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Solution of an Economic Dispatch Problem Through Particle Swarm Optimization: A Detailed Survey – Part II

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ABSTRACT Although particle swarm optimization (PSO) in its standard form performs extremely well for less complicated convex optimization problems involving reduced search space, it fails in finding global optimal solutions for more complicated nonconvex optimization problems with multiminima functions, thus exploring the promising search space less efficiently to ensure solution with superior quality. Guaranteeing the location of the global optimum through PSO becomes strenuous. The inherited premature convergence problem of PSO becomes more prominent while handling, especially the complex nonconvex problems. However, PSO has the ability to hybrid with other optimization techniques to ensure optimal global solution, better convergence characteristics, computational efficiency, and so on, while dealing with complex nonconvex problems. After presenting a detailed survey of the variants of PSO (involving variations in the basic structure of PSO) in part I, part II of this paper now comprehensively details all the hybrid forms (purely) of PSO applied to a constrained economic dispatch problem. How PSO overcomes its premature convergence problem while hybridizing with other optimization techniques is well-highlighted.

INDEX TERMS Convergence characteristics, economic dispatch (ED) problem, hybrid forms of particle swarm optimization (PSO), multiminima functions, optimal global solution, premature convergence problem, search space.

I. INTRODUCTION

Thermal unit economic dispatch (ED) problem is one of the established power engineering problem areas, which refers to the problem of the proper commitment of the committed units to meet the expected load demands in an ''economic'' way while fulfilling the system and operational constraints. The economic dispatch can be easily done with numerous advanced-calculus based methods or metaheuristic optimization techniques in their standard forms when the generator cost curves are nonsmooth, nonconvex and nonlinear. The addition of valve point loading (VPL) effects, ramp rate limits (RRL), network transmission losses, generator capacity limits, prohibited operating zones (POZ), etc. to the ED formulation makes the problem even more realistic and complicated. With the availability of rapidly growing applied mathematical methods and computational capability, the real dispatch problem can be tackled efficiently. Another prominent way is to hybrid the optimization techniques in finding the optimum economic dispatch. The hybrid metaheuristic optimization techniques are found robust and show competitive performance while treating complex nonconvex problems.

Experimental results reveal that customarily the hybrid forms of algorithms, metaheuristic or advanced calculus-based, offer superior results than that of their (separate) standard forms. Even in worst case, they are as competitive as their classical forms. Motivated by this well-existing fact, many researchers devote their attention to suggest hybrid forms of metaheuristic techniques especially for nonconvex and nonlinear optimization problems containing multiple minima. Salient features of the algorithms to be hybridized are extracted to construct a hybrid algorithm for achieving optimal solutions.

A number of hybrid forms of metaheuristic optimization techniques applied to ED problem are found in literature. In a hybrid form, a metaheuristic optimization technique may integrate either with an advanced calculus-based method or with some other metaheuristic optimization technique. Some of the instances of hybrid forms found in literature where metaheuristic techniques combine with numerical methods are the following: a hybrid CE-SQP algorithm combining cross-entropy (CE) algorithm and sequential quadratic programming (SQP) [1], a self-adaptive differential evolution (SADE) and augmented Lagrange multiplier method (ALM) based hybrid SADE_ALM approach [2], a hybrid GA–PS–SQP algorithm hybridizing genetic algorithm (GA), pattern search (PS) and SQP [3], a GA–DE–PS method [4], a hybrid algorithm combining simplex algorithm Nelder-Mead with bacterial foraging (BF) algorithm [5], a real-coded GA (RCGA) and direct search method (DSM) based 'hybrid real coded GA' [6], an evolutionary programming (EP) and SQP based EP-SQP approach [7], etc. On the other hand, all-metaheuristics based hybrid optimization techniques include: a GA-API approach hybridizing ant colony optimization (API) with RCGA [8], a HCRO-DE method amalgamating chemical reaction optimization (CRO) with DE [9], a FFA-ACO algorithm integrating firefly algorithm (FFA) with ant colony optimization (ACO) [10], a hybrid CSA-CRO algorithm combining cuckoo search algorithm (CSA) and CRO [11], a DE/BBO algorithm combining DE with biogeography-based optimization (BBO) [12], a hybrid genetic algorithm (HGA) using elitism, arithmetic crossover and mutation operations of GA with Hopfield neural network (HNN) [13], a hybrid HHS method blending harmony search (HS) algorithm with swarm intelligence (SI) [14], a differential harmony search (DHS) algorithm integrating the mechanisms of both DE and HS [15], a hybrid GWO (HGWO) algorithm incorporating the mutation and uniform or binomial crossover operator from evolutionary algorithm (EA) into the grey wolf optimizer (GWO) [16], etc. All the aforementioned hybrid techniques are found to tackle the constrained nonconvex ELD problem efficiently.

Although standard (original) PSO is one of the most extensively used metaheuristic optimization techniques to solve the nonconvex problem owing to its straightforward concept, easier implementation, robustness to control parameters, and computationally well efficient, and comes with optimal solution most of the time, but it may get trapped locally while solving specifically nonconvex nondifferentiable optimization problems involving multiple local minima. In hybrid form, PSO integrates with other optimization techniques (advanced-calculus based or metaheuristic) to counteract its premature convergence problem and to enhance its computational power. This paper comprehensively details purely all the hybrid forms of PSO suggested by various researchers for tackling the constrained ELD problems. In some forms, PSO acts as a local optimizer and in other forms, it acts as a global optimizer.

The construction of the paper is as follows: Section II presents the formulation of the ED problem in a tabular form to facilitate the readers. The comprehensive detail of the dispatch problem can be found in part I of the paper. Review of all the hybrid forms of PSO applied to (single-objective) thermal unit ED problem is described in Section III. While presenting the survey, critical points or concepts are well-mentioned. Review of some variants of PSO missing in part I of the paper is pinpointed in Section IV. Section V is dedicated to conclusion.

TABLE 1. Typical ED Problems.

Constraints	Mathematical Description of Constraints
Active Power Balance Equation	$\sum_{i=1}^{n}(P_i) = (P_{Load} + P_{Loss})$ where $P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00}$
Generator Capacity Limits	$P_{i,\min} \le P_i \le P_{i,\max}$
Generator Ramp Rate Limits (RRL)	$\begin{cases} P_i - P_i^0 \le UR_i, & \text{when generation raises} \\ P_i^0 - P_i \le DR_i, & \text{when generation lowers} \end{cases}$ $\Rightarrow \max(P_{i,\min}, P_i^0 - DR_i) \le P_i \le \min(P_{i,\max}, P_i^0 + UR_i)$
Prohibited Operating Zones (POZ)	$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^L \\ P_{i,k-1}^U \le P_i \le P_{i,k}^L & (k = 2,3,\ldots,Nz_i) \\ P_{i,Nz_i}^U \le P_i \le P_i^{\max} & (k = Nz_i) \end{cases}$
Line Flow Constraints	$\lvert P_{Lf,k}\rvert \le P_{Lf,k}^{\max}, \quad k = l,\ldots,L$
System Spinning Reserve Constraints	$\sum_{i=1}^{n} P_{i,\max} \ge P_{Load} + P_{Loss} + R$

II. MATHEMATICAL MODELLING OF ED PROBLEM

The ED problem has been formulated in a very comprehensive way in part I [17] of the paper. Here, in order to facilitate the readers, mathematical modelling of the ED problem is presented briefly in the tabular form. Table 1 pinpoints all the possible scenarios of the ED problem whereas Table 2 encompasses all the system and operational equality and inequality constraints that should be met while figuring out the constrained ED problem.

III. REVIEW OF HYBRID FORMS OF PSO APPLIED TO ED PROBLEMS

Many hybrid methods integrating heuristic and deterministic methods are reported in literature for the solution of (single objective) convex and nonconvex ED problems.

A. PSO AND QUASI-NEWTON (QN) METHOD

Many hybrid methods integrating PSO (a metaheuristic method) and deterministic methods are reported in literature for the solution of nonconvex ED problems. An idea of integrating PSO with one of the local search methods named Quasi-Newton (QN) was adopted in [18] to treat ELD problems with valve point loading. The resulting hybrid method was given the name PSO-QN. The PSO, in evolution phase, produces good potential solutions and the QN, in the learning phase, ensures fine-tuning of final solution

TABLE 2. ED problem constraints.

ED Problem	Mathematical Description of ED Problem
ED Problem	$\min F_T = \sum_{i=1}^{n} F_i(P_i)$ where $F_i(P_i) = a_i + b_i P_i + c_i P_i^2$
ED Problem with VPL Effects (EDVPL)	$\min F_T = \sum_{i=1}^{n} F_i(P_i)$ where $F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \lvert e_i \times \sin(f_i \times (P_{i,\min} - P_i)) \rvert$
ED Problem with MF Options (EDMF)	$\min F_T = \sum_{i=1}^{n} F_i(P_i)$ where $F_i(P_i) = \begin{cases} F_{i1}(P_i), & \text{fuel 1}, \quad P_{i\min} \le P_i \le P_{i1} \\ F_{i2}(P_i), & \text{fuel 2}, \quad P_{i1} \le P_i \le P_{i2} \\ \vdots \\ F_{ik}(P_i), & \text{fuel } k, \quad P_{ik-1} \le P_i \le P_{i\max} \end{cases}$ with $F_{ik}(P_i) = a_{ik} + b_{ik} P_i + c_{ik} P_i^2$ if $P_{i\min,k} \le P_i \le P_{i\max,k}$ fuel option $k, k = 1, 2, \ldots, k$
ED Problem with VPL Effects and MF Options (EDVPLMF)	$\min F_T = \sum_{i=1}^{n} F_i(P_i)$ where $F_i(P_i) = \begin{cases} F_{i1}(P_i), & \text{fuel 1}, \quad P_{i\min} \le P_i \le P_{i1} \\ F_{i2}(P_i), & \text{fuel 2}, \quad P_{i1} \le P_i \le P_{i2} \\ \vdots \\ F_{ik}(P_i), & \text{fuel } k, \quad P_{ik-1} \le P_i \le P_{i\max} \end{cases}$ with $F_{ik}(P_i) = a_{ik} + b_{ik} P_i + c_{ik} P_i^2 + \lvert e_{ik} \times \sin(f_{ik} \times (P_{i,\min} - P_i)) \rvert$, if $P_{i\min,k} \le P_i \le P_{i\max,k}$, fuel option $k, k = 1, 2, \ldots, k$;

of PSO. Both PSO and QN have advantages that complement each other, thus ensuring better exploration and exploitation characteristics. Recall, unlike Newton's method that involves extensive computations for the evaluation of Hessian matrix, QN method uses only the error function's first derivative for the approximation of the inverse of Hessian. The effectiveness and workability of PSO-QN is validated for a test system comprising 13 thermal units. PSO-QN gives less fuel cost with regard to PSO and QN.

B. PSO AND SEQUENTIAL QUADRATIC PROGRAMMING (SQP)

In [19], a hybrid form of PSO named PSO-SQP integrating PSO algorithm acting as a main optimizer for the fast convergence and nonlinear programming based SQP method acting as a local optimizer to fine-tune the potential solution provided by PSO during the progression of run, was proposed for figuring out ELD problems involving the valve throttling losses. Actually, SQP requires an initial point for its progression, which is provided by PSO, in this case. The way Newton's method handles unconstrained optimization problem, the gradient search SQP method tackles the constrained optimization problem in the same way, thus showing its resemblance to Newton's method. At each iteration, a Broyden–Fletcher–Goldfarb–Shanno (BFGS) quasi-Newton method approximates the Lagrangian function's Hessian matrix which assists in generating a QP subproblem whose solution is adopted to determine search direction for a line search procedure. Regarding an ELD problem, specifically speaking, SQP monitors *gbest* value computed through PSO at each iteration. If $gbest(t) < gbest(t-1)$, SQP solves the problem using current $gbest(t)$. Finally, global *gbest* is ensured through SQP. The performance of PSO is improved by employing the concept of craziness for randomizing the velocities of some of the particles during the simulation to ensure particle diversity. The feasibility of PSO-SQP method is validated through simulation results while applying it to three different ED problems containing 3, 13, and 40 generating units. PSO-SQP outperforms PSO, EP-SQP and other metaheuristic techniques in terms of solution quality, convergence property, reliability, and computation time. In another paper [20], Victoire and Jeyakumar suggested the same hybrid PSO-SQP algorithm to solve even the more complex and nonlinear reserve constrained dynamic ED (RCDED) problem considering also the valve throttling losses. Rather than using the fixed value of inertia weight factor, its linearly decreasing value is used in PSO to keep balance between global and local exploration abilities. When tested a 10 unit power system for different load curves through PSO-SQP, it furnishes superior convergence characteristics in comparison to EP-SQP. Victoire *et al.*, in another paper [21], proposed a hybrid deterministically guided PSO (DGPSO) algorithm integrating PSO with SQP for solving, however, the dynamic ED (DED) problem taking into account the valve point loading. In the first phase of a two-phase DGPSO approach, the global optimizer PSO well-explores the solution space freely to ensure optimal solution. In the second phase, the solution attained from PSO is further fine-tuned through SQP. When a 10 unit power system is tested under three different cases through DGPSO, it offers promising results than that of EP and EP-SQP.

Reference [22] also employed a hybrid PSO-SQP method to solve the ED problems with nonsmooth cost function incorporating the valve throttling losses and multi-fuel (MF) options. Again in the hybrid method, PSO (the main optimizer) assists in finding the optimal global region while SQP is utilized in fine-tuning the solution to come up with the optimal solution on later iterations. When applied to EDMF and EDVPLMF problems having 10 thermal units, PSO-SQP method offers promising performance than that of other optimization methods.

In [23], another hybrid EP-PSO-SQP algorithm integrating the combination of EP and PSO with SQP was suggested to deal with the nonconvex dynamic ELD problem involving the valve throttling losses, RRL, POZ and transmission losses. The proposed EP-PSO-SQP optimization method is essentially a two-phase optimizer. The first phase involves the treatment of the individuals (particles) through the EP and PSO techniques to explore the feasible region freely whereas the second phase involves the invoking of SQP on finding a feasible solution (in the first phase of the run) that can be improved. The hybrid algorithm explores effectively well the complex solution space. More specifically, both EP and PSO adopts probabilistic procedures in examining the search space openly in the beginning and slowly in a few valleys (where the actual global optimum locates) as the iteration proceeds on. SQP uses the gradient information to descend the valley rapidly. In other words, SQP fine-tunes the region efficiently. When demonstrated on various test systems, EP-PSO-SQP validates its efficacy and workability.

In [24], ED problems taking into account the VPL effects were solved more efficiently through a novel two-phased iterative hybrid algorithm called CPSO-SQP hybridizing the chaotic PSO (CPSO) algorithm and SQP technique. Again in the proposed hybrid algorithm, CPSO acts as a main optimizer whereas SQP serves as a fine-tuner to enhance the solution quality. In the first phase, incorporation of adaptive inertia weight factor (AIWF) and Tent equation based chaotic local search (CLS) into PSO enhances its (global) exploration and (local) exploitation characteristics. In the second phase, SQP takes the best values of all the agents as the initial starting values and fine-tunes them to further enhance the chances of exploring the global optimum solution. CPSO-SQP ensures best solution than that of CPSO and GA. Reference [25] also efficiently utilized the idea of the hybridization of PSO (main-optimizer) and SQP (fine-tuner) for tackling three different ED problems including the VPL effects. Results revel that PSO-SQP outperforms PSO and SQP in terms of calculating the fuel cost.

C. PSO AND DIRECT SEARCH METHOD (DSM)

Reference [26] proposed the application of the hybrid algorithm named PSODS incorporating a derivative-free local search DSM into PSO for dealing with economic dispatch (ED) problems considering losses due to transmission and valve throttling, and MF options. Here PSO is used with TVIW to accelerate global and local search. Parameters used by PSO are: $\omega_{max} = 0.9$, $\omega_{min} = 0.6$, and $c_1 = c_2 = 2$. PSO suffers from the problem of poor fine tuning of solution while exploring the search space. A particle approaching the global solution somewhere in the middle of the simulation may escape in the consecutive runs. DSM comes to rescue PSO, and gets activated as soon as there is an improvement in PSO solution and fine-tunes it. When assessed on two power systems comprising 10 and 13 thermal units, PSODS exhibits improved convergence characteristics with regard to other metaheuristic optimization techniques.

Pattern search (PS) is one of the simply-structured direct search methods (DSMs). Hybridization of PS with PSO with was reported in [27] for the resolution of the ELD problem neglecting the valve throttling losses. PSO involves a constriction factor in its velocity update formula. In the suggested PSO-PS method, the better optimal (global) solutions provided initially by PSO are further processed through PS for their (local) fine-tuning. In this way, requirement for PS method to have initial starting points is also fulfilled in the hybrid method. The final solution is free from the premature convergence problem. The hybrid method comes with the advantage that it consumes less computational time due to its simplicity and easier implementation. When a power system possessing 15 generating units is evaluated through PSO-PS, it offers less fuel cost in comparison to other optimization techniques.

In [28], a novel hybrid algorithm named DPSO-EDSM hybridizing the diversity based PSO (DPSO) with an enhanced DSM (EDSM) was employed to solve a large-scale NCED problem with valve throttling losses. In DPSO-EDSM, DPSO generates high quality solutions which are further tuned through EDSM to ensure enhanced exploration and exploitation capabilities. In DPSO, the social behavior incorporated in the form of *gbest* in PSO is improved by adding another behavior named 'the random another particle best position ($pbest_{ap}$)' which gives additional exploration capacity to swarm by exchanging information to guide the swarm to the global solution. The updated PSO's velocity formula can now be modelled as

$$v_{id}^{t+1} = \omega \cdot v_{id}^{t} + c_1 \cdot r_1() \cdot \left(pbest_{id} - x_{id}^{t}\right) + c_2 \cdot r_2() \cdot \left(gbest_{gd} - x_{id}^{t}\right) + c_3 \cdot r_3() \cdot \left(pbest_{ap} - x_{id}^{t}\right) \tag{1}$$

DSM is improved with the incorporation of the parallel nature of evaluation programming. This improves its exploring capability about global exploration and local optimization. When tried to solve large-scale power systems having 13, 40 and 80 generating units, DPSO-EDSM gives optimum average cost as compared to DPSO and EDSM.

Labbi and Attous [29] in another paper, utilized the same idea of the combination of DPSO and DSM (not EDSM) for the solution of large scale NCED problem. In addition, for the sake of evaluating the behavior of $pbest_{ap}$ to maintain population diversity, a novel diversity-based judgment mechanism is also introduced. The suggested hybrid method solves the two power systems involving 13 and 40 thermal units efficiently.

D. PSO AND GRADIENT METHOD (GM)

In [30], a hybrid algorithm named enhanced gradient-based SSOA (EGSSOA) hybridizing the (numerical) gradient-based optimization method (GM) and a novel enhanced simplified swarm optimization algorithm (ESSOA) was suggested to deal with NCED problem considering the valve throttling losses and transmission losses. In SSOA, a particle, without updating its velocity, updates only its position on the basis of four positions. The updated position equation for a particle thus varies from the original PSO's position equation. The fast and robust SSOA is further enriched by tuning its parameters through the combination of self-adaptive control parameters. However, ESSOA, like PSO, suffers from the problem of premature convergence which is eliminated by introducing a new mutation strategy. This diversifies the population. In addition, fine-tuning of the solution, in each iteration, generated by global optimizer ESSOA is carried out through the local optimizer, i.e., GM. The Lagrange function (to be minimized) used in GM is defined by

$$L = \sum_{i=1}^{n} F_i(P_i) + \lambda P_{Error} \quad (2)$$

where

$$P_{Error} = \left(\sum_{i=1}^{n} (P_i) - P_{Load} - P_{Loss} \right) \quad (3)$$

This ensures the global or near global optimum solution with fast convergence. When assessed on four test systems possessing 10, 15, 40, and 80 thermal units, EGSSOA outperforms the other optimization approaches.

In [31], a global-local hybrid algorithm named HPSO integrating PSO with the nonlinear nonheuristic conjugate gradient (CG) optimization method (comes with the MathCAD commercial software suite) was used for the solution of ED problem with valve throttling losses. Like other hybrid methods, PSO method acts as a global optimizer whereas CG method as a local optimizer. The solutions attained through the global search process are undergone through local search process to avoid premature convergence and ensure high-quality stable solutions. Two variants incorporating CG into PSO called randomly controlled HPSO (HPSO-RC) and randomly uncontrolled HPSO (HPSO-RU) are also investigated. When tested on three power systems possessing 6, 13 and 38 thermal units, the proposed hybrid method gives minimum fuel cost with regard to other methods.

From the reviews, it has been established that (advanced) calculus-based optimization techniques such as QN, SQP, GM, CG, DSM, PS, etc. when hybridize with metaheuristic techniques (PSO in our case), act as the local optimizers as is the case in most of the optimization problems solved through hybrid methods. The local optimizers fine-tune the potential solutions provided by PSO to ensure optimal global solution. They try to find solution in the vicinity of the (global) search space explored already by PSO. The local optimizers get invoked once the PSO stopping criteria is met.

E. PSO AND GENETIC ALGORITHM (GA)

Reference [32] proposed a reliable and efficient hybrid algorithm named GAPSO amalgamating GA and PSO for dealing with heavily-constrained ELD problem having nonsmooth cost functions with constraints in the form of POZ and RRL. The problem, however, ignores the valve throttling losses. In the suggested GAPSO, the evaluation value (score) on the basis of the evaluation function for each of the initially randomly-generated individuals/chromosomes (potential solutions) of the population is computed, which is then compared with *pbest*. Remember, *gbest* is the best value among *pbest*'s. PSO's velocity and position formulae use the refined *pbest* and *gbest* for their upgradation. GA's selection, crossover and mutation operators are further applied to the population to generate offspring. Chromosomes with the fittest values, for the next step, are selected on comparing the parents with offspring. A chromosome bearing the latest *gbest* corresponds to the optimal solution. When ED problems of different dimensions of complexity are treated through GAPSO, it takes less average CPU time to ensure optimal generation cost with regard to RCGA and PSO.

In [33], an improved hybrid PSO (HPSO) algorithm hybridizing the traditional PSO (with TVIW) with the crossover operation of GA (slightly different from the one adopted in conventional GA) was proposed for treating the ED problems including valve throttling losses. The effect of the introduction of crossover operation into PSO displays in the form that PSO no longer suffers from the problem of premature convergence, thus controlling the population diversity. In addition, promising regions in the search space are exploited and explored by crossover-embedded-PSO in an effective way. By mathematical point of view, the generation of the trial vector $\hat{X}_i = \left(\hat{P}_{i1}, \ldots, \hat{P}_{in}\right)$, at each iteration, after mixing jth element of particle i with $pbest_{ij}$ is accomplished as follows:

$$\hat{P}_{ij}^{t+1} = \begin{cases} P_{ij}^{t+1}, & \text{if } r_{ij} \le CR \\ pbest_{ij}^{t}, & \text{otherwise} \end{cases} \quad (4)$$

Here r_{ij} and CR are the uniformly distributed random number and the pre-determined crossover rate respectively both in the range [0, 1]. Experiments are performed carefully to determine the critical CR parameter. Correspondingly *pbest* and *gbest* are then updated. Simulation results reveal that HPSO surpasses the performance of PSO and other methods when it solves effectively an NCED problem of high dimension.

Reference [34] suggested that a novel modified PSO (MPSO) integrating the classical PSO algorithm (with constriction factor) and a GA-inspired roulette selection operator [35] could solve efficiently the ELD problem considering various equality and inequality constraints such as valve throttling losses, transmission losses, RRL and POZ while avoiding the premature convergence problem and speeding up the convergence property. In proposed MPSO, based on scaled fitness, Roulette wheel selection method selects a particle randomly on the basis of some selection probability, which is used to replace '*gbest*' in the velocity equation. When power systems having 3 and 10 generating units, MPSO provides solution of superior quality by performing fewer computations.

In [36], a hybrid approach called EPSO-GM hybridizing enhanced PSO (EPSO) involving constriction factor with Gaussian mutation (GM) generally applied to GA came up with for tackling the constrained ELD problem implicating valve throttling losses. A modified heuristic search approach is introduced into the traditional PSO to make it efficient (EPSO) which restricts the solutions from violating the constraints. In addition, through the introduction of Gaussian mutation (GM) into PSO, the diversity of global search is enhanced, thus preventing PSO from being trapped in local minima during search. Depending upon the mutation rate R_m (usually set to 1 initially and decreases linearly to 0 finally) and the number of particles m, the mutation probability P_m calculated by $P_m = R_m/m$ is compared with a uniform distribution based random number $rand_i$ between 0 and 1 generated for each particle. If $rand_i < P_m$, a particle is mutated by the following relation [37].

$$x^t_{i,mutate} = x^t_i \times (1 + gaussian(\sigma)) \tag{5}$$

where x^t_i and $x^t_{i,mutate}$ represent the current and mutated position of ith particle at iteration t respectively, and $gaussian(\sigma)$ designates a Gaussian distribution based generated random number usually calculated by $\sigma = 0.1\times$ search space length. The proposed EPSO-GM offers less average and best cost as compared to GA, IEP and EPSO when implemented on the 3-unit and 10-unit 24-hour power systems.

Similarly, in another paper [38], for the sake of boosting the population diversity associated with the conventional PSO algorithm thus to improve the global search capability, Sriyanyong proposed a hybrid algorithm called PSO-GM mingling the conventional PSO algorithm with Gaussian mutation (GM) operator for solving ED problem considering nonsmooth cost functions. As already remarked, the incorporation of Gaussian mutation into PSO increases the diversity of particles by mutating some selected particles, thus ensuring the improvement of PSO global searching ability. In order to compare the proposed PSO-GM with the traditional PSO regarding the searching ability, a diversity factor is also calculated. When applied to two power systems possessing 3 and 40 generating units, PSO-GM ensures less fuel cost than that of PSO.

In order to avoid from premature convergence and thus to enhance global search capability, [39] suggested a hybrid method named PSO-RVM which incorporated a real-valued mutation (RVM) operator into the PSO algorithm while treating practical ED problems having a nonsmooth operational cost function with simple equality and inequality constraints. First, already-existing three variants, namely standard PSO (BPSO), advanced PSO (CPSO), and PSO with both inertia weight factor and constriction factor (CBPSO) are employed for the dispatch problem solution. Second, to further enhance the diversity in the swarm, a real-valued mutation (RVM) operator is incorporated into the variants of PSO algorithms in such a way that the resultant hybrid PSO-RVM algorithm is PSO-dominated and retains the advantages of PSO while providing the swarm with fresh individuals. For the sake of investigating the impact and practicability of PSO-RVM, real ED problems involving 10 and 40 generating units along with six well-established benchmark functions are assessed through PSO-RVM, PSO variants, and PSO-GM. It has been observed that, for different kinds of PSO variants as well as dispatch problems/benchmark functions, RVM behaves differently and imparts varying effect on performance. The variant CBPSO embedded with RVM (CBPSO-RVM) demonstrates tremendous improvement in performance for most of the test cases relative to other aforementioned PSO algorithms.

Reference [40] suggested a GA and PSO based hybrid algorithm named GA-PSO for resolving the no-differentiable ELD problem without throttling losses near valve points, however, with and without transmission losses. Specifically, in GA-PSO, PSO assists GA in handling-well the dispatch problem as GA suffers from various limitations such as requiring more computational time and non-guaranteed in convergence to global minimum. In GA-PSO, the best solutions selected randomly on the basis of their fitness values from each of the two sub-systems executed by GA and PSO in parallel respectively are exchanged. Solutions of superior quality till the stopping criteria meets are ensured this way. The authenticity and workability of the suggested GA-PSO is validated through its application to a 5 generating unit (IEEE 25-bus) power system. GA-PSO ensures less fuel cost as compared to PSO, BFGS and BCGAs in less execution time.

In [41], a novel hybrid GA-PSO algorithm integrating GA and PSO was also proposed for tackling NCED problem accounting for the valve throttling losses. In GA, rather than using an arithmetic crossover operator which uses a linear combination of two chromosomes to generate a new child, a crossover operator involving a coefficient calculated on the basis of similarity of parent chromosomes is utilized. Moreover, a less-complex real coded GA consumes relatively less computation time as it does not need to have coding and encoding procedures. One of the two sub-swarms obtained from the partitioning of swarm is executed through GA and the other one through PSO in parallel. However, to speed-up the convergence rate early in the run, PSO is employed. When three power systems involving 6 thermal generators with POZ and RRL, 13 units with valve throttling losses, and 18 units with only MF options evaluated through the proposed GA-PSO, it exhibits promising results.

In [42], a hybrid algorithm PSOH integrating PSO with GA was implied for working out the ELD problem neglecting, however, the valve throttling losses. The idea of hybrid algorithm is to facilitate the particles (individuals) to explore regions in the search space not-approachable by the canonical form of PSO. All this is accomplished by incorporating the uniformly-distributed mutation operator from GA into canonical PSO. The mutation operator mutes only the *pbest* and *gbest* with some specific probability mutation p_m (in this case, decreases from 5% to 1%). This also avoids the algorithm from trapping in local minima. To keep balance between the local and global search, rather than using the fixed value of inertia factor, a linear updating strategy is adopted to change its value during the run. The introduced inertia factor is expressed by

$$\omega = (\omega_{\max} - \omega_{\max}) \times iter_{\max} \big/ iter \tag{6}$$

When power systems with 3, 13 and 20 generating units are evaluated through PSOH, PSOH shows promising results in comparison to other optimization algorithms.

In [43], a novel hybrid method called MPSO-GA hybridizing the modified PSO and GA was proposed for treating constrained ED problem accounting for valve throttling losses, POZ, etc. In MPSO as suggested in [44], premature convergence problem is avoided by controlling the diversity of a small population. In proposed MPSO-GA, the best GA's final population chromosomes obtained after the application of GA to initial population are fed to the MPSO as the input data. On processing the input data, MPSO ensures good quality solutions. MPSO has not to explore the entire search space, leaving less minimum local points. When tested on 6, 10 and 15 units containing test systems, MPSO-GA exhibits better convergence characteristics in comparison to other metaheuristic approaches.

F. PSO AND DIFFERENTIAL EVOLUTION (DE)

In [45], a modified genetic PSO (MGPSO) algorithm hybridizing the GPSO represented by the floating point representation and a modified heuristic crossover (MHC) operator derived from DE algorithm was applied to treat the ELD problem ignoring the throttling losses near valve points. Proposed by [46], GPSO which incorporates the genetic reproduction mechanisms, namely crossover and mutation into standard PSO is described for the dth component of particle i as

$$x_{id}^{t+1} = \omega(0,\omega_1)\cdot rand(x_{id}^t) + \omega(\omega_1,\omega_2)\cdot rand(pbest_{id}) + \omega(\omega_2,1)\cdot rand(gbest_{gd}) \quad (7)$$

where

$$\omega(a,b) = \begin{cases} 1, & \text{if } a \le R_1 < b \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

and

$$rand(y) = \begin{cases} \tilde{y}, & \text{if } R_2 < p_m \\ y, & \text{otherwise} \end{cases} \quad (9)$$

In above equations, $0 < \omega_1 < \omega_2 < 1$; $R_1, R_2 \in U(0,1)$ represents the uniformly distributed random numbers in the range [0, 1]; $rand(y)$ mutates y with a small probability p_m. By adopting the circle topology [47], each particle exchanges building blocks with personal and global experiences with its two immediate neighbors. To further ensure diversity, a modified heuristic crossover (MHC) borrowed from DE algorithm is incorporated into GPSO. Comparison of MGPSO with other PSO methods suggests that MGPSO provides better results, thus validating its feasibility and effectiveness.

Another hybrid form of PSO called PSOM hybridizing DE's mutation operators (activate only if velocity goes out of the boundaries or approaches zero) with conventional PSO was proposed in [48] and [49] to improve diversity exploration of PSO while solving the ED problem involving POZ but neglecting the valve throttling losses. Four scenarios of mutation operators actually referring to the distance between the different populations multiplied by a constant factor, are summarized in Table 3.

TABLE 3. DE mutation operator based PSOMs.

Equation for Mutation Operator	Scenario
$v_i^{t+1} = \mathrm{K}\left[\left(x_k^t - x_i^t\right) - \left(x_q^t - x_i^t\right)\right]$	PSOM1
$v_i^{t+1} = \mathrm{K}\left[\left(x_k^{t-\beta} - x_i^t\right) - \left(x_q^{t-\beta} - x_i^t\right)\right]$	PSOM2
$v_i^{t+1} = \mathrm{K}\left[\left(x_k^t - x_i^t\right) - \left(x_q^t - x_i^t\right) - \left(x_r^t - x_i^t\right)\right]$	PSOM3
$v_i^{t+1} = \mathrm{K}\left[\left(x_k^{t-\beta} - x_i^t\right) - \left(x_q^{t-\beta} - x_i^t\right) - \left(x_r^{t-\beta} - x_i^t\right)\right]$	PSOM4

In the equations, K represents a scaling factor having a value in the range [0.1, 2]; β represents the user defines previous iteration;k, q, and r represent the random indices of the particles. Simulation results reveal that PSOMs ensure better solution quality as compared to other metaheuristics when exercised on a power system comprising 6 thermal units.

In [50], another novel hybrid algorithm named particle swarm differential evolution optimization (PSDEO) hybridizing PSO with DE was suggested to ameliorate the exploration and exploitation characteristics while dealing with two NCED problems (one with POZ and the other one with valve throttling losses). Generally, the particles in PSO may loss diversity with the evolution of new generation and restrict their movement within the limited search space, thus enhancing their chances to get stagnated prematurely before finding the optimal solution. DE, on the other hand, ensures faster and superior solutions while meeting all the equality and inequality constraints through its mutation, crossover and selection operators without utilizing the *gbest* and *pbest* information associated with the particles as it bears no memory for the previous generation unlike PSO. Rather than using the traditional DE operators, the authors propose new mutation (''DE/global-local/1''), crossover and selection operators to ensure even better performance. The proposed PSDEO utilizes particle's *pbest* experience in PSO and newly-suggested efficient DE operators to well-tackle the nonsmooth ED problems. As mutation schemes use the social part (*gbest*) to enhance diversity, so *gbest* is not included in velocity formula. The modified velocity and position formulas of PSO take the following form.

$$v_{id}^{t+1} = \omega\cdot v_{id}^t + c_1\cdot r_1()\cdot\left(pbest_{id}^t - x_{id}^t\right) \quad (10)$$

$$x_{id}^{t+1} = x_{id}^t + \hat{u}_{id}^{t+1} \quad (11)$$

where

$$\hat{u}_{id}^{t+1} = \frac{v_{id}^{t+1}}{\left\|V_i^t\right\|} = \frac{v_{id}^{t+1}}{\sum_{d=1}^{m}\left(v_{id}^{t+1}\right)^2} = \text{Unit Vector} \quad (12)$$

When demonstrated on two NCED problems, PSDEO validates its efficacy and workability by giving superior performance in comparison to PSO, DE and other optimization techniques. To gain a better insight into DE operators and their application to ED problem, Table 4 is constructed.

TABLE 4. DE operators description.

Operator	Mathematical Description	Explanation	Operator Application to ED Problem
Mutation or Differential	$P_i^t = \left[p_{i,1}^t, p_{i,2}^t, \ldots, p_{i,m}^t\right]$, $i = 1, 2, \ldots, N_P$	The *m*-dimensional *i*th vector (or particle) of population N_P at current generation t is represented by P_i^t .	
	$Y_i^t = \left[y_{i,1}^t, y_{i,2}^t, \ldots, y_{i,m}^t\right]$	For each P_i^t , an associated mutant individual Y_i^t is generated through a mutation strategy.	
	"DE/rand/1": $y_{i,d}^t = y_{r_1^i,d}^t + F\left(y_{r_2^i,d}^t - y_{r_3^i,d}^t\right)$	"DE/rand/1" is the mutation strategy. $r_1^i, r_2^i, r_3^i \in [1, NP]$ represent the mutually exclusive integers. $F \in [0,2]$ is a control parameter.	"DE/global-local/1": $y_{i,d}^t = gbest_d^t + F\left(pbest_{i,d}^t - x_{r_1^i,d}^t\right)$
Crossover or Recombination	$Z_i^t = \left[z_{i,1}^t, z_{i,2}^t, \ldots, z_{i,m}^t\right]$ with $z_{i,d}^t = \begin{cases} y_{i,d}^t, & \text{if } rand \le CR \\ p_{i,d}^t, & \text{otherwise} \end{cases}$	The trial vector Z_i^t is generated by the mixing of P_i^t and Y_i^t through scheme $z_{i,d}^t$. $CR \in [0,1]$ represents the crossover probability and $rand \in [0,1]$ designates a uniformly distributed random number.	$z_{i,d}^t = \begin{cases} y_{i,d}^t, & \text{if } rand \le CR \\ pbest_{i,d}^t, & \text{otherwise} \end{cases}$
Selection	$P_i^{t+1} = \begin{cases} Z_i^t, & \text{if } f(Z_i^t) \le f(P_i^t) \\ P_i^t, & \text{otherwise} \end{cases}$	Selection of P_i^{t+1}	$gbest^t = \begin{cases} Z_i^t, & \text{if } f(Z_i^t) \le f(gbest^t) \\ gbest^t, & \text{otherwise} \end{cases}$ $pbest_i^t = \begin{cases} Z_i^t, & \text{if } f(Z_i^t) \le f(pbest_i^t) \\ pbest_i^t, & \text{otherwise} \end{cases}$

In [51], a novel hybrid approach named hybrid PSO (DE-PSO) synergistically combining the evolutionary operators, such as mutation, crossover, and selection of DE algorithm belonging to evolutionary algorithm (EA) family with PSO (involving TVIW) was implied to treat the ELD problem considering the throttling losses occurring at valve points. Integration of the DE operators into PSO enhances population diversity, thus avoiding PSO from being trapped in local minima. Percentage of population, at each iteration, evolved with DE is controlled through DE-PSO's driving parameter called hybridization coefficient (HC) whose value ranges from 0 to 1. Zero value of HC is the indicative of pure PSO procedure whereas its unity value represents the pure DE process. The all-thermal system considered here to check the effectiveness and practicability of DE-PSO contains only 3 units. Results reveal that hybrid DE-PSO displays improved convergence characteristics with regard to GA, DE, PSO, and GA-PSO.

Reference [52] suggested a modernistic hybrid algorithm (HA) integrating PSO, DE, Tent equation based chaotic sequences, and constraints handling strategy, for tackling ED problems considering the RRL, POZ, and network losses, however, ignoring throttling losses near valve points. In order to avoid from premature convergence problem, the mutation and crossover operators of DE are incorporated into PSO. The operators enhance the diversity of population by introducing new individuals into the population. Chaotic sequences are employed to make the linearly decreasing inertia weight chaotic before introducing it into the velocity update formula. This assists PSO in exploring the global search space effectively. In addition, the constraints are dealt with through the dynamic penalty price function. When a 15 unit power system is evaluated through the proposed hybrid method, it outclasses the other existing metaheuristic methods.

In [53], a new hybrid optimization technique named DEPSO integrating DE algorithm with PSO was proposed for the solution of four kinds of practical ED problems having cost functions exhibiting nonsmooth nonconvex characteristics. Strongly integrated DEPSO incorporates the PSO procedure as an ancillary mutation operator into the traditional DE approach. Unlike the other DE and PSO based hybrid algorithms, DEPSO uses two mutant vectors. One is the DE's classical mutant vector and the other one is generated through PSO updating rules for particle position. Correspondingly, in the crossover operation, two different trial vectors are generated for each parent or target vector which are involved in creating a new individual. The selection operator chooses a new individual scoring a better fitness value among the trial vectors and the parent vector. In this way, in DEPSO, avoidance from premature convergence problem, capability of global search, acceleration of convergence speed, and enhancement of population diversity are achieved. When demonstrated on various ELD problems with different constraints, DEPSO offers better convergence characteristics in comparison to DE and DERAND.

In [54], a hybrid algorithm named PSO-DE adopting the positive traits of PSO and DE was proposed to work out the generation and demand dispatch (GDD) problem taking into consideration the equality and inequality energy constraints. The GDD problem differs slightly from the ELD problem in a way that GDD problem involves the cost function which not only includes local generation costs but also includes the costs associated with energy purchased from other sources or from the regional distribution company. In PSO–DE, the search space is explored globally and locally in an efficient way using PSO and DE. The crossover and mutation operators of DE are employed to enhance information exchange among individuals (to explore new areas of the search space) and population diversity (to avoid the algorithm from being trapped into local minima) respectively. For the first 30% of the iterations, PSO is employed and for the remaining 70% of the iterations, DE with crossover and mutation operators is employed to ensure well-tuned optimal solution. When applied to solve an IEEE 30-bus test system, PSO-DE displays tremendous improvement in performance in contrast to PSO incorporating constriction factor and TVIW and DE.

For the sake of solving a complex nonlinear ELD problem with POZ and valve throttling losses, a hybrid metaheuristic named DPD (the name emerges from the fact that it combines various metaheuristic approaches such as DE, PSO and DE on a population) combining DE and PSO was proposed in [55]. In DPD, whole of the population is partitioned into three groups named inferior group, mid group and superior group. The inferior and superior groups are dealt with DE whereas PSO is employed to the mid-group. In hybrid method, both the algorithms overcome their shortcomings through the information sharing mechanism. To detain the best global solution found so far and to ameliorate the solution quality, two strategies named elitism and non-redundant search respectively are incorporated in DPD cycle. The proposed DPD is found efficient in treating an ELD problem.

In the shrinking hypersphere based PSO (SHPSO) suggested by Yadav and Deep [56], each iteration's *pbest* is actually the *pbest* among the *gbest* of global hypersphere and *pbest* of each *pbest*'s hypersphere. A well-refined and improved *pbest* is achieved this way, thus enhancing the exploration capability. The shrinking strategy derives its name from the fact that as the iterations proceed on, the radius of hypersphere gets reduced (shrinks). Theoretically, this analogizes to limiting the particles inside their radius to direct themselves toward the global minimum. Based on the integration of the SHPSO and DE, reference [57] recommended a hybrid co-swarm PSO (CSHPSO) for dealing with the constrained ELD problem incorporating valve throttling losses. The whole of the swarm is partitioned, on the basis of Euclidean distance, into two same-sized sub swarms keeping in view that particle lying close to each other are kept in different sub-swarms in order to ameliorate diversity. One of the sub swarms is treated through SHPSO whereas DE (through its operators such as, mutation, crossover and selection) is executed on the other sub swarms to find the personal bests for each of the sub swarms. According to parameter-free constraint handling strategy mentioned in the paper, the particles bounding out of the feasible region are penalized with the degree of constrained violation. When a test system containing 40 units is checked out through CSHPSO, it demonstrates its supremacy over SHPSO and DE.

G. PSO AND EVOLUTIONARY PROGRAMMING (EP)

In [58], a hybrid method named PSO-CEP integrating PSO and classical EP (CEP) with Gaussian mutation was prompted for handling nonconvex ELD problem involving valve throttling losses. Unlike the selection, mutation and crossover operators of GA, EP employs only mutation and competition operators to save time. The convergence rate and the efficiency of CEP are enhanced through mutation and competition operators embedded with PSO intelligence. More precisely, new population with individuals having high fitness values, for next generation, is created through EP, which is then evolved through PSO. Mathematically speaking, an offspring P'_j of offspring vector $p'_i = \left[P'_1, P'_2, \ldots, P'_m\right]$ corresponding to parent trial vector p_i (represents N_P parent individuals) is generated through a Gaussian random variable $N\left(0, \sigma_j^2\right)$ with zero mean and standard deviation σ_j. That is to say

$$P'_j = P_j + N\left(0, \sigma_j^2\right), \quad j = 1, 2, \ldots, m \tag{13}$$

with

$$\sigma_j = \beta \times \frac{f_{p_i}}{f_{\min}}\left(P_{j,\max} - P_{j,\min}\right) \tag{14}$$

Here β is a scaling factor usually tuned during the process of search for optimum, $f_{\min}$ is the minimum cost value among N_P trial solutions, and f_{p_i} is the objective function value associated with the trial vector p_i. Then $2N_P$ individuals (N_P from both vector p_i and p'_i) compete with one another for selection on the basis of stochastic tournament method based selection technique. Each individual is assigned a weight w_i according to the competition as follows:

$$w_i = \sum_{t=1}^{k} w_t \tag{15}$$

where

$$w_t = \begin{cases} 1, & \text{if } u < \frac{f_{p_i}}{f_{p_i}+f_r} \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

Here f_r is the fitness value of rth randomly selected competitor among $2N_P$ trial solutions, u is a uniform random numbers ranging over [0, 1]. All individuals are ranked in descending order on the basis of their corresponding score. On the application of PSO-CEP to a test system involving 40 units, it is revealed that PSO-CEP demonstrates improved convergence characteristics with regard to CEP and PSO.

For treating the ELD problem considering the throttling losses near valve points, however, ignoring the transmission losses, the same authors Sinha *et al.* [59] in another paper, suggested another hybrid algorithm named IFEP-PSO hybridizing PSO and self-adaptive improved fast EP (IFEP) techniques to enhance the convergence capability. In IFEP, an offspring vector is created not from the offspring generated through Gaussian mutation as in case of CEP, but from better of two offspring generated from each parent, one by Gaussian mutation and the other by Cauchy mutation. The two offspring P'_{1j} and P'_{2j} are created from the parent P_j by the following way:

$$S'_j = S_j \times \exp\left\{\tau N_j(0,1) + \tau' N(0,1)\right\} \tag{17}$$

$$P'_{1j} = P_j + S'_j \times N_j(0,1) \tag{18}$$

$$P'_{2j} = P_j + S'_j \times C_j(0,1) \tag{19}$$

Accomplishing this ameliorates the convergence capability of IFEP. New population generated by self-adaptive IFEP is then evolved through PSO. PSO uses the fixed values of its coefficients, i.e., $\omega = 0$, $c_1 = c_2 = 2$. A power system with 15 units is tested through IFEP-PSO which gives better solution quality and computational efficiency than that of CEP-PSO.

Reference [60] also utilized a hybrid algorithm named EP-EPSO integrating an EP algorithm with efficient PSO (EPSO) for the solution of ELD problem. The problem takes into account the transmission losses as well as valve throttling losses. EP, being a global or near global heuristic method, first ensures a global optimal solution with faster convergence speed. Generation of the offspring is accomplished through Gaussian mutation (GM). Selection and competition operations are then performed to select individuals with high fitness values. After fulfilling the stopping criteria, the solution attained through EP is taken as an initial starting point by EPSO which uses, here, gradient information to ensure final optimal solution. In this way, exploration and exploitation properties are ensured. EPSO suggests modifications in particle's position to handle inequality constraints. Then equality constraints are handled without altering the PSO's dynamic process. EP-EPSO effectively solves a test system bearing 40 generating units and outperforms EP, EPSO, NN-EPSO, and EP-SQP by coming up with less production cost.

In [61], application of a new hybrid PSO (HPSO) method integrating EP and PSO approaches to ED problems considering POZ and RRL, however, without valve throttling losses was also reported. Surely, HPSO exploits the salient features of both the metaheuristic techniques. Newly generated population (with best individuals) evolved after the application of Gaussian mutation of EP on the randomly initialized individuals satisfying all the equality and inequality constraints is further undergone through PSO to ensure exploration and exploitation characteristics. The potency and practicability of the hybrid metaheuristic is validated through the evolution of different standard systems involving 3, 6, 15 and 20 units. HPSO brandishes improved convergence characteristics with regard to EP and PSO.

H. PSO AND SIMULATED ANNEALING (SA)

In [62], simulated annealing (SA) like PSO (SA-PSO) algorithm was recommended for figuring out constrained NCED problem involving generation limitations, RRL, POZ, and transmission losses to augment search efficiency and solution quality. Although PSO contains parallel search techniques but it suffers from the premature convergence problem. On the other hand, SA offers probabilistic jumping property called the metropolis process controlled through the adjustment of the temperature. Moreover, SA technique offers high probability for the global optimum solution to be converged asymptotically. Resultantly, hybrid metaheuristic SA-PSO which incorporates a SA like cooling scheme and a metropolis-probability decision process into PSO helps PSO from avoiding premature convergence. Simulation results show that SA-PSO is more superior to PSO and GA methods. Reference [63] also utilized the idea of hybridization of PSO and SA as described in [62] for working out constrained ELD problem with throttling losses occurring at valve points, however, with and without transmission losses. The hybrid algorithm shows encouraging results when applied to an ELD problem possessing 3 thermal units.

Reference [64] suggested a novel efficient hybrid SA (EHSA) algorithm for dealing with both the convex and nonconvex ED problems with constraints in the form of transmission loss, generator capacity limits, RRL and POZ, however, neglecting the valve throttling losses. In EHSA, PSO utilizing the mutation operator of DE is integrated with simulated annealing to boost the exploration and exploitation characteristics. Specifically, a global solution achieved through the combination of PSO and DE acts as an initial solution for SA which further fine-tunes the solution to make it optimal. Specifically, SA evaluates and updates *gbest* while reducing its parameter temperature T. The mutation operator gets activated as soon as the velocity of the particle gets out of boundary, which is then recalculated as

$$v_{id}^{t+1} = F \times \left(\left(x_k^t - x_i^t\right) - \left(x_q^t - x_i^t\right)\right) \tag{20}$$

The position of the particle is then calculated using typical PSO position formula. When a test system with 6 units is evaluated through EHSA, it displays improved convergence characteristics with regard to SOH-PSO, BBO and new MPSO.

I. PSO AND ANT COLONY OPTIMIZATION (ACO)

Realizing the salient features such as the robust convergence, and flexibility to integrate with other methods of ant colony optimization (ACO), [65], [66] suggested a novel hybrid algorithm integrating PSO with ACO to solve ELD problems with and without valve point effects along with other equality and inequality constraints. Taking the *gbest* particles calculated by PSO as an input, ACO evaluates its response functions, compares, and exchanges information with the 'best ant' to eventually arrive at the best solution. ACO ensures diversification potentially through the 'pheromone' trail. The kth ant decides the next move from position i to destination j on the basis of the probabilistic policy $P_{ij}^{k}(t)$ which is given by

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k}[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}}, \quad j \in N_i^k \tag{21}$$

Here τ_{ij} represents the pheromone's quantity on path *i*-*j*; N_i^k designates the feasible neighborhood of kth ant at position i; parameters α and β signify the weights for the 'pheromone' trail and the ELD specific heuristic value of η_{ij} respectively. On the evolution of IEEE 30 and 26 bus systems with 6 generators, it is established that the proposed hybrid metaheuristic demonstrates better convergence characteristics with regard to other hybrid optimization methods.

J. PSO AND BACTERIAL FORAGING OPTIMIZATION (BFO)

In [67] and [68], a hybrid optimization algorithm named BPSO-DE hybridizing BFO and PSO-DE was effectively used to tackle DED problem involving valve point loading, POZ, RRL, and spinning reserve capacity. Although PSO offers encouraging heuristics, but it may converge locally without ensuring global optimal solutions for complex nonlinear dispatch problems. However, the diversity of PSO is enhanced by generating a new generation through the mutation, recombination, and selection operators of DE. PSO-DE algorithm acts as a main optimizer and explores the entire search space globally whereas BFOA, through its chemo-tactic movement operation, performs the local search. In this way, BPSO-DE keeps balance between exploration and exploitation properties. When tested on power systems containing 5 and 10 units, BPSO-DE shows its effectiveness over the other existing methods such as HDE and VSHDE. In another paper [69], the same authors Vaisakh *et al.* employed the same combination of PSO, DE, and BFOA for the solution of static ED problems of different dimensions of complexity. The proposed hybrid algorithm shows its supremacy over the other existing metaheuristic techniques through simulation results.

Another hybrid algorithm named HPSOTVAC/BFA integrating TVAC based PSO (HPSOTVAC) and BFA was proposed in [70] to tackle the real ED problem having nonlinear cost functions. PSO experiences the problem of poor local search ability thus premature convergence although it exhibits good global search ability. In the proposed technique, the BFA algorithm enhances the local search capability of PSOTVAC (also involves the constriction factor) through its adaptive reproduction and chemotaxis loop which can effectively explore the search space with high resolution. Hybrid metaheuristic HPSOTVAC/BFA comparatively gives less total generation costs with regard to other metaheuristics from which it is constructed.

In [71], a novel hybrid algorithm called modified PSO (MPSO) integrating PSO and bacterial foraging (BF) was successfully applied to work out the dynamic nonconvex ED (NCED) problem with throttling losses near valve points and transmission losses to guarantee better balance between local and global search. Total generation cost function considered in the paper takes a slightly different form; it includes not only the fuel cost but also the multiple fuel, emission, and maintenance costs, making itself even more complicated and nonlinear. While treating such kind of nonconvex and discontinuous cost functions, PSO might loss diversity as the iterations go on proceeding. A particle roams about in the reduced search space; its *pbest* nearly approaches *gbest*; it converges prematurely and becomes inactive. In the proposed MPSO algorithm, in order to bypass local minima easily, repellent feature of BF is incorporated into PSO's velocity formula along with inertial, cognitive and social components. The repellent effect is translated into a foraging random walk vector implementing a type of biased random walk. The updated velocity formula including the repellent characteristic (foraging random walk vector frw_{id}) of BF ensures more directed movement and is expressed by

$$\begin{aligned} v_{id}^{t+1} &= \omega \cdot v_{id}^{t} + c_1 \cdot r_1() \cdot \left(pbest_{id} - x_{id}^{t}\right) \\ &\quad + c_2 \cdot r_2() \cdot \left(gbest_{gd} - x_{id}^{t}\right) + c_3 \cdot r_3() \cdot \left(frw_{id} - x_{id}^{t}\right) \end{aligned} \tag{22}$$

where

$$frw_{id} = \begin{cases} pbest_{id} + random\left(\left|gbest_{gd} - pbest_{id}\right|\right), \\ \quad \text{if } gbest_{gd} \neq pbest_{id} \\ X_j^{\min} + random\left(X_j^{\max} - X_j^{\min}\right), \\ \quad \text{otherwise} \end{cases} \tag{23}$$

The particle's position is computed by

$$x_{id}^{t+1} = x_{id}^{t} + C(i) \times \bar{u}_{id} \tag{24}$$

where

$$\bar{u}_{id} = \frac{v_{id}}{\|V_i\|} = \frac{v_{id}}{\sqrt{\sum_{j=1}^{N} v_{id}^2}} = \text{Unit vector} \tag{25}$$

$$C(i) = \frac{\sum_{k=1}^{\zeta}\left|Error_{i,k}\right| + 1}{\sqrt{Iteration}} = \text{Foraging step length} \tag{26}$$

When a 10 unit power system dispatching power for a time period of 24 hours (daily load) is evaluated through the proposed hybrid metaheuristic, it ensures less cost in relatively less average execution time than that of EP and EP-SQP.

K. PSO AND GREY WOLF OPTIMIZER (GWO)

Reference [72] suggested that hybridization of GWO with PSO also improves the performance while solving the ED problem. Both the throttling losses occurring at valve points and transmission losses are considered. In the proposed hybridized method, GWO is first run to generate minimum values for all the individuals after initializing the population and constructing the solution space. These individuals are then passed to PSO as the starting points which gives the updated positions back to GWO till meeting the stopping criteria. Recall, GWO mimics the grey wolves' leadership hierarchy and hunting mechanism. The hybrid GWO-PSO method validates its effectiveness and workability by solving

ED problems of different dimensions of complexity. The proposed hybrid metaheuristic displays encouraging results in comparison to other metaheuristics.

L. PSO AND TABU SEARCH ALGORITHM (TSA)

In [73], integration of TSA with Sobol sequence incorporated PSO was implied for treating NCED problems of different dimensions of complexity. The authors call the suggested novel hybrid metaheuristic as distributed Sobol PSO and TSA (DSPSO-TSA). In Sobol PSO (SPSO), it has been observed that the Sobol sequence [74] based controlled inertia weight factor warrants solution of improved quality in comparison to TVIW. SPSO is made 'distributed' by splitting the group of particles into many subgroups. Each subgroup, just like the group, stores particle's current position, *pbest*, and *gbest* of among all the particles in its memory. The memories associated with the subgroups accumulatively are used to look for the best particle among all groups (*Gbest*). Thus, in DSPSO, a new updated velocity formula (involving constriction factor) incorporating two cognitive behaviors and two cognitive socials can be interpreted mathematically as

$$v_{id}^{t+1} = C \cdot \begin{pmatrix} \omega_{Sobol} \cdot v_{id}^{t} + \\ c_1 \cdot r_1() \cdot \left(pbest_{id} - x_{id}^{t}\right) + c_2 \cdot r_2() \cdot \left(gbest_{gd} - x_{id}^{t}\right) + \\ c_3 \cdot r_3() \cdot \left(pbest_{ij} - x_{id}^{t}\right) + c_4 \cdot r_4() \cdot \left(Gbest - x_{id}^{t}\right) \end{pmatrix} \tag{27}$$

The potential solution (*Gbest*) provided by DSPSO is further adjusted through TSA to guarantee the optimal global solution. The local optimizer TSA (in this case) makes use of its preeminent components, namely a tabu list (TL) and an aspiration criterion (AC) to accomplish the task of fine tuning. The proposed DSPSO-TSA outperforms the other metaheuristics such as PSO, TSA, GA, etc.

M. PSO AND HARMONY SEARCH (HS) ALGORITHM

Inspired from the improvisation process by a musician, a derivative-free HS algorithm usually employs its three components, namely harmony memory usage, pitch adjusting, and randomization to converge the solution for a problem. Hybridization of such a HS algorithm with PSO was proposed in [75] for tackling nonconvex and convex ELD problems considering constraints such as power balance, RRL, and POZ. In the proposed hybrid SI-based HS (HHS) algorithm, actually improved version of classical HS called IHS is used. In IHS, rather than using a too high or too low value of the pitch adjustment rate (PAR), dynamically varied value of PAR to ensure better solution quality is used, which is given by the expression

$$PAR = PAR_{\min} + \frac{(PAR_{\max} - PAR_{\min})}{generation_{\max}} \times generation \tag{28}$$

As can be observed, dynamic *PAR* is accomplished through adaptive PSO. In addition, in HS's improvisation process, particles update themselves on the basis of velocity rather than position to accelerate convergence speed. To keep better balance between exploration and exploitation, particle's rank based adaptive inertia weigh factor is employed in PSO. The proposed HHS algorithm solves efficiently different computational complex ED problems involving 6, 13, 15, and 40 thermal units while ensuring optimal global solution and improved convergence characteristics with regard to other optimization techniques. Pandi and Panigrahi [14] in another paper, employed the same HHS algorithm with dynamically varied PAR for figuring out the dynamic ELD problems. However, power systems possessing 5, 10, and 30 are assessed through the HHS algorithm this time. Results reveal that HHS exhibits better final fitness value in comparison to HS.

N. PSO AND GRAVITATIONAL SEARCH ALGORITHM (GSA)

In [76], a hybrid algorithm named PSOGSA combining (modified) PSO with GSA was recommended to tackle ELD problem with VPL effects considering various constraints in the form of POZ and RRL. Actually PSOGSA hybridizes PSO's social thinking (*gbest*) ability and GSA's local search capability to exploit exploration and exploitation characteristics. In modified PSO, each particle not only directs itself to move towards the global best position (as in case of traditional PSO) but also intends to move away from the worst position experienced by itself. Inclusion of the worst position experience into the velocity formula enhances the search ability. In addition, TVIW and TVAC are incorporated to ensure better local and global exploration, and convergence speed. To be specific, in hybrid PSOGSA method, initially randomly generated agents are accelerated using law of motion, ensuring fast convergence speed. The best solution found thus far is also noted. Mathematically speaking, the velocity of each agent, in hybrid method, is then computed by

$$v_{id}^{t+1} = \omega \cdot v_{id}^{t} + c_1 \cdot r_1() \cdot ac_i(t) + c_2 \cdot r_2() \cdot \left(gbest_{gd} - x_{id}^{t}\right) + c_3 \cdot r_3() \cdot \left(x_{id}^{t} - pworst_{id}\right) \tag{29}$$

where $ac_i(t)$ represents the acceleration of the ith agent at iteration t. A particle's position is then computed using updated velocity. The feasibility and effectiveness of PSOGSA has been validated by exercising it to work out ELD problems having 6 and 40 thermal units.

Rather than employing the modified PSO, [77] proposed the hybridization of standard PSO with memory-less GSA to solve NCED problem considering valve throttling losses but with and without transmission losses. The hybrid algorithm was designated as (standard) PSOGSA. In PSOGSA, once the acceleration associated with the mass is computed and the best solution found so far is updated after each iteration, the velocity of each agent is then computed by

$$v_{id}^{t+1} = \omega \cdot v_{id}^{t} + c_1 \cdot r_1() \cdot ac_i(t) + c_2 \cdot r_2() \cdot \left(gbest_{gd} - x_{id}^{t}\right) \tag{30}$$

where $ac_i(t)$ represents the acceleration of the ith agent at iteration t. The position is calculated using PSO's position formula. In the paper, modifications are also suggested in

PSOGSA to ensure even better global optimum solution. In modified PSOGSA (fuzzy logic based PSOGSA), the velocity of each agent in GSA being suffered from oscillations and divergence is constrained within the interval ranging from $-V_{max}$ to $+V_{max}$. The parameter h involved in $+V_{max}$ is optimized by employing the fuzzy logic algorithm to ensure optimum global solution. FPSOGSA offers encouraging results than that of PSOGSA when exercised on various dispatch problems with varied complexity.

Based on the hybridization of PSO with gravity-inspired GSA, [78] suggested a hybrid algorithm named gravity local search particle swarm algorithm (GLSPSA) for resolving transmission losses-incorporated convex ED problem. Social thinking operator of PSO and local thinking operator of GSA are amalgamated to ameliorate the performance. Instead of TVAC, fixed values of acceleration coefficients are used, i.e., $c_1 = 2.5$, $c_2 = 1.8$. When power systems with 3, 6, and 5 generating units are reckoned through GLSPSA, GLSPSA comes up with less fuel cost and computational time in comparison to other heuristic techniques.

Application of PSO and GSA based hybrid algorithm named PSOGSA was also reported in [79] for working out large-scale ELD problems of different dimensions and complexity levels, however, without valve throttling losses. PSOGSA integrates the global search ability of PSO and local search capability of GSA to ensure better exploration and exploitation properties. When exercised on various complex dispatch problems involving 6, 18, 20, and 54 generating units, PSOGSA offers better robustness and efficiency over the existing metaheuristic approaches. It has been observed from the aforementioned references that GSA acts as a local optimizer in its hybrid form with PSO while resolving the ED problems.

O. PSO AND CULTURAL ALGORITHM (CA)

As already remarked, PSO inherently experiences the premature convergence problem. This may be due to the lack of population diversity. On the other hand, cultural evolution process based CA may diversify the population using its three fundamental components, namely a population space, a belief space and the communication protocol. Realizing the positive traits of PSO and CA, many researchers have adopted their combination to tackle the nonconvex constrained ED problems.

In [80], an improved (hybrid) cultural PSO algorithm with feedback mechanism integrating the cultural algorithm (CA) with PSO was proposed to tackle the ELD problems involving throttling losses manifesting at valve points. In the proposed algorithm, the population space (contains a set of possible solutions) and the belief space (an information repository where the individuals store their experiences for the other individuals) are linked through a communication protocol for ameliorating the population diversity. The evolution velocity weight of the particle while keeping in view of its current fitness value is controlled through a PID controller. In addition, constraint handling strategies are also introduced. When exercised on two systems consisting of 3 and 6 units, cultural PSO shows better global convergence performance and higher convergence speed with regard to other metaheuristic approaches.

In [81], a hybrid method named SCAPSO integrating the knowledge-based CA which increases the population diversity in order to enhance the global search ability of PSO which employs a new velocity update strategy rather than using the standard one, solved efficiently the ELD problem considering the valve point loading. The new velocity update strategy assists in widening the search space. Actually, in SCAPSO, population space enhances the population diversity under the guidance of belief space, thus avoiding the individuals from being trapped in the local convergence. In return, belief space is provided with the elites by population space. Through mutual interaction and dual evolution mechanism of the spaces, both exploration and exploitation characteristics are achieved. The updated velocity formula gets simpler as it removes the previous velocity term (inertial component). When a power system having 40 generating units is figured out through SCAPSO, the hybrid metaheuristic exhibits better convergence characteristics and robustness with regard to other metaheuristics.

P. PSO AND CLONAL SELECTION ALGORITHM (CSA)

Reference [82] suggested a hybrid P-CLONAL algorithm utilizing the positive traits of an immune based CLONAL algorithm and PSO (with TVIW) for treating nonlinear nonconvex ELD problems considering the throttling losses existing at valve points and the transmission losses. Although PSO offers fast convergence speed, but it experiences the problem of being trapped into the local optima. On the other hand, CLONAL algorithm has the ability of escaping from local optima as it ensures more qualified population. The (initial) population is further improved by (standard) PSO with parameters $c_1 = 2.8$, $c_2 = 1.2$ and TVIW. Proliferation phase then involves the selection of the particles/antibodies with higher fitted values keeping in view the proliferation rate. Lastly, the particles are mutated through Gaussian mutation. The well-refined version of population helps in obtaining the optimal global solution in quicker time. The hybrid P-CLONAL algorithm shows encouraging results in comparison to other metaheuristic approaches when exercised on two different power systems comprising 13 and 40 generating units.

In [83], extension of P-CLONAL algorithm in the form of another new hybrid optimization method called PG-CLONAL hybridizing the clonal selection algorithm (CSA) with PSO and gases Brownian optimization (GBMO) was proposed for handling nonlinear nonconvex ELD problem with valve throttling losses. In PG-CLONAL method, local search is performed (additionally as compared to P-CLONAL) on the solutions attained after the processing of PSO and mutation as described in [82] through GBMO which employs its turbulent rotational motion operator for this purpose. Finally, best global solutions are then sorted on the basis of objective functions values among initial solutions, PSO solutions, mutated solutions, and GBMO solutions. Improvement in initial population quality and local search makes the hybrid method more efficient. When two systems considering 3 and 13 generating units are evaluated through PG-CLONAL, it outperforms the other hybrid methods.

Q. PSO AND FUZZY LOGIC (FL)

Niknam *et al*. contributed research tremendously in the form of hybrid forms of PSO involving the linguistic fuzzy rules in order to treat the practical ED problems considering the valve throttling losses. Reference [84] suggested a fuzzy adaptive modified PSO (FAMPSO) algorithm to avoid the premature convergence experienced by classical PSO while figuring out the nonconvex ED problem contemplating the valve point loading. Specifically, the premature convergence problem is avoided by incorporating a newly-introduced mutation operator into PSO. This, actually, diversifies the PSO population, thus enhancing the chances of well-exploring the search space. The performance of MPSO is enhanced further by adjusting dynamically the inertia weight (ω) and learning factors/acceleration coefficients (c_1 and c_2) of the velocity equation through fuzzy IF/THEN rules. Simulation results reveal that fuzzified PSO parameters, i.e. ω, c_1 and c_2 make the algorithm less sensitive against the initial parameters set for the experiments as compared to non-fuzzified parameters which are either constant or generated randomly. When compared, FAMPSO shows its superiority over other optimization techniques while solving two test cases involving 13 and 40 generating units. Inspired form the work of Niknam *et al*., concept of tuning both the learning factors and inertia weight through fuzzy IF/THEN rules was also utilized in [85] to deal successfully with the NCED problem considering valve throttling losses, MF options and POZ. When ED problems of different dimensions of complexity (involving 6 and 15 units in this case) are evaluated through the proposed FAPSO metaheuristic, it shows encouraging results with regard to PSO and SOH-PSO.

Reference [86] also employed the innovative but pre-existing idea of controlling dynamically the PSO's three most significant parameters, ω, and c_1 and c_2 through fuzzy rules while working out a large-scale constrained ED problem involving valve throttling losses and POZ. In addition, however, a decomposition procedure is also executed to reduce the fuel cost. The resulted algorithm is designated as an improved fuzzy controlled parallel PSO based decomposed network (FCP-PSO) by the authors. In the first phase of FCP-PSO, fuzzy rules are constructed to tune the output parameters ω, and c_1 and c_2 on the basis of the input parameters, i.e., the best fitness (BF) and the number of generations for the best unchanged fitness (NU). The second phase is about the decomposed network strategy which involves exploring the efficient partitioned networks to adjust the first solution found thus far. The sum of the real power calculated for each of the partitioned networks is made equal to power demand. When demonstrated on a large-scale 40 thermal unit power system, the proposed algorithm exhibits its robustness.

Almost same kind of idea of using fuzzy rules was also proposed by [87] while introducing a novel hybrid fuzzy dynamic velocity feedback PSO (HFDVF-PSO) algorithm for the solution of practical nonconvex ED problem including MF options and VPL effects. In the proposed HFDVF-PSO method, the average of the absolute value of the velocity of the particles is taken as a feedback to the fuzzy inference system (FIS) in order to adjust, in a dynamic and nonlinear manner, the inertia weight factor which assists in ensuring the balance between global and local search abilities of the PSO. TVAC are set to a fixed value of 2, i.e., $c_1 = c_2 = 2$. When tested on a standard 10 thermal unit test system, HFDVF-PSO gives optimum fuel cost as compared to the traditional PSO method and the other metaheuristic methods reported in literature.

Particles in PSO find the best position by changing their positions at each iteration to ensure feasible solution. Differential evolution (DE) intends to ensure fast convergence even at the cost of the degradation of the performance. The reduction of its search capability leads to a higher probability towards obtaining a local optimum. In [88], Niknam *et al*. proposed a solution to this limitation by introducing a hybrid method called FAPSO–VDE integrating the variable DE (VDE) with the fuzzy adaptive PSO (FAPSO) used for tackling VPL effects considered ED problem. In VDE, DE algorithm's the most influential parameters, namely the mutation (F) and the crossover (C_r) controlling the differential variation amplification and the population diversity respectively change themselves on the basis of self-adaptive parameter control strategy during the progression of the optimization process, thus avoiding the algorithm from being trapped in local optima. As a result, in the hybrid method, VDE acts as a main optimizer whereas the fine-tuning for every improvement in the solution of the VDE run is accomplished through FAPSO. FAPSO utilizes fuzzified inertia weigh factor to keep balance between global and local search. However, rather than using the fixed or fuzzified acceleration coefficients, they are calculated on the basis of fitness of global optimum solution $F\left(gbest_{gd}\right)$ during the run and are expressed by

$$c_j = 1 + \left[\frac{1}{1 + \exp\left(-\alpha \times F\left(gbest_{gd}\right)\right)^{n1}}\right], \quad j = 1, 2 \tag{31}$$

where

$$\alpha = \frac{1}{F\left(gbest_{gd}\right)} \tag{32}$$

FAPSO-VDE displays better convergence characteristics in less computational time when evaluated on power systems having 13 and 40 thermal units, thus validating its effectiveness and workability.

In another paper [89], diversification of PSO population to avoid PSO from premature convergence was accomplished through the already-suggested idea of incorporating a new mutation operator into a canonical PSO. The novel algorithm is given the name a modified adaptive PSO (MAPSO). Ramp-rate limits are taken into consideration. In the proposed mutation technique, each particle limits itself to find a new solution within a specific radius through a random walk. Particle's current position which is the center of the area, is compared with the new position attained through mutation. The final position refers to the position having better fitness function. MAPSO offers encouraging results while solving nonconvex dynamic ED problems (with throttling losses appearing at valve point) involving 5 and 10 unit power systems.

In [90], rather than adopting the mathematical equation to tune the inertia weight, Niknam *et al* proposed the tuning of the inertia weight through fuzzy IF/THEN rules. In their previous work, the authors also adjusted the cognitive and the social parameters through fuzzy IF/THEN rules. However, in this paper, both the clamping velocity and the acceleration coefficients adjust themselves self-adaptively after their incorporation into the own optimization problem. They have neither assumed a constant value, like in standard PSO, nor have they assumed a time varying function, like in adaptive PSO variants. In addition, a mutation technique is integrated with adaptive PSO (APSO) to avoid premature convergence by diversifying the population. The simulation results reveal that the new adaptive PSO (NAPSO) algorithm shows relatively improved convergence characteristics with regard to PSO and FAPSO when test systems involving 6, 15 and 40 generating units are calculated through them. The same NAPSO algorithm, in another paper [91], was also utilized to tackle constrained NCED problems (with valve throttling losses, POZ, and MF options) of different dimensions of complexity involving, however, 6, 10, 15, 40 and 80 generating units.

Applicability of fuzzy PSO (FPSO) to the constrained ELD problem with valve throttling losses, RRL and POZ was also reported in [92]. In FPSO, tuning of inertia weight factor is accomplished through fuzzy logic during execution in order to avoid PSO from premature convergence problem. TVAC are kept fixed, i.e., $c_1 = c_2 = 2.05$. When tested on four dispatch problems with varying complexity, FPSO ensures minimum fuel cost within less computational time as compared to PSO.

Proposition of an enhanced adaptive PSO (EAPSO) algorithm was reported in [93] to treat the DED problem including the losses due to transmission and throttling near valve points, and RRL. Various tasks are accomplished to enhance PSO performance. The complex constraints without imposing any restrictions are managed through an equality constraint-handling scheme to enhance randomness and solution quality. Rather than considering the same and also constant social and cognitive parameters usually obtained by trial-and-error approach, for all particles through the optimization procedure, each particle self adaptively designs its own social and cognitive factors. Accomplishing this forces the swarm to search smartly the feasible space for the global optimum solution. A mutation technique is formulated to boost the population diversity, thus preventing the algorithm from experiencing premature phenomena. In other words, this leads the swarm toward search space where the global solution exists, much more effectively. In EAPSO, rather than adjusting the inertia weight factor through fuzzy rules, or decreasing it linearly as in PSO, or keeping the constant value, a novel nonlinear approach is suggested to adjust the inertia weight factor dynamically according to the optimization process performance. To control balance between the local and global search, a nonlinear inertia weight factor is made flexible using the nonlinear sinusoidal function y which is interpreted mathematically by

$$y = \sin\left(\frac{\pi}{r} \times l\right), \quad l = \frac{iter_{\max} - iter}{iter_{\max}}; \tag{33}$$

where $r \in [0, 10]$ signifies a coefficient. Being a function of parameters r and l, parameter ω heavily depends on them. Parameter y is normalized as follows

$$y_n = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \tag{34}$$

Therefore ω is nonlinearly tuned as follows

$$\omega = y_n \times (\omega_{\max} - \omega_{\min}) + \omega_{\min} \tag{35}$$

In this way, ω acts as a linear inertia weight factor for a larger value of r while it has nonlinear behavior as r decreases. EAPSO shows relatively encouraging results with regard to other optimization techniques when applied to three power systems bearing 5, 10 and 30 generating units.

R. PSO AND ARTIFICIAL NEURAL NETWORKS (ANN)

The idea of hybridization of PSO and ANN was applied to solve ELD problems with nonconvex cost functions in [94]. The data in the form of best total costs for each optimized combination generated by PSO are trained through ANN with different hidden neurons and learning rate. Unlike the traditional methods of training, PSO does not train a network, but a network of networks after initializing all network weights randomly. Global best (*gbest*) refers to the network with the highest fitness value. Remember, position refers to the weight of a neuron and velocity to the weight upgrading. In other words, PSO performs global search whereas local search is performed through ANN to get global minimum. Simulation results reveal that PSO-ANN exhibits better exploration and exploitation properties when exercised on a power system involving 3 generating units.

S. PSO AND WAVELET THEORY BASED MUTATION

Reference [95] also suggested a hybrid algorithm named WPSO (PSO with wavelet mutation operation) in order to augment the searching ability of PSO by incorporating a wavelet theory based mutation operation while working out NCLD problem considering valve throttling losses. PSO also uses constriction factor along with TVIW. Rather than keeping fixed the mutation space throughout the exploration of the search space, variation of the mutation space's size with the progression in iterations on the basis of the wavelet theory is recommended in the paper. Accomplishing this enables the algorithm to explore solution space more efficiently for optimal solutions. When a large-scale 40 generating unit power system is evaluated through WPSO, it comes with less fuel cost in less time with regard to the other approaches.

IV. REVIEW OF VARIANTS OF PSO APPLIED TO ED PROBLEMS

Review of some of the variants of PSO that could not be discussed in part I of the paper, in spite of the best effort, is presented here. Reference [96] utilized the well-established concept of making the inertia weigh factor (more precisely, TVIW) of PSO chaotic on the basis of Tent map for treating ELD problem recognizing the VPL effects. The resulting modified tent-map-based chaotic PSO (TCPSO) does not experience the premature convergence problem, and validates its effectiveness and workability when assessed on three test systems over the classical PSO and other optimization techniques while ensuring a balance between the global and local search in a batter way.

In [97], two PSO algorithms, namely "PSO classical" and "PSO accelerated" were applied to tackle ELD problems neglecting both type of losses, i.e. transmission losses and throttling losses occurring at valve points. PSO classical involves TVIW and constant/fixed acceleration coefficients whereas, as the name implies, PSO accelerated uses TVAC while solving the problem. The paper actually highlights the well-established fact that PSO with varying acceleration coefficients ensures better solution quality and less computational time as compared to the one with non-varying acceleration coefficients. The fact is validated through the application of both PSO algorithms to three power systems containing 4, 6, and 20 thermal units.

A. PSO AND LAPLACE CROSSOVER

In [98], the constrained ED problem with valve throttling losses was solved through another cost effective and reliable variant of PSO named Laplace crossover PSO (LXPSO) which incorporated the Laplace crossover into PSO with constriction factor. Rather than using the information of *pbest* and *gbest*, particles, in LXPSO, utilize the developed interaction model between any two randomly selected particles. Simulation results reveal that LXPSO gives relatively minimum fuel cost with regard to other metaheuristics when exercised on a 40 unit system.

B. PSO AND AUGMENTED LAGRANGIAN METHOD (ALM)

Reference [99] suggested that the integration of augmented Lagrangian method (ALM) and (classical) PSO could treat the ELD problem ignoring the VPL effects efficiently. The hybrid algorithm was designated as augmented Lagrangian PSO (ALPSO). In ALPSO, main optimizer is the PSO whereas ALM is employed to tackle both the equality and inequality constraints. For the typical design example, the parameters of PSO are kept fixed, i.e., $\omega_{\min} = 0.4$, $\omega_{\max} = 0.9$, and $c_1 = c_2 = 2.05$. ALPSO solves efficiently a 3 unit power system giving optimal fuel cost.

Reference [100] suggested a modified PSO to handle the constrained ELD problem involving a piecewise quadratic function. The problem considers both type of losses, i.e. transmission losses and throttling losses occurring at valve points. In the proposed algorithm, authors claim that acceleration coefficients with values $c_1 = 0.2$ and $c_2 = 2$ as compared to $c_1 = c_2 = 2$ usually taken in standard PSO intelligently solve the dispatch problem and keep balance between exploration and exploitation characteristics. In addition, a new strategy is introduced for the allocation of initial power values to the thermal units. Through the evolution of ED problems differing in complexity involving 3, 6, 15, and 40 units, the proposed modified PSO validates its feasibility and workability, and offers encouraging results with regard to PSO and GA.

V. CONCLUSION

In part II of the paper, a review of hybrid forms of PSO reported in literature for solving constrained ED problems is presented in a comprehensive way. Inherently suffered from premature convergence problem, PSO when hybridizes with other deterministic numerical techniques or metaheuristic optimization techniques, exhibits promising performance especially while dealing with complex nonconvex optimization problems. Experiments reveal that, even in worst case, PSO hybrid forms are at least as competitive as the algorithms from which they are constructed. In hybrid forms, PSO, sometimes, acts as a main optimizer and the other times, it acts as a local optimizer depending upon the exploration and exploitation characteristics of the other optimization techniques. All (advanced) calculus-based optimization techniques such as QN, SQP, GM, CG, DSM, PS, etc. are used for fine-tuning the potential solution provided by PSO (main optimizer) in the vicinity of global search space. Similarly, role of metaheuristics such as TSA and GSA are found to be local optimizers. Cultural evolution process based CA assists PSO in diversifying the population. This avoids PSO from experiencing the premature convergence problem. From the review conducted in the paper, it is revealed that PSO weaknesses can be mitigated through hybrid strategies integrating the salient features of the algorithms. In hybrid forms, the algorithms need to be associated judiciously by avoiding assembling their respective defects. Hybridization of PSO with other algorithms can be employed to tackle more complex constrained multiobjective (combined) ED problems. Future work may involve the investigation in the form of a survey about the additional steps to be taken by PSO, and its modified and hybrid versions to deal with multiobjective power system problems.

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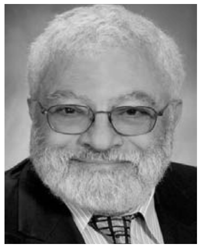

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