A Comprehensive Review of Optimization Algorithms for Nonlinear Systems

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The practical problems are full of nonlinearity and uncertainty due to their dynamic behavior. The uncertainties, parameters variations and other constraints make nonlinear systems very complex. To deal with such system dynamics and uncertainties, soft computing techniques are widely used. Optimization algorithms are one of the most effective and simple soft computing techniques.In literature, several controllers and control mythologies are being discussed to evaluate the system performance. Optimization algorithms are one of the popular soft computing techniques, used with different controllers like conventional PID, fuzzy logic, ANN, and many others to handle system nonlinearities and enhance the performance. These optimization algorithms not only improve the performance effectively but also gave robust response towards the nonlinearities. The proper selection of algorithm is a very important aspect to find the best solution. Here three categories of algorithms i.e. from swarm-based algorithms particle swarm optimization (PSO), grasshopper optimization algorithm (GOA), grey wolf optimization (GWO), whale optimization algorithm (WOA), gravitational search algorithm (GSA) from physics based and teaching learning based optimization (TLBO) from human-based have been reviewed for nonlinear systems. Most of the algorithms are suffering from either of abilities i.e. exploration or exploitation so sometimes they are not able to give optimal solution. To overcome with this problem, recently hybrid approach of algorithms has been widely used in which the better sides of the individual algorithms are utilized.

Keywords: PSO, GWO, GOA, WOA, GSA, TLBO, hybrid PSOGSA, hybrid PSOGWO.

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1 Introduction

Most of the practical systems are highly nonlinear and exhibits complex dynamics. Due to uncertainties and nonlinearities present in the system, the overall performance of system becomes unsatisfactory. A suitable controller should be used with optimized parameters to improve performance and handle the nonlinearities of the system. Conventional PID controller is still the first choice for industrial and practical applications due to it having few control parameters and simple structure. The process dynamics and uncertainties causes change in model parameters, which can deteriorate controller performance therefore controller needs to be regularly retuned [1]. The several mathematical methods, error and trail method, Ziegler-Nicolas method are used to find the optimal gain for conventional PID controller. These methods take more computational effort, time consuming and did not gives optimal solution while handling the nonlinear systems. Various control methods and optimization algorithms have been suggested in literature for nonlinear systems [8]. Almost all the practical systems are having dynamic behavior which changes with time which makes it very complex. Due to uncertainties and unpredictability nonlinear systems seek more attention of researchers [9]. In literature, there have been many controllers used to handle nonlinearities and improve system performance. In this chapter various optimization algorithms with different categories have been reviewed in terms of variants, modification and applications [10]. The reviews of hybrid algorithms are also carried out with applications in various fields.

2 Classification of Optimization Techniques

The classification of optimization algorithms is shown in figure 1. Mathematical optimizations are based on gradient information, to find the best solution [11]. Although, such techniques are still being used by researchers[2]. 'Meta' means above or beyond and 'heuristic' means to find. Metaheuristic is a guided random search techniques which guide subordinate heuristic in iterative manner to explores and exploits the search space and avoid getting trapped in local minima[3]. It also uses search experience intelligently to guide further search to find optimal solutions [4]. Metaheuristic optimization algorithms are widely used because: (i) simple concept and implementation is easy(ii) do not require gradient information (iii) local minima can avoideasily.

Due to simplicity, robustness and efficiency metaheuristic algorithms have performed significantly to solve most nonlinear multimodal real world problems[5]. In first group i.e. evolutionary based algorithms are based on natural evolution. In these algorithms, best individuals are combined for next generation, hence population optimize over the course of generation [6]. The evolutionary algorithms are Genetic algorithm (GA), evolution strategy (ES), genetic programming etc. Physics based algorithms imitate the physics rules like gravitational force, law of motion and attraction and other. The most popular algorithms widely used are simulated annealing (SA) which is based on metallurgic annealing process, , Ray Optimization (RO)[13], gravitational search algorithm (GSA)[26], and many others. The third category is a swarm based algorithms which basically simulates the intelligence behavior of social creatures. These algorithms have some advantages[7]:

- **(i)** Maintained search space information at the time of iterations.
- **(ii)** Have less number of parameters as compare to evolutionary algorithms
- **(iii)** Required less memory space for finding optimal solutions.

3 Review on optimization algorithms

3.1 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a swarm intelligence based algorithm proposed by Kennedy and Eberhart [12]. Due to less number of parameters and no gradient information required from objective function it has been widely used in every field. Initially each particle has velocity and they placed randomly to evaluate the fitness value. With iteration each particle moves to new position and gives better fitness value to previous one [13]. In PSO, velocity update has three parts:

(i) Momentum of particles incorporates the effect of previous and current velocity.
(ii) Cognitive part pulls particles velocity towards its personal best.
(iii) Social part pulls particles velocity towards swarm's best.

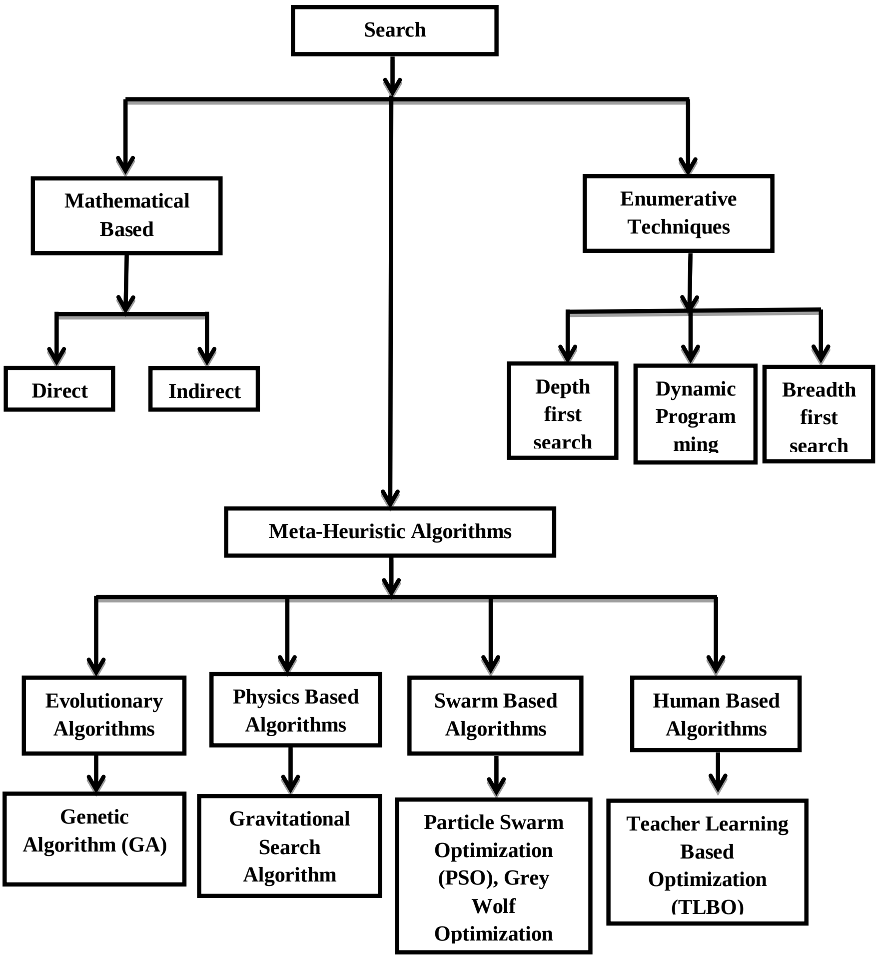

Fig. 1. Classification of optimization techniques

Inertia controls the effect of last iteration on current iteration. Higher value of "w" improves the global and small value improves local search abilityrespectively. The typical value of inertia is 1, and for optimization process it lies between 0.9 to 0.4, which allows particles initially to explore and nearby area in later with reduced speed [13]. Random numbers prevent algorithm from getting stuck in local minima. In PSO particles have chance to get trapped in local minima because of premature solution, which results in not finding the best solution during optimization process[14]. To overcome with these search problems, there is a time to time update in algorithm[15]. To improve the performance of PSO algorithm1 divided the swarm according to their fitness value namely as better particles, simpleparticles, and the worst particles[16]. A modified quantum behaved PSO (QPSO), has been used to analyze the effect premature controlling search[17]. Gholizadeh and Moghadas [18] used an improved QPSO on two numerical examples to evaluate the performance for optimum design process. Martins et al. [19] implemented a simplified PSO, on nonlinear benchmark functions to analyze the performance. This simplified PSO not only reduces the computational effort but gives considerable performance. Panda et al. [20] used PID controller for an automatic voltage regulator and compared its performance with different algorithms like ABC, DE. Vastrakar and Padhy [21] used PID controller with PSO algorithm for unstable search process. The search space divides in sub spaces to find local minima and global minima. Chang and Chen [22] , optimizes the gain of PID controller using PSO algorithm for multi input multi output systems. Xiang et al. [23] discusses sensor less scheme which shows the satisfactory response for tracking performance. PSO algorithms help system in tracking under different conditions. Huang and Li [24] used improved PSO to tune PID controller gains and iterative learning control (MC) controllers. Jaafar et al.[25] implemented PSO algorithm with PID controller on nonlinear gantry system to improve the system performance.

3.2 Gravitational Search Algorithm (GSA)

Gravitational search algorithm is proposed by Rashedi [26] based on physics laws of gravity and motion. GSA is widely used in several domains due its accuracy. Duman et al. [27] implemented on power flow problem to find the optimal value of control variables and evaluated the performance of GSA in terms of robustness. Sonmez et al. [28] compares GSA with PSO and simulated annealing (SA) algorithm to minimize the fuel cost. The GSA shows better results as compare to others. Amoozegar et al. [29] uses the GSA and PSO for software designing problem. GSA gives better performance as compare to PSO in minimizing the computing time for software design. Pei et al.[30] introduced modified GSA (MGSA) by adding three local search operators. The MGSA has implemented on vehicle scheduling problem and shows the robust performance. Doraghinejad et al [31] uses improved GSA on network connectivity problem to minimize the interference in the system. In improved GSA, the discrete local search operator is combined with standard GSA which shows the better performance as compare to Discrete PSO algorithm. Li et al.[32] also uses chaotic GSA (CGSA) to identify the parameter of Lorentz system. In CGSA logistic mapping function has been used for local search and compares performance with GA and PSO algorithms. CGSA shows competent results in terms of accuracy and computing time to other. Naji et al.[33] replaced GSA sequential approach with multi agent system to improve the convergence speed and maintain high performance level. Precup et al.[34] an adaptive GSA has been used on fuzzy controlled servo system to find optimal tuning parameters. The result of adaptive GSA shows a reduced time constant and sensitivity. Rashedi et al.[35] introduced new technique namely binary GSA (BGSA) in which probability of velocity changes in state between 0 to 1. The BGSA is more efficient and gives better results for nonlinear benchmark functions.

3.3 Grey Wolf Optimization (GWO)

GWO is developed by Mirjalili et al. [36] and widely used in every filed of science and industry. This algorithm shows the social hierarchy and intelligence of grey wolves in hunting. There is time to time improvement in GWO algorithm based on variants and applications. Wen et al. [37], Introduced an improvement in standard GWO algorithm name as (IGWO). In IGWO authors used penalty function method and converted constraints problem into unconstrained problem. Emaryet al. [38],proposed binary GWO in which to find the optimal solution binarization of individual step has been done and updated binary position of wolf are exploited form the domain with accuracy. BGWO gives better results as compare to standard GWO. Mittal et al. [39] proposed a modified GWO (MGWO) in which authors' balances between search ability and attacking ability to find optimal solution. MGWO is compared with GWO which shows better results for nonlinear programming problem. Li et al. [40] proposed modified discrete GWO (MDGWO) in which GWO is first converted in to discrete form and parameters are changed accordingly for finding optimal solution. Mirjalili et al.[41] introduced multi objective GWO (MOGWO) by integrating fixed size external archive into standard GWO. Kohli and Arora[42] proposed chaotic GWO (CGWO) in which authors introduce a randomness in the algorithm using chaotic maps and then try to regulate the tuning parameters of GWO algorithm. This technique enhances the search ability and convergence towards optimal solution. Gao and Zhao [43] uses variable weights in place of fixed weights and governing equations changes accordingly. The author also tested and verifies results on many experiments. Joshi and Arora [44] an enhanced GWO (EGWO) was introduced in which they amending random parameter in standard GWO and improves the convergence ability. This EGWO was further implemented on pressure vessel problem and found better results as compare to other optimization algorithms. Long et al. [45] uses an exploration enhanced GWO (E-EGWO) which is used to solve high dimension numerical problems. As on comparative study shows that E-EGWO show less role of control parameters which enhance the position of grey wolf. The performance has been analyzed on three different data sets and results shows that GWO is efficient. Kumar et al [46] uses multi objective GWO and presented a frame work for reducing the cost of nuclear power plant system. Pant et al.[47] for highly complex nonlinear equations GWO algorithms has been compared with other metaheuristics algorithm.

3.4 Grasshopper Optimization Algorithm (GOA)

Pinto et al. [48] used BGOA based on percentile theory on knapsack optimization problem. The performance has been compared with different set of methods and found that BGOA achieves satisfactory results as compare to other. Crawford et al.[49], used percentile based GOA on combinational arrangement problem in industries. The performance of BGOA is verified through standard instances and satisfactory results have been achieved. Luo et al.[50] presents a modified version of GOA and implemented on continuous optimization problems and financial forecast problem. The author did the modifications in search abilities by adding Gaussian mutation operator, Levy-flight process which improves the randomness and finally opposition based learning method enhanced the more powerful search space. These modifications enhanced the effectiveness of GOA and gives better performance. The propose CGOA is implemented of several benchmark functions which shows satisfactory results as compare to other. Suriya et al. [51] used CGOA in transmission development system in which the aim is to reduce the cost of installation stagey .This CGOA not only gives optimal results and reduce the cost significantly. Mirjalili et al. [52] propose multi objective optimization algorithm (MOGOA) to solve complex nonlinear problems. MOGOA has been implemented on test functions and performance is compared in terms of convergence and minimization of error with GOA which shows better results to other multi objective algorithms.

Elmi et al. [53] implanted MOGOA on robot path arranging problem. The MOGOA gives optimal results in terms of cost, energy, distance and time. The MOGOA gives best fitted objective function which help to arrange right path for robot. The MOGOA is compared with PSO algorithm and found better results. Hekimogˇlu et al. [54] used GOA with PID controller on automatic voltage regulator (AVR). The GOA is used to tune the PID controller parameters and the optimal tuning improves the performance of the system. The performance is also analyzed in terms of squared error, which reduced significantly as compare to other algorithm based control. Potnuru et al. [55] used GOA on electronically commuted motor drive system to control the speed. The GOA minimizes the squared error objective function and improves the system transient and steady state performance to a good extent.

3.5 Whale Optimization Algorithm (WOA)

Mirjalili and Lewis [56] proposed, whale optimization algorithm (WOA). The WOA is inspired from bubble net hunting method of humpback whales. It is widely used in various applications of science and engineering due to its simple structure, less operator, fast convergence and high efficiency[57]. Touma [58] used WOA to solve economic dispatch problem on standard IEEE 30 bus system. The WOA gives remarkable performance in reducing reactive power output, and minimizing fuel cost as compare to PSO, ACO and GA. Trivedi et al.[59] also used WOA on economic load dispatch problem with two case i.e. with emission and without emission. The WOA performance is compared with gradient method (GM), ACO and PSO and found that WOA significantly reduced the fuel cost. Jain et al.[60] presented modified WOA (MWOA) to solve the feature selection problem and found better convergence rate and accuracy to existing methods. Kaur and Arora [61] introduced a chaotic WOA (CWOA) and implemented on several benchmark problems. The convergence of CWOA is improved as compare to standard WOA in finding optimal solution. Trivedi et al.[62] proposed an adaptive version of WOA (AWOA) to solve optimization problem effectively and effectively. Xu et al [63] introduced an improved WOA (IWOA) to solve optimization problem. They added inertia weight term in basic WOA with improves search ability of algorithm. The proposed algorithm is applied on high dimensional test functions and compared with WOA and ABC algorithms. Kaveh and Ghazaan [64] introduce enhanced WOA (EWOA) to solve the truss and frames problems. The EWOA improves precision, reliability, convergence speed as compare to existing algorithm.

3.6 Teaching Learning Based Optimization (TLBO)

Teaching learning based optimization (TLBO) algorithm is motivated from teacher- students learning process in the classroom proposed by Rao et al. [65]. In this algorithm students can gain knowledge from teacher and mutual interactions with other students. The algorithm is divided in to Phase(1) Teacher Phase (2) student or Learner Phase. The TLBO have advantages over other algorithms in terms of accuracy, computational effort, convergence and robustness, therefore it is widely used in past few years. Rao et al. [66] used TLBO algorithm on mechanical design problems. TLBO algorithms are implemented and verify on benchmark functions and compared with other existing algorithms. TLBO requires less computational effort then other to find optimal solution. Cˇrepinšek et al. [67] claimed about TLBO algorithm that it is not parameter less algorithm and suggest some correction in the formula. Rao and Patel [68] addressed all the questions and well explained that TLBO algorithm is a specific parameter less algorithm. They also introduce Elitist TLBO (ETLBO) in which the worst solution is replaced by elite solution. Rao and Patel[69] presented improved TLBO (ITLBO) by adding some new concepts such as teaching by multiple teachers which help students in gaining knowledge avoid the immature converging, adaptive teaching factor which means learners gain some partial knowledge from teacher which is 0 or 1 in case of TLBO. Learning through tutorial and self-motivated learning is also introduce in TLBO which enhance the knowledge of learner which is helpful in finding the best solution. Chen et al. [70] presented an improved version of TLBO. The author introduced a concept of local learning and self learning which further improves the leaner knowledge and finally convergence towards the optimal solution. Zou et al.[71] introduced new concept which is based on learning experience of learner name as LETLBO. In this author provided various learning methods for the learners.

Every algorithm has some limitations and disadvantages because of that sometimes they are not able find best solution so hybrid approach of algorithms are used to solve complex nonlinear problems. In this approach the powerful side of individual algorithm is integrated with each other. Every algorithm search process can be divided into exploration and exploitation ability. Hybrid approach utilizes and maintains balance between these search abilities to find best solution. Here hybridization and related work of some above mentioned algorithms like PSO, GSA and GWO are discussed.

3.7 Hybrid PSOGSA

Talbi et al. [72] presented hybrid concepts for heuristic algorithms. The author divided hybridization in three categories (1) high level or low level (2) relay or co evolutionary (3) homogenous or heterogeneous. Based on above classification PSOGSA is a low level, co- evolutionary and heterogeneous hybrid algorithm. In PSOGSA the exploitation ability of PSO is combined with exploration ability of GSA [73]. Jiang et al. [74] used PSOGSA to solve economic emission load dispatch problem. PSO and GSA in parallel and updates the particle position with PSO velocity and GSA acceleration. The results of PSOGSA shows effectiveness as compare to PSO,GSA and other algorithms related to this problem in literature. H.C. Tsai [75], hybridize PSO and GSA algorithm and named that gravitational particle swarm (GPS) algorithm. In these techniques authors assume any particle in the population as PSO a particle or GSA agent. Now the position of particle or agent updated with contribution of PSO velocity and GSA acceleration. R. David [76], used PSOGSA to tune fuzzy PI controller parameters for nonlinear second order processes. The PSOGSA performance in terms of accuracy and sensitivity is compared with PSO and GSA and found satisfactory results.

3.8 Hybrid PSOGWO

PSOGWO algorithm is a recent hybrid algorithm in which the good exploration ability of GWO is integrated with PSO exploitation ability. In other words GWO algorithms support PSO local search ability to find the best solution. Singh and Singh[77], used hybrid PSOGWO algorithm in which they incorporated PSO exploitation ability with GWO exploration ability. The performance of PSOGWO was tested on some unimodel, multi model and other test functions. The results show quality performance of PSOGWO in comparison of individual algorithms in terms of convergence. Chopra et al. [78], used PSOGWO algorithm to solve economic load dispatch problem. PSO and GWO were used serially to update the population. Updated population by one algorithm was fully transferred to the other in next iteration. The objective is to reduce the generation cost and maintains the load demand constraints. The PSOGWO shows effective results as compare to other existing techniques in literature. Kamboj[79], used PSOGWO on single area unit commitment problem on different existing models. The objective was to reduce the generation cost of the system. The PSOGWO shows better results and reduce the generation cost effectively as compare to other PSO variants. Eid and Abraham [80] used hybrid PSOGWO to solve plant identification problem using leaf biometrics. They used SVM model to identify the key features such as shape, color and texture of leaf. The PSOWO algorithm improves identification rate significantly. Jain et al.[80] used PSOGWO on odor source localization team mobile robot problem. In this robots randomly try to locate their position and the performance of the algorithm shows good results over other algorithms.

4 Conclusion

In this paper extensive literature review has been carried out on optimization algorithms. Optimization algorithms like PSO, GSA, GWO, GOA, WOA and TLBO are reviewed in terms of their variants and applications. Almost all the mentioned algorithms have different variants like modification, improvement, discrete, binary,adaptive, multi objective and these variants are well used with different controllers like PID, FOPID, NL-PID, NL-FOPID, fuzzy PID, fuzzy FOPID and many others. Due to some limitations of individual algorithms like premature solution, convergence speed, control parameters, computational effort and efficiency, hybrid algorithms are widely used for nonlinear systems. Here PSO algorithms used with GSA and GWO algorithms. The literature survey reveals that hybrid approach well handles system nonlinearities and gives the optimal solution for most of the nonlinear problems. The algorithms based controllers are also reviewed for nonlinear applications. The various algorithms and their variants have been implemented nonlinear systems. The performance of algorithms are also reviewed in terms of speed, computational time, fitness value are also compared with existing methods and control scheme.

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