INVESTIGATION ON METAHEURISTIC ALGORITHMS FOR OPTIMIZING FRACTIONAL ORDER CONTROLLER PARAMETERS

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ABSTRACT

Optimization problems are of prime importance for industrial as well as the scientific community in diverse disciplines. There are various optimization problems that present traits like high non-linearity .and multimodality, the solution of which is usually complex. Further, in many cases, some intricate optimization problems present noise and/or discontinuities which make conventional deterministic methods inefficient to obtain global solutions. Thus, global optimization approaches based on metaheuristics provide a viable alternative for solving complex optimization problems and do not require any information regarding the properties of the objective function. Metaheuristic algorithms are nowadays attaining popularity among researchers extensively owing to their success to find the optimum solution and steadfastness in solving real-world problems. They are generally utilized to solve several complex problems in science and engineering, finance as well as management. Metaheuristic algorithms have four inherent properties. First of all, they are primarily motivated by natural phenomena in the universe. Secondly, they constitute a stochastic method wherein an optimum solution is not guaranteed and is randomly searched in a feasible search space. Moreover, they do not require the derivative term to obtain the maximum or the minimum value. Last but not the least; they are always associated with some user-defined values at the initial stage to function suitably. Therefore this work gives the detail review on metaheuristic algorithms for optimizing fractional order controller parameters.

Key words: Optimization, metaheuristic, fractional order, Stochastic.

1. INTRODUCTION

Metaheuristic algorithms have emerged as powerful tools for modelling and control these days. The term meta- implies 'beyond' or 'higher level'. They are far superior to ordinary heuristics. The variety of solutions obtained using metaheuristics is often accomplished with the help of randomization. Though metaheuristic algorithms are widely popular, still there is no clear-cut definition of heuristics and metaheuristics available in the literature. Several researchers even use them almost interchangeably. However, the general trend aims to label all stochastic algorithms via randomization and global exploration as metaheuristic. Randomization contributes valuably to move away from local to global search. Thus, almost all metaheuristic algorithms are highly suitable for nonlinear modelling and control. Metaheuristic algorithms provide an efficient means to yield acceptable solutions by trial and error to a complex problem in reasonably good time. The aim of these algorithms is not to find every possible solution in the search space but to find a feasible solution within acceptable time limit. However, there is no guarantee that the best solutions can be obtained.

There are two major components of any metaheuristic algorithms namely exploration (diversification) and exploitation (intensification). Exploration generates diverse solutions so as to utilize the entire search space, while exploitation focuses on the search in a local region by exercising the information that a current good solution is found in this region. A good balance of these two will ensure the attainment of global solution [1]. Though human beings' problem-solving abilities have always been heuristic or metaheuristic since the early periods of human history, yet its scientific study is relatively a budding venture. Alan Turing was apparently the first to use heuristic search method during World War II. The 1960s and 1970s witnessed the development of Genetic Algorithms (GA). Another breakthrough contribution is the proposition of Simulated Annealing (SA) method in 1982. In 1992 and 1995, significant progress took place through the developments of Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) respectively. In around 1996 and later in 1997, a vector-based evolutionary algorithm coined as Differential Evolution (DE) came into existence. With the advent of 21st century, things became even more fascinating. Many new algorithms like Bacterial Foraging Algorithm (BFA), Harmony 2 Search (HS), Artificial Bee Colony (ABC) optimization, Firefly Algorithm (FA), Cuckoo Search (CS), Bat Algorithm (BA) and Flower Pollination Algorithm (FPA) also evolved [1].

Few metaheuristic algorithms directly associated with this research work are described as follows. Bacterial Foraging Algorithm (BFA), coined by Passino, is based on the foraging strategy of Escherichia Coli (E. Coli) bacteria that reside in the human intestine. Foraging strategy is a habit of animals for searching, managing and consuming their food. Bacteria apprehend the route towards food source depending on the amount of chemicals in their surroundings. Likewise, bacteria give off attracting and repelling chemicals into the neighbouring atmosphere and can recognize each other in a similar fashion. Bacteria can also encompass their environment, sometimes chaotically (tumbling and spinning), and other times moving in a directed manner (swimming) with the help of flagella. Bacterial cells are considered as agents in an environment, utilizing their sense of food and other cells as an encouragement to manoeuvre, and stochastic tumbling and swimming like movement to advance. Based on the cell-cell interactions, cells may flock towards a food source, and/or may drive away or avoid each other. Thus, a bacterial foraging system consists of four key steps namely chemotaxis, swarming, reproduction and elimination-dispersal [2].

However, investigation with complicated problems discloses that the BFA possesses poor convergence and its performance highly decreases with dimensionality and the problem complexity. Another newcomer in the list of metaheuristic algorithms viz. Firefly algorithm (FA) is motivated by the communication behaviour and flashing patterns of fireflies found in the tropical climatic conditions. The mathematical model of the algorithm is developed based on the following simplifications:

- ❖ All fireflies are assumed to be unisex such that one firefly is attracted towards other fireflies irrespective of their sex
- ❖ Attractiveness is proportional to their brightness; thus for any two flashing fireflies, the less-bright one will move towards the brighter one.
- ❖ The attractiveness is dependent on brightness and they both decrease as their distance enhances. If no one is brighter than a particular firefly, then it moves randomly

The brightness or the light intensity of a firefly is decided by the landscape of the objective function to be optimized. Thus, there are two aspects in FA viz. variation of light intensity and formulation of attractiveness. For the sake of simplicity, it is.assumed that the attractiveness of a firefly is determined by its brightness or light intensity which in turn is correlated with the encoded objective function. The attractiveness, on the other hand, varies with the distance between any two fireflies. As the light intensity diminishes with distance from the source, the light is also absorbed in the media; hence, it is concluded that the attractiveness should vary with the degree of absorption [1].

This algorithm has shown promising superiority over several algorithms in the recent past. An additional entrant in the tally of metaheuristic algorithms is the Flower Pollination Algorithm (FPA) inspired by the flower pollination process of flowering plants and follows a set of assumptions as enumerated below:

- ✓ Biotic and cross-pollination are treated as global pollination process with pollen bearing pollinators carrying out Lévy flights.
- ✓ Abiotic and self-pollination are deliberated as local pollination.
- ✓ Flower constancy can be contemplated as the reproduction probability which is dependent to the similarity of two flowers associated.
- ✓ Local and global pollination are controlled by a switch probability p [0, 1].

Owing to the physical proximity and other factors such as wind, local pollination can have a high fraction p in the total pollination activities. Undoubtedly, each plant can have several flowers, and each flower patch can deliver millions of pollen gametes. For the sake of simplicity, it is assumed that each plant only has one flower, and each flower only produces one pollen gamete. There are two fundamental mechanisms in FPA, global and local pollination respectively. In the global pollination step, pollens are carried by insects, thus they can travel a considerable distance as insects can often fly and move quite a large range. This guarantees the pollination and reproduction of the fittest. Local pollination mimics the flower constancy in close vicinity. Most flower pollination activities can take place both on locally as well as globally.

As a routine, adjacent flowers are more likely to be pollinated by local flower pollens than those at a distance. Due to this, a switch probability p is employed to shift between the common global pollination to intensive local pollination [1]. Even dynamism in switch probability often leads to improved solutions for different optimization problems. Grey Wolf Optimizer (GWO) is another metaheuristic algorithm that simulates the leadership hierarchy and hunting mechanism of grey wolves. Grey wolves are treated as apex predators, ruling at the topmost point of the food chain. They reside in groups, each group containing 5- 12 members on an average. The members of the group maintain a stringent social hierarchy. In the hierarchy, alpha wolves are considered the most dominating member. The subordinates to alpha are beta and delta, which help to control the omega wolves.

In GWO algorithm, the hunting is controlled by alpha, beta and delta wolves. The omega wolves follow these three wolves. During hunting, the grey wolves normally encircle the prey. The hunting operation of the grey wolves is provided leadership by the alpha wolves. The beta and delta wolves occasionally take part in the hunting process. It is assumed that the alpha, beta and delta type grey wolves have better awareness about the potential location of prey. Hence, the first three best solutions acquired are recorded and the other search agents are required to update their positions as per the location of the best search agents. The grey wolves complete the hunting by attacking the prey when it finally stops moving [3]. GWO is tremendously popular among the researchers and thus has wide acceptance in diverse fields. Though several new algorithms [4-7] have also evolved, yet pure algorithms cannot always deliver an optimal solution and are almost inferior to hybridizations.

Moreover, Pattern Search (PS) algorithm [8] acts as a potential candidate to offer good local search capabilities and has been widely employed to constitute a hybrid combination with other metaheuristic algorithms. Further, it is also found that chaos plays an important role to improve upon the performance of any metaheuristic algorithm [9]. In the literature of identification and control, there have been numerous methods developed over the last five decades on discrete-time systems utilizing the potential of digital computers. Parallely, there has been a similar attempt in developing methods in continuous time identification and control in system theory because of the very fact that the physical signals are continuous-time in nature. Modelling, identification and control using delta operator is a holistic approach in which the signals and systems are modelled in discrete domain and leads to converge to its corresponding continuous-time signals and systems at a high sampling frequency thereby unifying both discrete and continuous-time signals and systems [10].

Metaheuristic algorithms and their hybridizations prove to be an emerging area in the literature of system identification [11-12]. Linear systems with static nonlinearities at the input termed as the Hammerstein model, and linear systems with static nonlinearities at the output known as the Wiener model are two widely prevailing models in the literature. Parameter estimation using these models has traditionally been carried out in discrete-time using either shift operator in the time domain and z-transformation in the complex domain [13]. A considerable volume of literature also exists in the continuous-time system using classical techniques [14]. Hammerstein and wiener model identification in the continuoustime domain using metaheuristic approaches is very rarely being reported in the literature.

Model Order Reduction (MOR) furnish an organized approach for modelling, analysis, design and implementation of large-scale systems and extensively applied in different fields 5 of engineering [15]. Diminution of higher-order systems has been investigated across the world for several decades and several methods have been developed to obtain reduced models in both time and frequency domain [16-17]. Recently, several metaheuristic algorithms and their variants [18-22] have either been employed alone or in combination with classical techniques for order reduction of both continuous and discrete-time systems. The bottom line of these evolutionary based techniques in order reduction is usually based on minimization of a performance index, obtained between the step responses of higher order and reduced order systems.

In controller design, a given plant is compensated so that the controlled system follows the reference model either exactly or approximately, satisfying certain time and frequency domain specifications. With the development of the delta operator, interest has kick-started in the discrete-time controller design methodologies as well. Few noteworthy contributions in this context include predictive control [23], optimal frequency matching control [24], fractional order control [25], sliding mode control [26] and optimal control of network control system [27]. Most commonly used control applications namely, control of fighter planes, fuel injectors, automobile spark timer etc. possess a mathematical model with a higher order. These models are often difficult to handle for which lower-order system modelling is preferred, which helps in reducing the computational burden and implementation issues involved in the design of controllers and compensators for higher-order systems. Although intelligent control techniques like fuzzy logic [28] and neural network [29] for speed control of permanent magnet synchronous motor drives are reported in the literature, yet Proportional-Integral (PI) controller continues to attract industries owing to its simple structure and robust performance for a wide range of operating conditions.

2. LITERATURE REVIEW

2.1 BFA: applications and variants

Bhushan et al. [11] explored the use of BFA to estimate the nonlinear parameters of a dc motor and control its speed adaptively. Das et al. [30] investigated chaos synchronization in a master-slave configuration with a fractional order PID controller tuned by BFA. Santos et al. [31] introduced the concept of bacterial foraging to determine the efficiency of an induction motor in field conditions with unbalanced voltages. Rajasekar et al. [32] applied BFA to estimate solar PV model parameters under environmental conditions. Hussain et al. [33] utilized BFA technique to address mobile robot navigation in an unrecognised environment containing dynamic obstacles.

Supriyno et al. [34] developed three novel adaptive mechanisms for the chemotactic step size of BFA to model flexible manipulator systems. Daryabeigi et al. [35] proposed a smart BFA method to optimize controller parameters for the speed control of switched reluctance motor drives. Panda et al. [36] incorporated adaptive chemotaxis of BFA with crossover mechanism of GA to attain linear discriminant analysis-based face recognition. Wang et al. [37] proposed a new bacterial foraging algorithm based on control mechanisms and updating population strategies in order to achieve feature selection to classify images. Pandi et al. [38] integrated bacterial foraging with differential evolution to develop a hybrid algorithm in order to solve congestion management problem in restructured power system scenario. Kim [39] dealt with a hybrid combination of BFA and GA to establish an intelligent controller for an automatic voltage regulator.

Gollapudi et al. [40] hybridized particle swarm optimisation technique with bacterial foraging algorithm to validate a few unimodal and multimodal test functions. Further, this algorithm had also been applied to determine the resonant frequency of rectangular microstrip antenna. Hooshmand et al. [41] made a combination of BFA and NM algorithms for phase balancing and network reconfiguration simultaneously in a distribution network. Vaisakh et al. [42] incorporated particle swarm and differential evolution operators in the original bacterial foraging algorithm to introduce a new hybrid topology and applied it to solve dynamic economic load dispatch problem. Okaeme et al. [43] combined BFA and GA for the controller design of electric drives. Nasir et al. [44] made a blend of bacterial foraging and spiral dynamics to evolve two new hybrid strategies. The performance of the algorithm was validated with some well-known benchmark optimization problems as well as controlling flexible manipulator system. El-Wakeel et al. [45] proposed a hybrid algorithm with the fusion of PSO with BFA to determine the tuning parameters of a PID controller required for speed control of a permanent magnet BLDC motor.

Panda et al. [46] put together BFA and Many Optimization Liaisons (MOL) for the design of FACTS based damping controller necessary in order to improve the stability of power system. Zhao et al. [47] mixed bacterial foraging and gravitational search algorithms to test twenty-three numerical benchmark functions as well as to identify the parameters of a chaotic system. A gravitational search strategy was assimilated with the chemotaxis step of the bacterial foraging algorithm so as to adjust its unit length as per the swarming information. Then a swarm heterogeneity strategy was combined with the reproduction step so as to increase the reproduction mode based on this concept.

Wu et al. [48] made an aggregate of BFA, PSO and fuzzy support vector machine to identify the fatigue status of electromyography signal. Vishnuvarthanan et al. [49] made a merger of BFA with modified fuzzy-k means algorithm for improved tumour and tissue segmentation in magnetic 7 resonance brain images. Turanoğlu et al. [50] developed a hybrid strategy with the union of bacterial foraging with simulated annealing algorithm to address the dynamic facility layout problem. Roy et al. [51] connected BFA with ANN for energy management of microgrid. The proposed method proved better as compared to some existing methods like GA and ABC.

2.2 Some new metaheuristic algorithms

Meng et al. [5] developed a new nature-inspired optimization technique based on the social behaviours and interactions of bird swarms. The algorithm was successfully evaluated using eighteen benchmark problems from the literature. Meng et al. [52] further developed another bio-inspired technique simulating the hierarchy in the chicken swarm and the behaviours of the chicken swarm, including roosters, hens and chicks. Both unconstrained and constrained optimization problems were handled successfully using this technique. Mirjalili [53] developed a novel metaheuristic approach based on the navigation strategy of moths found in nature. The algorithm was tested with twenty-nine benchmark functions and seven real-time engineering problems. Mirjalili [54] formulated a new algorithm based on the hunting behaviour of ant-lions found in nature. Mirjalili [55] developed another nature-inspired algorithm mimicking the static and dynamic swarming behaviours of dragon fireflies.

Mirjalili et al. [56] drew inspiration from the three concepts in cosmology viz. white hole, black hole, and wormhole to develop a new metaheuristic algorithm coined as multi-verse optimizer (MVO). Mirjalili [57] presented a novel algorithm utilizing a mathematical model based on sine and cosine functions. The performance of the algorithm was evaluated for a set of unimodal, multi-modal and composite functions. Mirjalili et al. [58] came up with a new nature-inspired metaheuristic algorithm based on the bubble-net hunting mechanism of humpback whales. The strength of the proposed method was assessed using twenty-nine test functions and six structural design problems. Saremi et al. [59] formulated a new optimization algorithm imitating the swarming behaviour of grasshoppers available in nature. The performance of this algorithm was verified using CEC2005 test benchmarks.

Mirjalili et al. [6] stated a novel optimization algorithm based on the salp swarms while they navigate and forage in oceans. The proposed technique was evaluated using well-known benchmark test functions. Ali et al. [60] presented a new real coded GA to solve complex optimization tasks.

2.3 Identification using metaheuristic approaches

Al-Duwaish [61] applied GA to solve the problem of hammerstein model identification. Tötterman et al. [62] applied support vector method to identify wiener models. Nanda et al. [63] developed two new versions of PSO to identify hammerstein plant model. Xu et al. [12] proposed a hybrid combination of PSO and BFA to identify nonlinear system models. Sun et al. [64] applied an adaptive particle swarm optimization technique with a maximum likelihood estimate to identify non-linear Hammerstein model parameters. A simulation example from the discrete-time system had been taken up to justify the effectiveness of the proposed method. Chen et al. [65] dealt with the problem of parameter identification of Hammerstein system with continuous non-linearity applying particle swarm optimization algorithm. The applicability of the proposed method was illustrated with the help of a simulation example.

Gotmare et al. [66] addressed the problem of nonlinear system identification of hammerstein model using cuckoo search. Pal et al. [13] presented the identification of several practically relevant open and closed-loop discrete-time Wiener systems using brain storm optimization algorithm. Prawin et al. [67] presented a three-stage parameter identification algorithm integrating dynamic quantum PSO with neighbourhood search strategy.

2.4 GAPS IN THE RESEARCH

From the literature, it can be concluded that though the firefly algorithm has been hybridized with many metaheuristic algorithms, still there is a lot of scopes to formulate new hybrid topologies. Even hybridizations of firefly algorithm with bacterial foraging and grey wolf optimizer are missing in the literature. Moreover, pattern search proves to a good candidate in the hybrid algorithm for its local search abilities and hence can be considered to be integrated with firefly algorithm.

Further, it is seen from the literature that chaos feature incorporated in a metaheuristic algorithm enhances its performance to a considerable extent.

Though Hammerstein and wiener model identification with metaheuristic approaches are popular in the discrete-time domain, similar analyses are rarely reported for continuous-time systems. Hence system identification with hybrid metaheuristic techniques can be thought of to unify both continuous and discrete-time systems leveraging the properties of delta operator.

Moreover, model order reduction via soft computing techniques has so far been performed in the continuous and discrete-time system separately; therefore, there is a need to provide a unified framework for model order reduction in delta domain, capitalizing the benefits of hybrid metaheuristic algorithms.

In classical control literature, "Truxal" method is an established technique in control system synthesis, based on the philosophy of exact model matching in which first the parameters of the reference model are computed to meet the given time and frequency domain performance specifications and then the controller parameters are computed such that the overall closedloop controlled system match both time and frequency responses of the reference model.

The main drawback of exact model matching is that the controller so designed does not give guarantee for its physical hardware implementation. To overcome the same, approximate model matching may be a viable alternative in which model order reduction scheme as proposed above can be applied to design control scheme in the delta domain. A new application area involving identification and control of converter fed electric drives in the delta domain may also be thought of.

Though literature supports modelling and control of electric drives for the continuous and discrete-time domain, yet practically no work in electric drives has been explored using the delta operator approach. Thus, order reduction and suitable controller design in the delta domain could be devised for converter fed permanent magnet synchronous motor drives, in particular applying hybrid metaheuristic algorithms.

3. CONCLUSION AND FUTURE SCOPE

Metaheuristic algorithms, namely bacterial foraging, pattern search, firefly algorithm, flower pollination algorithm, grey wolf optimizer and their variants are emerging areas of research in the literature on artificial intelligence and evolutionary computation. A significant volume of works has been reported on its applications in different fields of science, engineering, economics, management, sociology, medicine and others as an alternative of classical optimization techniques. Applications of these tools are also gaining momentum in the area of system and control theory. Based on a survey of literature and gaps identified, the objectives future work carried out are as follows:

To study and explore the available bacterial foraging algorithm (BFA) techniques.

To develop hybrid metaheuristic algorithm based search tools.

To develop unified method for identification and control in the delta domain based on above.

To apply the hybrid metaheuristic algorithm search based unified approach for identification and control of electric drives.

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