF1 to TF6. For each transfer function we have run our BSO and PSO algorithm several times and we found five best results giving minimum error are shorted out for both algorithm and finally we have compared the best response of BSO against the PSO.

In the subsequence section we will discuss the results of our different transfer functions or discuss the detail and compared in the form of step response plot and peak over shoot values for both algorithms. Figure 4 shows the PID controller connections to various transfer functions.

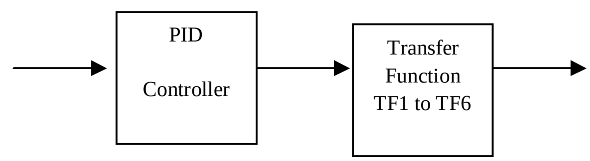

Figure 4:PID controller connections to various transfer functions

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The TF1 transfer function has following equations it is a fourth order system with Type1 without having 0.

$$TF1 = \left(\frac{S+5}{S^4+17S^3+60S^2+10S}\right)$$

Fig 5(a) shows the five best responses obtained by the BSO algorithm with the step response having minimum steady state error and error in the peak overshoot. Similarly fig 5(b) demonstrate the step response obtained by running PSO algorithm for best five optimum values of PID gain with minimum steady state error and peak over shoot out of these five responses from both PSO and BSO. We have taken the step response having minimum peak over shoot in PSO and BSO these two shorted out step responses are shown in fig 5(c). In table 1 we have also given the peak over shoot of all the five cases of both algorithms for TF1 this table is giving a clear idea about the variation in peak values from steady state response that cannot be easily observed from the fig 5(a) and 5(b). From the table 1 we can conclude that case 2 for PSO and Case 5 for BSO giving minimum peak over shoot. These response are shown in fig 5(c).

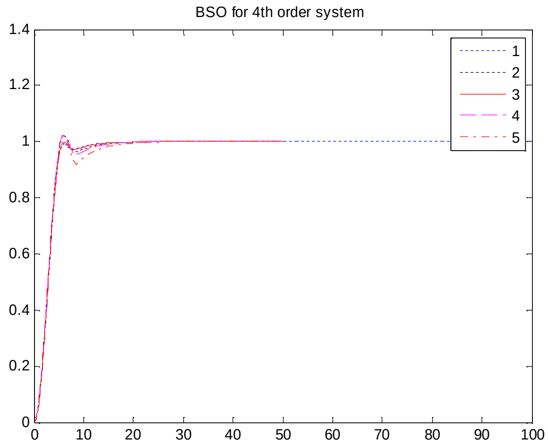

Figure 5(a): Step Response for BSO based optimum PID value

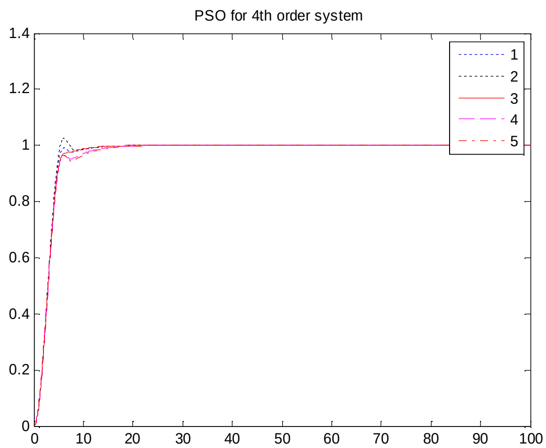

Figure 5(b): Step Response for PSO based optimum PID value

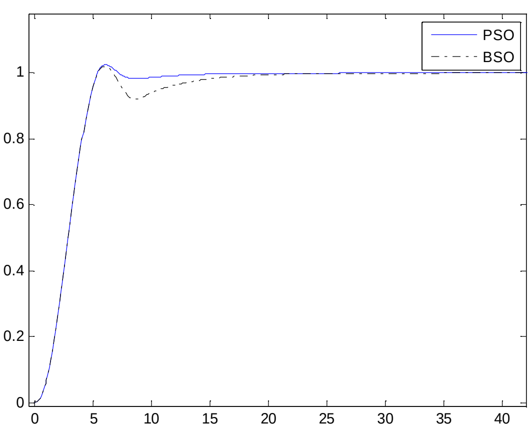

Figure 5 (c): Comparison of Step Response for BSO(-.-) and PSO(__) based optimum PID value

Table 1 shows the value of peak overshoot value by BSO and PSO. We found the min peak overshoot in case of PSO in case 2 and in case of BSO in case 5

Table 1: Peak Overshoot values by BSO and PSO

	Peak overshoot by PSO:	Peak overshoot by BSO:
Case1	-0.000000000000196	-0.000000000000158
Case2	0.024897113162271	0.023107101222726
Case3	-0.000000000000158	-0.000000210061198
Case4	-0.000000000001012	0.022295867486398
Case5	-0.000000000001429	0.020736526713352
Min. Peak Overshoot	0.024897113162271 (case 2)	0.020736526713352 (case 5)

5. CONCLUSION

In this paper a new hybrid optimization method is proposed via combining benefits of Particle swarm and Bacterial Foraging technique with a view to get higher optimization values with better accuracy and in much less time. The proposed hybrid optimization BSO approach is utilized to the trouble of tuning of PID controller on reduced model order at the minimal cost of peak over shoot and steady state errors and is in comparison with simply Particle swarm optimization. Results received with the aid of the use of (BSO) set of rules are presented in phrases of step response and peak overshoot values.

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