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

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ABSTRACT A number of modern metaheuristic optimization techniques are being exploited to work out a single-objective economic dispatch (ED) problem. The dispatch problems even become more complicated and complex when they consider operational and system constraints, such as network transmission losses, valve-point loading effects originating due to sequential opening of a number of steam admission valves to meet the ever-increasing demand, ramp rate limits, prohibited operating zones, multiple fuel options, spinning reserve, and so on. The heavy constraints make the otherwise convex linear smooth dispatch problem as highly nonconvex nonlinear nonsmooth one. Finding optimal solution for such kind of a constrained nonlinear problem through the deterministic numerical and convex characteristics-based optimization techniques is a difficult task to accomplish. Researchers have frequently employed one of the metaheuristic optimization techniques with powerful computational ability named particle swarm optimization (PSO) to deal with this rather a complicated and toilsome dispatch problem. In Part I of the two-part paper, a comprehensive review or a survey of PSO and its modified versions (involve alterations in the basic structure of PSO) to resolve the constrained ED problem is presented. Part II covers purely the survey of hybrid forms of PSO (hybridization of PSO with other optimization techniques) to tackle the ED problem. The survey is presented in such a way that readers may understand how PSO can be made computationally more efficient.

INDEX TERMS ED problem, optimization techniques, operational and system constraints, PSO and its variants and modified versions, POZ, survey, VPL effects.

I. INTRODUCTION

One of the hottest issues of power system planning and operation is the optimum solution of the practical ED problem. With the ever increasing energy or power demand, shortage of the energy resources, and rapid escalation in fuel prices, ensuring accomplished and optimum economic operation of thermal power generating units is the need of the hour. Efficient scheduling of the committed units results in significant cost savings. The situation becomes even more complicated when more and more thermal power generating units need to be introduced into the power system to meet the load demand while diminishing the total fuel cost. Scheduling optimally the all-thermal generating units while considering all the practical constraints in the form of equalities and inequalities even complicates the thermal dispatch problem. In addition, selection of multi-fuel (coal, oil, or natural gas) operated generating units should be made with care to ensure economic operation.

In an idealized form, the input-output characteristics of a boiler–turbine–generator unit are characterized by a smooth and convex curve [1], [2]. The electrical power output measured in megawatts of a thermal power unit is related to the input fuel cost measured in dollars per hour quadratically. Traditionally, a quadratic cost curve has been considered for the purpose of the ED problem solution. The ED problem considering the smooth and convex curves can be easily solved using the various mathematical programming techniques. However, inclusion of network transmission losses, POZ, VPL effects, MF options, etc. makes the convex ED problem as the nonconvex and nonlinear one. The inherited nonsmooth, nonlinear, and nonconvex cost curve of a generating unit may have multiple local points.

The classical calculus-based methods or the deterministic numerical methods such as Lagrangian multipliers (LM) method [1], the lambda-iteration method [3], the base point and participation factors method [3], the interior point method [4], [5], the gradient method [6], the gradient projection algorithm (GPA) [7], the Newton method [1], the linear programming (LP) [8]–[10] and nonlinear programming (NLP) [11], [12] algorithms, the quadratic programming (QP) [13]–[15] algorithm, the dynamic programming (DP) method [16]–[20], the decomposition technique [21], the advantageous decision spaces approach [22], the Maclaurin series approximation [23], [24], etc. cannot be employed to solve the more complicated and nonlinear dispatch problem for optimal scheduling as they often trap at local minimum. Either these methods do not suit effectively to ELD problems involving nonlinear or nonconvex fuel cost functions or suffer from the "curse of dimensionality". These methods require a monotonically increasing incremental cost function, where the derivative information of the cost function exists for their better convergence. Although DP method does not impose any restriction on the shape of the cost curve and may be employed to solve both convex and nonconvex dispatch problems, but it requires much more simulation time to solve particularly the power systems having larger sizes. Another method proposed in [21] solves the ED problem with prohibited operating zones by decomposing nonconvex decision space formed due to disjoint sub-regions into a small number of subsets so that conventional Lagrangian relaxation (LR) approach may be employed.

In order to ensure the most optimal solution of the highly nonlinear real ED problem, many modern metaheuristic optimization techniques have been disclosed in the literature. They include: particle swarm optimization (PSO) [25], genetic algorithm (GA) [26]–[29], differential evolution (DE) [30]–[32], evolutionary programming (EP) [33]–[35], biogeography-based optimization (BBO) [36]–[38], simulated annealing (SA) [39], [40], ant colony optimization (ACO) [41], [42], bee algorithms (BAs) [43], [44], bacterial foraging optimization (BFO) [45], [46], firefly algorithm (FA) [47], [48], cuckoo search algorithm (CSA) [49]–[52], bat algorithm (BA) [53]–[55], grey wolf optimization (GWO) [56], [57], shuffled frog leaping algorithm (SFLA) [58], [59], krill herd algorithm (KHA) [60], [61], flower pollination algorithm (FPA) [62]–[64], teaching learning based optimization (TLBO) [65], [66], Tabu search (TS) algorithm [67], [68], harmony search algorithm (HSA) [69]–[71], gravitational search algorithm (GSA) [72]–[74], cross-entropy (CE) method [75], [76], imperialist competition algorithm (ICA) [77], [78], artificial immune network (AIN) algorithm [79]–[81], distributed auction-based algorithm [82], big-bang and big-crunch (BB-BC) [83], [84], chemical reaction optimization (CRO) [85], [86], Hopfield neural networks (HNN) [87]–[89], artificial intelligence (AI) technique [90], mean-variance mapping optimization (MVMO) [91], etc. These metaheuristic techniques have the potential to ensure global or near global solution while handling non-differentiable and discontinuous cost curves.

Even though literature is enriched with the optimization techniques employed to solve the practical ED problem but still a lot of papers are being published incorporating the dispatch problem through the variants of metaheuristic optimization techniques. Among the metaheuristic techniques, PSO has been brought into play extensively to solve the thermal ED problem. This is due to the fact that PSO offers many salient features such as simple implementation, well-balanced mechanism, flexibility, robustness, less memory storage, ability to find global superior quality solutions with less computational time, substantial convergence characteristics than that of other metaheuristic optimization approaches, incorporation of inherent parallelism feature in its structure, etc. Owing to these characteristics, researchers and power system designers are intended to employ preferably PSO in dealing with the economic load dispatch (ELD) problem. In addition, in order to enhance both the exploration and exploitation characteristics of PSO, a number of its modified versions have been addressed in the literature.

In this paper, special attention has been devoted to review PSO and its modified forms applied to solve the practical ED problem considering the heavy constraints such as the VPL effects, MF options, etc. during the realistic operation. The other purpose of the paper is to provide, to a larger extent, a complete and a comprehensive literature review or survey of the PSO handling the dispatch problem so that engineers and designers may mainly focus on the modified and improved versions (not yet introduced) of the PSO algorithm rather than consuming time to review the literature. While presenting the survey, special attention has been devoted to mention all the possible amendments proposed in PSO to improve its performance.

The paper is constructed in the following way. Section II provides a comprehensive detail about the formulation of a single-objective ED problem with operational and system constraints. A table summarizing all the objective or evaluation functions to be minimized available in the literature is constructed to facilitate the researchers. Section III details briefly the overview of PSO algorithm to understand its working principle. A detailed and comprehensive survey of PSO along with its modified versions applied to solve ED problem considering equality and inequality constraints is presented in Section IV. Review of the modifications suggested or proposed in each of the PSO parameters while solving the ED problem is presented in separate subsections. Some remarks about the already-conducted PSO surveys (giving limited information) are given in Section V. Conclusion is drawn in Section VI.

II. FORMULATION OF THE DISPATCH PROBLEM

The ED problem is essentially a constrained optimization problem in which the total fuel cost of all the online thermal units of a power plant has to be minimized while determining the power output level of each of the generating units over a specific period of time. The constraints are in the form of equalities and inequalities that need to be fulfilled while solving the ED problem. The constrained dispatch problem may take different forms the comprehensive detail of them is given in this subsection.

A. ED PROBLEM

The objective function of a standard ED problem neglecting the VPL effects is constructed by [92]

$$\min F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(a_i + b_i P_i + c_i P_i^2\right) \tag{1}$$

where F_T and $F_i(P_i)$ denote the total fuel cost and the cost of the ith generating unit in \$/h respectively; P_i stands for the ith generating unit's output power in MW, n represents the total number of generating units; a_i, b_i, and c_i are the cost coefficients of the ith generating unit. From (1), it can be examined that the fuel cost of each of the units is directly related to the output power delivered by it to the power system and is typically modelled by a quadratic function.

B. ED PROBLEM WITH VPL EFFECTS (EDVPL)

In large steam turbine generators due to the sequential opening of a number of steam admission valves to meet the ever-increasing demand, the input–output characteristics of a generating unit vary from convex to nonconvex. This results in nonlinear, nonconvex and nonsmooth cost curves. In order to incorporate the VPL effects, a higher-order nonlinearity is introduced into the quadratic cost function. The objective function (to be minimized) involving the cost function taking into account the VPL effects is expressed by

$$\begin{aligned} \min F_T &= \sum_{i=1}^{n} F_i(P_i), \quad \text{if } P_{i,\min} \le P_i \le P_{i,\max} \\ &= \sum_{i=1}^{n} \left(a_i + b_i P_i + c_i P_i^2 + \left|e_i \times \sin(f_i \times (P_{i,\min} - P_i))\right|\right) \end{aligned} \tag{2}$$

where e_i and f_i represent the ith generating unit's cost coefficients reflecting the VPL effects. Consideration of ripples in the heat-rate curve of boilers in the form of recurring rectified sinusoidal term into basic quadratic cost curve introduces multiple minima thus making the ED problem nonconvex and nonlinear. While minimizing F_T, operational limitations and constraints should be taken into consideration to ensure the most feasible and optimal solution. The detail of dispatch problem's equality and inequality constraints is given below.

1) ACTIVE POWER BALANCE EQUATION

One of the basic constraints of the dispatch problem is the power balance equation. Surely, the total generated power of all the thermal units should be the sum of the total system demand and the transmission network losses. The equality constraint in the form of a power balance equation is given by

$$\sum_{i=1}^{n} (P_i) - (P_{Load} + P_{Loss}) = \varphi = 0 \tag{3}$$

where P_{Load} and P_{Loss} represent the total system demand and transmission losses respectively. The transmission losses are considered due to the fact that load center is usually far away from the remotely-spread power plants. In order to incorporate these losses, usually a (traditional) B matrix loss formula proposed by Kron [92] is employed which is given by

$$P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00} \tag{4}$$

where B_{ij}, B_{i0} and B_{00} signify the loss coefficients or the B coefficients. Specifically, B_{ij} represents the ijth element of the loss coefficient square matrix, B_{i0} the ith element of the loss coefficient vector, and B_{00} the loss coefficient constant.

Alternatively, in some of the papers, network transmission losses are calculated on the basis of the solution of the load flow problem (LFP) taking into account the equality constraints (real and reactive power) at each bus as follows [93]

$$\begin{aligned} &P_i - P_{Load,i} - V_i \sum_{j=1}^{n_B} V_j \\ &\quad \times \left[G_{ij}\cos(\varphi_i - \varphi_j) + B_{ij}\sin(\varphi_i - \varphi_j)\right] = 0 \end{aligned} \tag{5}$$

$$\begin{aligned} &Q_i - Q_{Load,i} - V_i \sum_{j=1}^{n_B} V_j \\ &\quad \times \left[G_{ij}\sin(\varphi_i - \varphi_j) - B_{ij}\cos(\varphi_i - \varphi_j)\right] = 0 \end{aligned} \tag{6}$$

where $i = 1, 2, \ldots, n_B$; n_B represents the number of buses; Q_i and $Q_{Load,i}$ are the generator and demand reactive power respectively; B_{ij} and G_{ij} are the susceptance and the transfer conductance between bus i and bus j respectively. V_i and V_j are the voltage magnitudes at bus i and bus j respectively; φ_i and φ_j are the voltage angles at bus i and bus j respectively.

The nonlinear constraint described in (5) and (6) obtained through the solution by Newton–Raphson method and the LFP solution, give all bus magnitudes and angles. Then, the real power loss is calculated as

$$P_{Loss} = \sum_{k=1}^{n_L} g_k \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\varphi_i - \varphi_j)\right] \tag{7}$$

where n_L is the number of transmission lines; g_k is the conductance of kth line that connects bus i to bus j.

2) GENERATOR CAPACITY LIMITS

Each of the power generating units should operate within its minimum and maximum limits while delivering the economic power output. The inequality constraint pertaining to the power limits is given by

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{8}$$

where $P_{i,\min}$ and $P_{i,\max}$ designate the minimum and maximum output power of the ith generating unit respectively.

3) GENERATOR RRL

Online generating units should settle down to new generation values within no time when there is a change in load demand. Accomplishing this specifically in case of larger steam generator units considering limits is a challenging task. Practically by imposing down and up ramp rate limits during each scheduling period, operating range of all the committed thermal units can be constricted. The operation of the units thus is restricted between the two adjacent operation periods. The inequality constraint pertaining to the generator ramp rate limits is characterized below:

$$\begin{cases} P_i - P_i^0 \le UR_i, & \text{when generation raises} \\ P_i^0 - P_i \le DR_i, & \text{when generation lowers} \end{cases} \tag{9}$$

where UR_i and DR_i denote the up ramp limit and the down ramp limit of the ith generator (MW/h) and P_i^0 represents the previous output power of the ith generator. Combining (8) and (9) gives the refined power limit for ith generator as

$$\max\left(P_{i,\min}, P_i^0 - DR_i\right) \le P_i \le \min\left(P_{i,\max}, P_i^0 + UR_i\right) \tag{10}$$

4) POZ

Multiple reasons such as introduction of shaft bearing tremor due to a steam admission valve, fault due to the machine or its associated supplementary equipment such as pump, boiler, etc. cause POZ [21], [94], [95] in the cost curve of a thermal unit. A thermal unit exhibits discontinuous input-output characteristics due to POZ making the cost curve highly nonlinear, noncontinuous and nonsmooth. By intelligently circumventing operation in these zones, best economy can be ensured. The POZ shown in Fig. 1 should be taken into account for the most optimal ED problem solution. The output power delivered by the ith generator while considering POZ is given by

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^L & \\ P_{i,k-1}^U \le P_i \le P_{i,k}^L & (k = 2, 3, \ldots, Nz_i) \\ P_{i,Nz_i}^U \le P_i \le P_i^{\max} & (k = Nz_i) \end{cases} \tag{11}$$

where Nz_i designates the number of POZ in the cost curve of the ith generator, k is the index of POZ of the ith generator, $P_{i,k}^L$ and $P_{i,k}^U$ represent the lower and higher limit of the kth prohibited zone of ith generator.

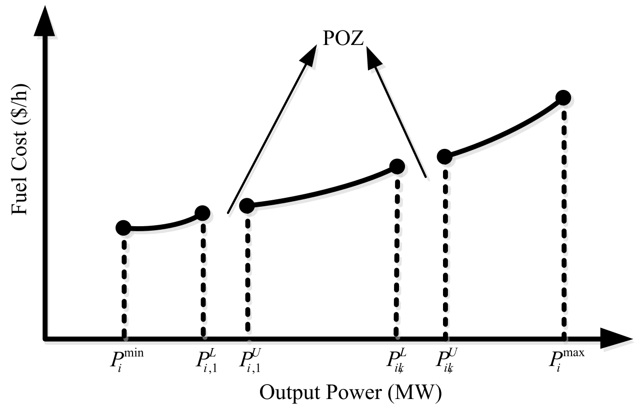

FIGURE 1. Fuel cost curve with POZ.

5) LINE FLOW CONSTRAINTS

In order to incorporate the effect of undesired line loadings due to power distribution, the line flow constraint is introduced which is given by

$$\left|P_{Lf,k}\right| \le P_{Lf,k}^{\max}, \quad k = l, \ldots, L \tag{12}$$

where $P_{Lf,k}$ and $P_{Lf,k}^{\max}$ represent the real power flow and the power flow up-limit of line k respectively, and L denotes the number of transmission lines.

6) SYSTEM SPINNING RESERVE CONSTRAINTS

System reliability is maintained through adequate spinning reserves. That is to say

$$\sum_{i=1}^{n} P_{i,\max} \ge P_{Load} + P_{Loss} + R \tag{13}$$

The ED problem in its simpler form considers only the active power balance constraint (equality) and the generating capacity limits (inequality). However, the practical ED problem considers most of the constraints described from (3) to (13). The more the constraints are utilized, the more the dispatch problem is realistic.

C. ED PROBLEM WITH MF OPTIONS (EDMF)

The power generating units may use multi-fuels for their operation. Each of the units may be characterized by several piecewise quadratic functions. The piecewise quadratic function of the ith generator considering multiple fuels (neglecting the VPL effects) is expressed by

$$F_i(P_i) = \begin{cases} F_{i1}(P_i), & \text{fuel } 1, \ P_{i\min} \le P_i \le P_{i1} \\ F_{i2}(P_i), & \text{fuel } 2, \ P_{i1} \le P_i \le P_{i2} \\ \quad\vdots & \\ F_{ik}(P_i), & \text{fuel } k, \ P_{ik-1} \le P_i \le P_{i\max} \end{cases} \tag{14}$$

where

$$F_i(P_i) = a_{ik} + b_{ik}P_i + c_{ik}P_i^2$$
$$\text{if } P_{i\min,k} \le P_i \le P_{i\max,k}$$
$$\text{fuel option } k, \quad k = 1, 2, \ldots, k \tag{15}$$

where $P_{i\min,k}$ and $P_{i\max,k}$ represent the minimum and maximum power generation limits of generator i with fuel option k respectively; a_{ik}, b_{ik}, and c_{ik} refer to the fuel cost coefficients of generator i for fuel option k. The objective of the EDMF problem is to minimize total generator fuel cost subject to the constraints.

D. ED PROBLEM WITH VPL EFFECTS AND MF OPTIONS (EDVPLMF)

To ensure the most optimal solution to the precise and practical ED problem, both the MF options and the VPL effects should be incorporated simultaneously into the fuel cost function. The cost (quadratic) function of ith generator considering the MF options looks like as described in (14). However, the cost function of ith generating unit considering both the MF options and the VPL effects is expressed as

$$\begin{aligned} &F_i(P_i) \\ &= a_{ik} + b_{ik}P_i + c_{ik}P_i^2 + \left|e_{ik} \times \sin(f_{ik} \times (P_{i,\min} - P_i))\right|, \\ &\quad \text{if } P_{i\min,k} \leq P_i \leq P_{i\max,k} \\ &\quad \text{fuel option } k, \quad k = 1, 2, \ldots, k \end{aligned} \tag{16}$$

In constrained EDVPLMF problem, minimization of the total fuel cost is the ultimate objective to be achieved. Different authors use different single-objective fitness or cost or evaluation functions to solve the ED problem. For better understanding, the cost or fitness functions used in the literature with necessary detail are summarized in Table 1.

III. OVERVIEW OF PARTICLE SWARM OPTIMIZATION (PSO)

Inspired and motivated from the observations of the social behavior of animals, such as fish schooling, bird flocking, and swarm theory, particle swarm optimization (PSO) first suggested by Kennedy and Eberhart [96] in 1995 is a population-based self-adaptive stochastic modern heuristic global search algorithm which has found its extensive use for the solution of heavily constrained ED problem considering the VPL effects and other operational and system constraints in the form of equalities and inequalities.

In PSO, the initialization process starts with the generation of a fixed number of randomly generated particles (potential solutions) scattered in a multidimensional solution space. A swarm of birds (particles) moves around in a multidimensional search space (where the solution really exists) until they find the food (optimal solution). Each particle in the swarm represents a candidate solution to the problem and moves towards the optimal point by appending a velocity with its position. Using its own experience (*pbest*) and the experience attained by the neighboring particles in the swarm (*gbest*), each particle updates its position during its flight. In this way, each particle makes use of the *pbest* and *gbest*. The update mode is termed as the velocity of particles. Particles update their positions and velocities in a heuristic manner. The velocity and the position of ith particle for fitness evaluation at $(t+1)$ iteration in m-dimensional search space are computed by

$$\begin{aligned} v_{id}^{t+1} &= \omega.v_{id}^t + c_1.r_1().\left(pbest_{id} - x_{id}^t\right) \\ &\quad + c_2.r_2().\left(gbest_{gd} - x_{id}^t\right) \end{aligned} \tag{17}$$

$$\begin{aligned} x_{id}^{t+1} &= x_{id}^t + v_{id}^{t+1}, \quad v_i^{t=0} = 0, \\ &\qquad i = 1, 2, \ldots, n, \ d = 1, 2, \ldots, m \end{aligned} \tag{18}$$

where

i	particle's index;
t	discrete-time index;
d	dimension being considered;
n	number of particles in a group;
m	dimensions of a particle;
ω	inertia weight factor;
c_1, c_2	acceleration coefficient for the cognitive and social component respectively
r_1, r_2	uniform random values in the range [0, 1];
$pbest_i$	best position found by ith particle (personal best);
$gbest$	best position found by swarm (global best);
v_{id}^t, x_{id}^t	velocity and position of particle i in dimension d at iteration t respectively.

As can be seen, three components, namely, inertial, cognitive, and social impinge the velocity of a particle. The inertial component, i.e., the inertia weight factor ω administrates both the local and global exploration capabilities of the particle while ensuring less iteration on average to find a sufficiently optimal solution. In the simplest form of PSO, it usually takes a fixed value between 0 and 1 for all the particles in a single generation. Large value of inertia weight enables the PSO to explore globally whereas its small value enables the PSO to explore locally. By practice, a larger inertia weight factor is employed to ensure global exploration at the beginning of the search and its value is gradually decayed to ensure local exploration at the end of the execution. All this is accomplished through the time-varying inertial weight (TVIW) introduced in [97] and [98] and is defined by

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \left(\frac{iter}{iter_{\max}}\right) \tag{19}$$

In some of the papers, TVIW takes a slightly different form given by (20)

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \left(\frac{iter_{\max} - iter}{iter_{\max}}\right) \tag{20}$$

where $\omega_{\max}$ and $\omega_{\min}$ represent the initial and final weights respectively; $iter_{\max}$ is the maximum number of iterations (generations); $iter$ is the current number of iteration.

Through empirical studies conducted by Shi and Eberhart [99], it has been observed that usually a value of ω changes in a linear fashion from about 0.9 (at initial iterations) to 0.4 (at final iterations) during a simulation time.

The constants c_1 and c_2 signify the learning factors, or the acceleration constants/coefficients for the cognitive and social component respectively, or the weighting of the

TABLE 1. Typical cost (fitness) functions to be minimized.

Single-Objective Cost (Fitness) Function	Explanation/Description
$F_T=\sum_{i=1}^{n}F_i(P_i)$ where $F_i(P_i)=a_i+b_iP_i+c_iP_i^2$	It is the simplest form of the total fuel cost function (without constraints) to be minimized [92].
$F_T=\sum_{i=1}^{n}F_i(P_i)$ where $F_i(P_i)=a_i+b_iP_i+c_iP_i^2+\lvert e_i\times\sin(f_i\times(P_{i,\min}-P_i))\rvert$	The total fuel cost function (unconstrained) includes the VPL effects [144].
$F_T=\sum_{i=1}^{n}F_i(P_i)+\alpha\left[\sum_{i=1}^{n}(P_i)-(P_{Load}+P_{Loss})\right]$	The fitness function is constructed on the basis of penalty function method (pfm). Here α represents the penalty price factor (ppf) for real power balance constraint [157], [234], [249].
$F_T=\sum_{i=1}^{n}F_i(P_i)+\alpha\left[\sum_{k=1}^{n_c}(violation)_k\right]^2$	The evolution function involves ppf for 'security' constraint violation [33].
$F_T=\sum_{i=1}^{n}F_i(P_i)+\alpha\left(\sum_{i=1}^{n}(P_i)-P_{Load}-P_{Loss}\right)^2+\beta\left(\sum_{j=1}^{n}V_{k,j}\right)$ where $V_{k,j}=\begin{cases}1, & \text{if } P_{k,j} \text{ violates the } POZ\\ 0, & \text{otherwise}\end{cases}$	Here α and β are ppf associated with the power balance and POZ constraints, respectively [200], [255].
$F_T=\sum_{i=1}^{n}F_i(P_i)+\alpha\left[\sum_{i=1}^{n}(P_i)-(P_{Load}+P_{Loss})\right]^2+\beta\left[\sum_{k=1}^{n_i}P_i(violation)_k\right]^2$	Here α and β are the ppf for real power balance and POZ constraints respectively, and $P_i(violation)$ is an indicator of falling into the POZ [158], [145].
$F_T=\sum_{i=1}^{n}F_i(P_i)+\alpha\left[\sum_{i=1}^{n}(P_i)-(P_{Load}+P_{Loss})\right]^2+\beta\sum_{i=1}^{n}\lvert P_i-P_i^{\lim}\rvert$ $+\gamma\sum_{i=1}^{n}\lvert P_i-P_i^{poz\lim}\rvert$	Here α is the penalty parameter for real power balance constraint, β handles power generation limits and ramp-rate constraints, and γ handles the POZ constraints. The penalty parameters may assume a value of 5000 [177].
$F_T=\sum_{i=1}^{n}F_i(P_i)+\alpha\sum_{i=1}^{nl}\left(I_i-I_i^{\max}\right)^2+\beta\left(P_1-P_1^{\max}\right)^2+$ $\gamma\sum_{i=1}^{NL}\left(V_{Li}-V_{Li}^{\lim}\right)^2$	Security penalty functions for the line flow limits and the bus voltages at each bus along with the total fuel cost is included in the overall objective function [133].
$F_T=\dfrac{1}{F_{T,Norm}+F_{L,Norm}}$ where $F_{T,Norm}=1+abs\left[\dfrac{\sum_{i=1}^{n}F_i(P_i)-F_{\min}}{F_{\max}-F_{\min}}\right]$ $F_{L,Norm}=1+\left[\sum_{i=1}^{n}(P_i)-(P_{Load}+P_{Loss})\right]^2$	Another form of the cost function which is the reciprocal of the combination of the generation cost function and power balance constraint. $F_{T,Norm}$ and $F_{L,Norm}$ represent the normalized values of the functions in the range between 0 and 1 [100], [138], [188].
$F_T=\dfrac{10^{\text{round}(\log_{10}^{F_{\max}})}}{F_T(I)+PF(I)}$ where $F_T(I)=\sum_{i=1}^{n}F_i(P_i)$ $PF(I)=\alpha\left\lvert\sum_{i=1}^{n}(P_i)-(P_{Load}+P_{Loss})\right\rvert+V(I),\quad \alpha=200,$ with $V(I)=\sum_{k=1}^{ic}C_k\lvert\min(\text{ULD,LLD})\rvert$	Here $F_{\max}$ refers to a priori value of maximum fuel cost calculated through several trials and errors; $PF(I)$ is the penalty function for individual I; $V(I)$ denotes the generic violation function incorporating the RRL and POZ constraints; C_k represents the constants; the number of inequality constraints is denoted by "ic"; ULD and LLD designate the upper limit and lower limit constraints violations respectively [235].

stochastic acceleration terms that pull each particle towards the local best position *pbest* and the global best position *gbest* position respectively. Far the lower values of acceleration coefficients, particles wander far from the feasible region (global best position) whereas for the higher values, particles move abruptly toward the best position.

To keep balance between exploration and exploitation, Kennedy and Eberhart [96] suggested a relatively higher value of the cognitive component than the social component at the beginning whereas a relatively higher value of the social component than the cognitive component at later iterations. It has been observed from the practical studies that setting the mean of both acceleration coefficients equal to one forces the particles to over fly only for half of the time of search. By default, the acceleration coefficients are usually set to 2, i.e., $c_1 \approx c_2 \approx 2$. However, these parameters may be selected in the range of 0 to 4. In other words, memory of the bird about its *pbest* and *gbest* is modelled through cognitive and social components respectively.

Although v_i can assume any value, however, it is usually bounded in some range $\left[\left(v_i^{\min}=0\right) \leq v_i \leq \left(v_i^{\max}\right)\right]\cdot$ Particles possessing higher values of user-defined parameter $v^{\max}$ may fly past high quality solutions without noticing them whereas particles with lower values of $v^{\max}$ offer poor exploration capability beyond local search. The parameters r_1 and r_2 are the two uniform probability distribution function based random numbers in the range [0, 1]. Throughout the paper, the random numbers will be considered as uniformly distributed ones unless otherwise specified.

The parameters discussed above are often held constant or changed deterministically for the entire run of a PSO. Constant or deterministically-changed parameters may work fine to determine the solution of high quality for the ELD problem. However, this approach may not yield optimal results for many ELD problems. The situation becomes even worst for the nonlinear constrained optimization problems like the ELD problem with VPL effects, POZ, etc. In order to cater these problems, several modifications in these parameters or the other ways are suggested in the literature.

IV. REVIEW OF PSO APPLIED TO ECONOMIC DISPATCH PROBLEM

A. STANDARD OR CLASSICAL PSO

PSO in its standard or traditional form has been extensively adopted to deal with the constrained ED problem. In [25] and [100], a PSO method in its standard form was utilized for solving the ELD problem taking into consideration various heavy constraints such as RRL and POZ, however, without the VPL effects. The author defines a normalized evaluation function in the range between 0 and 1 which is a reciprocal of the combination of the ED cost function and the power balance constraint. The algorithm penalizes with a large positive constant all unfeasible individuals. A detailed step-by-step design procedure is well-outlined in the paper. When applied to power systems consisting of 6, 15 and 40 thermal units, PSO algorithm outperforms the real-coded GA and the other metaheuristic approaches with regard to solution quality and computation efficiency.

In [101], a (modified) PSO technique which was more precisely a discrete form of the continuous PSO was used to work out the ELD problem having a piecewise fuel cost quadratic curve. The discrete PSO where the particles of swarm are guessed to fly about to the problem search space in a discrete time step rather than continuous time step is described b

$$v_{id}^{t+1} = \omega.v_{id}^{t} + c_1.r_1.\left(\frac{pbest_{id} - x_{id}^{t}}{\Delta t}\right) + c_2.r_2.\left(\frac{gbest_{gd} - x_{id}^{t}}{\Delta t}\right) \tag{21}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}.\Delta t \tag{22}$$

where Δt represents the time step and usually assumes a unity value. In addition, in the paper, in order to make certain whether the particles fly out of the search space bounds or violate the equality and inequality constraints, a position check strategy is introduced. All this is accomplished after updating the position of each particle. A particle detected violating the bounds or constraints is forced to return to the feasible region through a repair algorithm. The discrete PSO with a position check strategy and a repair algorithm exhibits better convergence characteristics when applied to tackle ELD problems considering the network transmission losses.

Application of the standard PSO algorithm with TVIW was also reported in [102] to work out a number of ED problems such as, multi-area ED (MAED) with tie line constraints, ED problem with piecewise quadratic cost function (PQCF), ED problem with MF options, combined economic environmental dispatch (CEED) problem, and the ED problem with POZ. However, all these ED problems ignore the VPL effects. Comparative analysis shows the supremacy of PSO method over the classical EP (CEP) and other metaheuristic optimization approaches. In [103], applicability and pertinency of traditional PSO with TVIW was also justified while resolving the nonconvex ED problems with nonlinearities (POZ and RRL) possessing 6 and 15 generating units. Results reveal that PSO consumes less CPU time while calculating the total optimal generation cost in comparison to GA.

Realizing the significance of PSO technique as it has the capability of finding global superior quality solutions in less computational time, and offers substantial convergence characteristics than that of other metaheuristic optimization approaches, [104] also employed PSO to figure out the constrained ELD problem neglecting the VPL effects. The idea of ELD problem with the combined cycle cogeneration plants (CCCP) having non-differentiable cost characteristics is also presented. Traditional Lambda iterative method fails in ensuring good quality solution for ELD problem with CCCP. In the paper, an equality constraint (power balance equation) handling technique is also illustrated. Simulation results exhibit that PSO ensures good quality solutions than that of the conventional method and GA method while solving a 3 unit and a 6 unit thermal systems with transmission line losses. Reference [105] proposed a new idea of estimating the block incremental cost curve with and without VPL effects optimally through PSO with a constriction factor. In order to bid the power outputs in blocks with the corresponding price of each block, block incremental cost curves from higher order instantaneous incremental cost curve are developed. The paper then mentions a mechanism in estimating optimal block incremental cost of a generating unit from the instantaneous incremental heat rate curve using PSO approach. In [106], a user-friendly graphical user interface (GUI) was constructed using MATLAB environment to facilitate the electrical engineering undergraduate students to understand the applicability of PSO to solve the ELD (with VPL effects) and the mathematical optimization problems. The windows-based educational simulator comes with the advantage that one can get insight into the effects of the PSO parameters such as inertial weight factor, acceleration coefficients, and population size on the solution quality. Separate windows are introduced to enter user data and display results. In order to ensure the effectiveness and feasibility of the simulator, two power systems consisting of 3 and 40 units are tested.

In [107], applicability and feasibility of the standard PSO was also validated while solving the constrained ELD problem neglecting the VPL effects. In order to convert a constrained ELD problem into an unconstrained one, Lagrange multiplier is employed. For this purpose, four power systems comprising 3, 6, 15 and 40 thermal generating units are considered. When tested on these cases, PSO outperforms QP and GA. Some notions about the setting of population size, stopping criteria, etc. are also presented in the paper. Reference [108] also employed the standard PSO algorithm with one of the acceleration coefficients being constant to solve the ELD problem without the VPL effects. In [109], (traditional) PSO with TVIW was found proficient in tackling the large scale ELD problem with VPL effects. Transmission losses are ignored. Each of the acceleration coefficients is set to a value of 2. When tested on a 13 and 40 unit test systems, PSO shows better performance than that of GA. In [110], PSO algorithm in its standard form with linearly decreasing inertia weight factor was applied for the resolution of the ED problem with VPL effects. Transmission line losses are also considered. When tested on various test systems of IEEE, PSO shows better convergence properties than that of GA, DE, etc.

An effective and reliable (standard) PSO technique with linearly decreasing inertia weight was employed in [111] for the solution of ELD problem with and without transmission losses. VPL effects, however, are not taken into consideration. In the paper, description of quadratic programming (QP) method has also been given as it has to be compared with PSO. When demonstrated on power systems having 3 and 6 generating units, PSO offers encouraging results as compared to QP method. In [112], PSO in its the most simplest form (even without the inertia weight factor) was suggested for the solution of ELD problem (without the VPL effects) considering three different bus systems. Simulation results reveal that PSO offers better convergence as compared to the Lambda iteration method. Reference [113] also employed the classical PSO to work out the ED problem possessing a 5 thermal generating unit system with transmission losses and VPL effects. In [114], an ELD problem with and without transmission losses but without VPL effects possessing 3 and 6 generating units was also solved through classical PSO with TVIW. In [115], a power system possessing 6 generating units, 26 buses and 46 transmission lines neglecting the VPL effects was computed through TVIW based PSO. PSO demonstrates its primacy over GA and the advanced calculus based traditional method when tried to resolve such an ED problem. Also in [116], by taking combinations of parameters, namely independently-generated random numbers, acceleration coefficients and inertia weight factor of PSO, four different (so-called) improved PSO (IPSO) methods named IPSO1, IPSO2, IPSO3, and IPSO4 were suggested to solve the ED problems considering the transmission losses. The method involves the movement of the acceleration coefficient for the social component and cognitive component in opposite direction while keeping other parameters constant. This results in tremendous reduction in number of iteration. IPSOs are compared themselves for the number of iteration and the fuel cost when applied to three standard test systems.

Performance-wise comparison of PSO with other optimization techniques is also reported in various papers. A comparative analysis of four evolutionary metaheuristic optimization techniques such as PSO, DE, EP, and GA was also made in [117] while applying them to solve two IEEE 30 bus systems having 6 and 15 generating units. This time, line flow constraints are considered in the ELD problems, although VPL effects are neglected. Simulation results revel that, for the typical ELD problems, PSO converges more rapidly as compared to other three optimization techniques. In [118], a comparative analysis of the performance of various optimization techniques like SA, GA, PS, *fmincon*, *minimax*, HGA, and PSO applied to solve an ELD problem (without VPL effects) having an IEEE-30 bus 6 generating units system was presented. The number of trials for each of the approaches is set to 10. Simulation results revel that PSO offers best results as compared to other metaheuristic optimization approaches. In [119], the performance of conventional PSO and GA was also compared when they were applied to figure out an ELD problem consisting of 15 generating units with and without transmission losses, however, neglecting the VPL effects. Although both the metaheuristic techniques show superior convergence characteristics but, on observing the results minutely, it is observed that PSO comes with less fuel cost than that of GA. This shows the supremacy of PSO over GA for the typical ELD problem. In [120], the performance (minimization of fuel cost) of various optimization techniques such as QP, GA, PSO, ABC, SA, and DE applied to a convex ED problem taking into account transmission losses possessing 6 thermal units was compared. Computer results reveal that DE outshines other techniques for the considered case. Reference [121] compared the performance of various metaheuristic optimization techniques such as PSO, GA, and CS while applying them to compute power systems possessing 3 and 6 generating units without considering the nonlinear VPL effects. For the typical considered examples, CS approach has the edge over PSO and GA.

An enhanced time effective PSO (actually a standard PSO) was also suggested in [122] to handle constrained practical ELD problem with VPL effects. When demonstrated on two test cases involving 3 and 13 thermal generating units, PSO shows its feasibility and effectiveness. In [123], the solution of ELD problem with VPL effects and transmission losses possessing a 3 unit system was successively accomplished through PSO with TVIW. The ED problems comprising 3 and 10 thermal generating units with VPL effects and network transmission losses had also been solved through the simplest form of PSO in [124]. In [125], the solution of ELD problems (without transmission losses and VPL effects) having 3, 6, 15, and 20 thermal generating units for different load demands was carried out through the (standard) PSO and the teaching-learning based optimization (TLBO) algorithms. Both PSO and TLBO offers the optimum solution with lowest fuel cost as compared to classical Lambda iteration method.

In [126], standard PSO was also employed to solve an ED problem with a solar energy system considering solar radiations on an hourly basis. Total fuel cost for both the situations (with and without solar generation) for a ten generating units system incorporated with solar powered generators is calculated. PSO shows outstanding convergence characteristics. Effect of the population size on the convergence characteristics is investigated in [127] while applying PSO to the ELD problems without VPL effects. In the paper, some notions about the already-suggested PSO variants (hybrid, adaptive, multiobjective, and discrete PSO) are also given. In [128], solution of ELD problem (with transmission losses) having 6 and 15 generating units was also accomplished through PSO with TVIW that exhibits better convergence characteristics. Reference [129] validated the supremacy of the metaheuristic PSO method in the form of easier-implementation and solution quality over the classical Dantzig-Wolfe (D-W) composition approach through a comparative analysis. For this purpose, two large-scale nonconvex dynamic ED problems with 20 and 100 thermal units were computed through these techniques. PSO ensures less fuel cost.

B. VARIATIONS IN CONSTRICTION FACTOR

To ensure balance between (global) exploration and (local) exploitation of a swarm, Clerc and Kennedy [130] in 2002 proposed another parameter named constriction factor C. The improved exploration-exploitation capabilities of PSO actually are translated into its enhanced convergence characteristics. In the proposed model, the quick convergence is attained by excluding inertia weight factor ω and the maximum velocity parameter V_{max}. The constriction factor C, calculated on the basis of user-defined acceleration coefficients c_1 and c_2, is introduced into the velocity update formula as

$$v_{id}^{t+1} = C\left[v_{id}^{t} + c_1.r_1.\left(pbest_{id} - x_{id}^{t}\right) + c_2.r_2.\left(gbest_{gd} - x_{id}^{t}\right)\right] \quad (23)$$

and is given by the expression [131], [132]

$$C = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|}, \quad \text{where } \varphi = c_1 + c_2,\ 4.1 \le \varphi \le 4.2; \quad (24)$$

From (24), one may observe that with the increase in φ, the factor decreases, slowing the convergence becomes slower due to the reduction in population diversity. Resultantly, φ is not made lesser than 4.1 to guarantee both stability and fast convergence. Usually $4.1 \le \varphi \le 4.2$ ensures quality solutions. In this constriction factor approach (CFA), both the velocity and position update formulas of standard PSO are considered as difference equations. Unlike other PSO methods, CFA utilizes mathematical theory to ensure the convergence of the search procedure to generate high-quality solutions than the basic PSO approach. The only weakness associated with CFA is to consider dynamic behavior of only one agent while ignoring the effect of the interaction among agents.

Regarding the literature review, in order to ensure balance between exploration and convergence, [133] suggested one of the simplest forms of PSO (proposed by Clerc) with constriction factor named Type I PSO to deal with the ELD problem taking into account the line flows and voltage constraints. However, valve point loading (VPL) effects are ignored. Type I PSO essentially involves the constriction factor with PSO. When tested on three different power systems, Type I PSO method shows promising results than that of LP, QP, and GA methods. In [134], an ELD problem (ignoring the VPL effects and transmission losses) with the quadratic and more complex cubic cost functions was solved through PSO with constriction factor. When tested on various test cases, the proposed PSO involving constriction factor outperforms the other heuristic methods. In [135], constriction factor based PSO (CPSO) algorithm was proposed to tackle ED problem having a 3 generator power system with VPL effects. For the design example solution purpose, the acceleration coefficients c_1 and c_2 are kept fixed to 2.05 giving φ equal to 4.1. This results in $C = 0.729$. CPSO is compared with other metaheuristic techniques like GA, EP, etc. in order to ensure its feasibility. Reference [136] also proposed a constriction coefficient PSO (CPSO) method that incorporated a constriction factor in the particle's velocity update formula to ensure fast convergence of PSO while solving ELD problem with VPL effects. CPSO ensures better velocity control. In order to validate the effectiveness of CPSO, it was tested on two systems possessing 3 and 6 generator units respectively with VPL effects. Transmission losses are ignored. When compared, CPSO converges more quickly than that of standard PSO (SPSO) and inertia based PSO (IPSO). Acceleration coefficients in velocity update formula are kept fixed while calculating the constriction factor. Reference [137], however, suggested a time varying constriction factor based PSO (VCF_PSO) for the solution of ELD problems taking into account the VPL effects. In VCF_PSO, the dynamic time-varying acceleration coefficients (TVAC) based time varying constriction factor exhibits enhanced exploitation and exploration characteristics. When tested on two IEEE test systems possessing 3 and 13 generating units, VCF_PSO shows faster convergence characteristics than that of other existing methods.

C. VARIATIONS IN INERTIAL COMPONENT

Both the local and global exploration characteristics of PSO are enhanced through time-varying inertial weight (TVIW). However, TVIW concept associated with classical PSO does not guarantee of fine-tuning of the optimum solution due to the deficiency of diversity at the end of the search. For the complex nonlinear optimization, linearly changing inertia weight factor (from higher to lower values) as the iterations proceed on, does not remain as effective as to ensure exploration. So to ensure optimal solutions for the real-world applications modelled as nonlinear dynamic systems through PSO, improved modified versions of inertia weight factor are required. In this subsection review of PSO involving variations in inertia weight factor is presented.

Two chaotic PSO (CPSO) methods that integrate PSO with adaptive inertia weight factor (AIWF) and chaotic local search (CLS) based on the logistic and Tent equations were proposed in [138] to work out the ELD problems considering generator's equality and inequality constraints, however, without VPL effects. The proposed CPSO is essentially a two phase iterative strategy. In the first phase, PSO is combined with AIWF to ensure global exploration whereas in the second phase PSO incorporates CLS into it to perform local-oriented search (exploitation). The suggested AIWF is characterized by

$$\omega = \begin{cases} \omega_{\min} + (\omega_{\max} - \omega_{\min}) \left(\dfrac{(f - f_{\min})}{(f_{avg} - f_{\min})} \right), & f \le f_{avg} \\ \omega_{\max}, & f \ge f_{avg} \end{cases} \tag{25}$$

where f signifies the particles' current objective value whereas f_{avg} and $f_{\min}$ their average and minimum objective values respectively. The adaptiveness introduced in inertia factor well-ensures the local and global exploration. Sensitively-dependent on initial conditions, both the logistic equation [139] and the Tent equation (the famous chaos systems) imported into the CLS process are defined by (26) and (27) respectively.

$$cx_i^{t+1} = 4cx_i^t \left(1 - cx_i^t\right), \quad cx_i^0 \notin [0.25, 0.5, 0.75, 1], \quad i = 1, 2, \ldots, n \tag{26}$$

$$cx_i^{t+1} = \begin{cases} 2cx_i^t, & 0 < cx_i^t \le 1/2, \\ 2\left(1 - 2cx_i^t\right), & 1/2 < cx_i^t < 1, \end{cases} \quad i = 1, 2, \ldots, n \tag{27}$$

where cx_i^t denotes the ith chaotic variable at iteration t distributed in the interval [0, 1]. The two proposed CPSO methods show tremendous improvement in performance (optimal solution, stable convergence characteristic, etc.) than that of classical PSO when applied to two test systems.

In [140], concept of embedding AIWF and CLS into PSO was also efficiently utilized to tackle the hierarchical ELD problem. Moreover, during the CLS process, the paper gives notions about the restructuring of a particle's position that assists it not to trap to the local optimum. Rani *et al.* [141] employed the same CAPSO algorithm as suggested by Cai *et al.* [138] for the solution of a rather complicated ED problem considering cubic fuel cost functions rather than quadratic cost functions. Exploration and exploitation characteristics are ensured through PSO with AIWF and logistic and gauss equation based CLS respectively. AIWF, however, varies exponentially for better trade-off between exploration and exploitation. When applied to a test system having 5 generating units, CPSO shows promising convergence characteristics as compared to PSO.

In [142], a novel heuristic optimization approach called adaptive PSO (APSO) was proposed for the solution of constrained ELD problems taking care of various constraints like transmission losses, RRL, POZ, and MF options. In APSO, in order to ensure convergence, adjustment of the particle's position is made in such a way that the highly-fitted particle (best particle) is made slower than lowly-fitted particle. This can be accomplished by assigning different ω values to each particle according to its rank. The value between $\omega_{\min}$ and $\omega_{\max}$ is assigned according to the following equation

$$\omega_i = \omega_{\min} + Rank_i . \left(\frac{\omega_{\max} - \omega_{\min}}{Population_{Total}} \right) \tag{28}$$

From (28), it can be seen that minimum value of inertia weight for the best first-ranked particle is set whereas a maximum value of inertia weight is set for the lowest fitted particle, making that particle to advance with a high velocity. The newly introduced weighting strategy based APSO shows promising results than that of GA, PSO and other optimizations methods when applied to three test cases consisting of 3, 6, and 15 generator systems.

Chaturvedi *et al.* in another paper [143] introduced an idea of crazy particles with PSO (CRAZYPSO) not only to deal with the premature convergence problem of traditional PSO but also to avoid from saturation through the re-initialization of the velocity vector while solving the real ED problem with VPL effects. In crazy particles concept, the velocities of some of the particles designated as "crazy particles" chosen by employing a certain probability are made randomized when they find a premature convergence of the procedure. In [144], the probability of craziness ρ_{cr} (identification of agents and randomizing its velocity), calculated on the basis of inertia weight, is expressed by

$$\rho_{cr} = \omega_{\min} - \exp\left(-\frac{\omega^t}{\omega_{\max}} \right) \tag{29}$$

where ω^t is the inertia weight at the tth iteration of the run. Following logic is then employed to randomize the velocities of particles:

$$v_j^t = \begin{cases} r(0, v_{\max}), & \text{if } \rho_{cr} \geq r(0,1) \\ v_j^t, & \text{otherwise} \end{cases} \tag{30}$$

From (29), it is clear that, at the beginning, a higher value of ρ_{cr} is employed to generate crazy particles to avoid PSO from saturation whereas a comparatively lower value is exploited at later stages of search. This retains the significance of control of inertia weight in the PSO algorithm. In addition, constriction factor is also involved in the velocity update formula to enhance exploration. When tested on two model test systems possessing 3 and 6 thermal generating units, CRAZYPSO exhibits improved convergence characteristics than that of real-coded GA and classical PSO.

Reference [145] proposed an improved PSO (IPSO) approach which employed two-tier approach to avoid from premature convergence and saturation while figuring out five different static and dynamic NCED problems considering the system limitations and constraints. Firstly, it introduces crazy particles with randomized velocities as suggested in [143] to maintain momentum in the search and to avoid saturation. However, randomization of the velocity vector is accomplished through the constriction and the inertia weight factors. Secondly, tuning of the cognitive and social parameters is carried out through a novel parameter called automation strategy in a dynamic way to ensure both exploitation and exploration characteristics. IPSO offers promising performance than that of the classical PSO (CPSO) involving constriction factor.

In [146], solution of the complex and nonlinear EDP problem was accomplished through a novel hybrid PSO algorithm involving dynamic inertial weight and CLS to enhance the global search ability and improve the convergence speed. In the suggested algorithm, the initial position of each particle within its limit is set chaotically through the Logistic map. Introduction of chaotic mapping into PSO actually improves diversity thus the global convergence. Accomplishing this also diminishes the impact imposed by the initial position of the particle. Regarding the inertia weight, it is controlled dynamically according to the measure function of PSO performance. Two variables, namely e (represents particle's evolution degree) and a (represents particle's polymerization degree) are defined and are given by

$$e = P_{gbest(t)}/P_{gbest(t-1)} \tag{31}$$

$$a = \left(P_{size} \times P_{gbest(t)}\right) \Big/ \sum_{i=1}^{P_{size}} P_{ibest(t)} \tag{32}$$

where $P_{gbest(t-1)}$ and $P_{gbest(t)}$ representing the previous and the current global optimal value respectively show evolution degree of swarm speed, P_{size} is a particle number, and $\sum_{i=1}^{P_{size}} P_{ibest(t)}$ representing all particles' fitness of current iteration shows the concentration-dispersion properties of the current particle swarm. Dynamic inertia weight factor ω in terms of e and a is expressed as

$$\begin{aligned} \omega &= f(e,a) = \omega_0 - 0.5e + 0.1a, \\ \omega_0 &= \text{Initial Value} \approx 0.9 \end{aligned} \tag{33}$$

From (33), it is clear that ω decreases with increasing evolution degree and raises with increasing polymerization degree. The performance of PSO can be controlled by changing ω dynamically. When tested on two test systems, the proposed hybrid PSO algorithm comes with lower fuel cost than that of standard PSO.

Through an improved PSO (IPSO) framework proposed in [147] and [148], both the exploration and exploitation capabilities were enhanced by combining the chaotic sequences based on Logistic map with the conventional TVIW and adopting a crossover operation scheme. The crossover operation galvanized by GA enhances the diversity of the population in the PSO mechanism. In addition, constraints in the form of equalities and inequalities are handled effectively well through a constraint handling framework. The chaotic inertial weight approach (CIWA) based on Logistic map suggested in the paper is given by

$$c\omega^t = \underbrace{\left(\omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter\right)}_{\omega} \cdot \left(4cx^{t-1}\left(1 - cx^{t-1}\right)\right) \tag{34}$$

where $c\omega^t$ is a chaotic weight at iteration t. ω^t decreases monotonically from $\omega_{\max}$ to $\omega_{\min}$ whereas $c\omega^t$ decreases and oscillates simultaneously increasing the searching capability of the proposed algorithm. In other words, combination of the chaotic sequences with TVIW makes the weights chaotically dynamic. When tested on three different nonconvex ED problems, proposed IPSO shows promising results than state-of-the-art optimization methods.

Same IPSO algorithm proposed in [147] amalgamating the PSO with the chaotic sequences and crossover operations (borrowed from GA) was reutilized in [149] for figuring out the NCED problems with VPL effects and MF options. In addition, to enhance further the solution quality without blistering the computational efficiency, an effective constraint handling strategy is suggested. When compared, IPSO outperforms the other optimization methods and the conventional GA when applied to a 10 generating units system.

In [150], a newly-introduced (inertia) weight-improved PSO (WIPSO) method was suggested for the resolution of practical OPF and ELD problems taking into account the VPL effects. The introduced randomized inertia weight factor exhibiting better local and global exploration is defined by

$$\omega_{new} = \omega_{\min} + \underbrace{\left(\omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter\right)}_{\omega} \times r() \tag{35}$$

Along with ω_{new}, TVAC are also utilized. Simultaneous utilization of these coefficients enriches the local and global experience of the particles. When applied to deal with OPF and ELD problems, WIPSO validates its accuracy, convergence speed and applicability by calculating optimal total fuel costs and losses with less computational time.

Hybridization of a novel PSO with the direct search method (DSM) handled well the ELD problem with VPL effects according to [151]. The traditional TVIW associated with the particles suffers from the problem that it decreases linearly at the same time for all the particles as the iteration proceeds on. In the proposed algorithm, a newly-introduced inertia weight function incorporated into PSO monitors the TVIW associated with the particles and assists in further enhancing both the global and local exploration abilities. The proposed inertia weight function is characterized by

$$\omega_{qi}^{t} = \begin{cases} \omega_{\max} - \dfrac{\omega_{\max} - \omega_{\min}}{Z}.Z_{iter,qi}^{t}, & \text{if } v_{qi}^{t}.(x_{i,gbest}^{t} - x_{qi}^{t}) > 0 \\ \omega_{qi}^{t-1}, & \text{if } v_{qi}^{t}.(x_{i,gbest}^{t} - x_{qi}^{t}) < 0 \end{cases} \tag{36}$$

where ω_{qi}^{t} represents ith inertia weight of particle q in iteration t. From (36), if the v_{qi}^{t} and $(x_{i,gbest}^{t} - x_{qi}^{t})$ move in the same direction, ω_{qi}^{t} increases linearly not to permit the particles to fly past the target position, otherwise remains same without decreasing to facilitate a free movement of particles in the feasible search region. In addition, the DSM algorithm's ability of fine-tuning with a reduced computing time to determine the eventual global optimal solution plays the trick to find feasible solution. The practicability and potency of the proposed hybrid algorithm is validated through numerical results.

Reference [152] suggested exponentially varying inertia weight factor (EVIWF) based PSO (PSO-EVIWF) for tackling multi-area economic dispatch (MAED) problem with tie line constraints taking into account the VPL effects in order to enhance global exploration. The proposed EVIWF in response to the objective values of the particles is calculated by

$$\omega = \left(\omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \left(1 - \exp\left(-a_0 \times \frac{iter}{iter_{\max}}\right)\right)\right) \tag{37}$$

where a_0 signifies the convergence factor. When verified on a 4 interconnected areas with a 16 generator standard test system, PSO-EVIWF displays better quality solutions and smooth convergence characteristics than that of PSO-TVIW.

Local and global exploration is achieved in traditional PSO using TVIW without getting any feedback from problem solution and by multiplying TVIW with total velocity at each iteration in a linearly decreasing manner. In order to avoid from premature convergence and to increase velocity to explore optimal point, a novel intelligent inertia weight factor calculated on the basis of each particle's cost and its standard deviation of cost of best group response is proposed in PSO with smart inertia factor (PSO-SIF) algorithm [153]. Thus, each particle has its own inertia factor which becomes influential in the speed and position of next particle. Based on cost of population, the newly-suggested inertia factor ω_g is calculated by

$$\omega_g = \frac{0.6 \times (\lambda_j - 1)}{\underbrace{\left[\delta_1 - \left(\dfrac{iter}{iter_{\max}}\right) \times \delta_2\right]}_{\delta_{\max}}} + 0.3, \quad \lambda_j = \frac{cost_j}{cost_{gbest}},$$
$$\delta = \lambda_j - 1; \tag{38}$$

where δ and λ_j represent the cost and the percent change in cost of jth population from best group cost respectively; δ_1 and δ_2 are the adjustable parameters. When implemented on four test cases, PSO-SIF ensures better convergence characteristics than that of PSO.

Reference [154] suggested an improved PSO (IPSO) and then compared its performance with water cycle optimization (WCO) while figuring out a dynamic ELD problem. In the proposed variant of PSO, the value of inertia weight factor is made exponentially decreased on the basis of the number of pass iterations and is expressed mathematically by

$$\omega = \omega_{\max}.\exp\left(-a_0\left(\frac{iter}{iter_{\max}}\right)\right) \tag{39}$$

Moreover, constriction factor is also exercised in particle's velocity equation to safeguard exploration and exploitation. When a 6 unit power system to meet hourly-changing 24 hour load demand is tested through IPSO, it shows better results than that of deterministic numerical techniques like Lambda iterative and Brent methods but takes a little bit more time than that of WCO.

Reference [155] claimed and proved that PSO with TVIW and constriction factor took fewer iterations while resolving ED problem (neglecting both transmission losses and VPL effects) having 4 and 6 generating units in comparison to PSO with TVIW and PSO with constriction factor, although all the three PSO approaches gave almost the same total operating cost.

D. VARIATIONS IN COGNITIVE AND SOCIAL COMPONENTS

Another modified version of traditional PSO named new PSO (NPSO) proposed in [156] utilized the idea of segregation of the cognitive component of the classical PSO into the good experience and bad experience components in order to effectively inspect the search space. The good experience component just like the cognitive component of the traditional PSO keeps in memory the previously visited best position whereas the bad experience component assists the particle in remembering its previously visited worst position. Resultantly, the new updated velocity equation taking into consideration the bad experience additionally of the particle is expressed by

$$v_{id}^{t+1} = \omega.v_{id}^{t} + c_{1g}.r_1().\left(pbest_{id} - x_{id}^{t}\right) + c_{1b}.r_2().\left(x_{id}^{t} - pworst_{id}\right) + c_2.r_3().\left(gbest_{gd} - x_{id}^{t}\right) \quad (40)$$

where the acceleration coefficients c_{1g} and c_{1b} are responsible in accelerating the particle toward its best position and away from its worst position respectively. The modification suggested in cognitive component gives additional exploration capacity to the swarm to identify the promising solution region. More precisely, the introduction of the bad experience component forces the bird (particle) to sidestep its *pworst* and attempt to occupy a better position. Regarding the particles' positions, they are updated using the original PSO position equation. In addition, a direct search method (DSM) based local random search (LRS) procedure is embedded with NPSO to ensure exploitation of the promising solution region. When tested on three ED problems involving constrains such as VPL effects, MF options, transmission losses, NPSO-LRS method shows better convergence behavior than that of PSO-LRS and NPSO.

Reference [157] came up with a new PSO strategy called anti-predatory PSO (APSO) to resolve the nonconvex economic dispatch (NCED) problem with VPL effects. Along with cognitive and social behaviors based foraging activity of the swarm as in classical PSO, an anti-predatory activity is also included in the newly proposed variant of PSO. The idea behind the introduction of the anti-predatory property is to assist the swarm in escaping from the predators. In APSO, the predators are modeled as the worst result points. In order to incorporate the anti-predatory property into APSO, both the cognitive and social behaviors of the classical PSO are split into personal/global good experience and personal/global bad experience components. The velocity-update formula for APSO then takes the following form

$$\begin{aligned} v_{id}^{t+1} = \omega.v_{id}^{t} &+ c_{1g}.r_1().\left(pbest_{id} - x_{id}^{t}\right) \\ &+ c_{1b}.r_2().\left(x_{id}^{t} - pworst_{id}\right) \\ &+ c_{2g}.r_3().\left(gbest_{gd} - x_{id}^{t}\right) \\ &+ c_{2b}.r_4().\left(x_{id}^{t} - gworst_{gd}\right) \end{aligned} \quad (41)$$

The bad experience components resulted from the division of cognitive and social behaviors give additional exploration capacity to the swarm. The positions are updated using the original position equation. APSO comes with less generation cost than that of traditional PSO.

In [158], a new self-organizing hierarchical PSO (SOH-PSO) algorithm was suggested for solution of the NCED problem to eliminate the problem of premature convergence. SOH-PSO further combines with time-varying acceleration coefficients (TVAC) to optimally find the feasible solution. More precisely, both the exploration and exploitation characteristics are ensured through the integration of TVAC with SOH-PSO. It has been observed that in order to restrict the particles to roam about the search space instead of advancing toward the population best prematurely, a large cognitive component and a small social component at the beginning is required. Similarly, a small cognitive component and a large social component during the latter stage permit the particles to converge to the global optima. All this is achieved by expressing TVAC as [159]

$$c_1 = \left(c_{1f} - c_{1i}\right)\frac{iter}{iter_{\max}} + c_{1i} \quad (42)$$

$$c_2 = \left(c_{2f} - c_{2i}\right)\frac{iter}{iter_{\max}} + c_{2i} \quad (43)$$

where c_{1i}, c_{1f}, c_{2i} and c_{2f} are the initial and the final values of cognitive and social acceleration factors, respectively. The authors incorporated these TVAC in their proposed SOH-PSO. In addition, the *pbest* associated with a stagnated particle remains unchanged for a number of iterations. Similarly when such more particles stagnate, the *gbest* associated with them also undergoes the same fate. This forces PSO to converge prematurely to a local optima and velocity becomes zero. In other words, setting the previous velocity term in traditional velocity equation to zero forces the particles to rush towards a local optimum solution rapidly. The particles stagnate due to the absence of momentum (zero velocity). In proposed SOH-PSO method, this stagnancy problem in the search space is then avoided by reinitializing the velocity vector of a particle randomly. The new velocity update formula for SOH_PSO with TVAC is then

$$\begin{aligned} v_{id}^{t+1} = &\left(\left(c_{1f} - c_{1i}\right)\frac{iter}{iter_{\max}} + c_{1i}\right).r_1().\left(pbest_{id} - x_{id}^{t}\right) \\ &+ \left(\left(c_{2f} - c_{2i}\right)\frac{iter}{iter_{\max}} + c_{2i}\right).r_2().\left(gbest_{gd} - x_{id}^{t}\right) \end{aligned} \quad (44)$$

with

$$v_{id} = \begin{cases} r_4 \times V_{d\max} & \text{If } v_{id} = 0 \quad \text{and } r_3 < 0.5 \\ -r_5 \times V_{d\max} & \text{otherwise} \end{cases} \quad (45)$$

When tested on different benchmarks involving ELD problem, SOH-PSO involving TVAC outperforms classical PSO and passive congregation-based PSO (PC-PSO). Inspired from the work of Chaturvedi *et al.*, [160] proposed a new improved PSO (NIPSO) algorithm which utilized exactly the same idea of SOH and TVAC in order to tackle NCED problem.

In [161], although the authors gave the comparative analysis of improved fast EP (IFEP), GA, and various form of PSO algorithms, namely canonical PSO, hybrid PSO with inertia weight as well as with constriction factor approach, and velocity update relaxation momentum factor induced PSO (VURMFIPSO), but they majorly focused on applying a novel PSO algorithm named CRAZYPSO to a constrained ELD problem with VPL effects. Regarding the concept of CRAZYPSO, either too large or too small values of independently and randomly generated two weighting parameters corresponding to personal and social experiences do not ensure quality solution. The proposed algorithm uses only one random parameter in such a way that if one weighting parameter gets large, the other becomes small, and vice versa by making the sum of the two interrelated weighting parameters equal to 1. In addition, the balance of global and local searches is controlled through the introduction of another random parameter r_2 along with the parameter $sign(r_3)$ in the velocity equation. This models the reversal of the direction of the bird's velocity so that it may fly back to the promising region. The velocity formula now extends to [162]

$$v_{id}^{t+1} = r_2.sign(r_3).v_{id}^t + (1-r_2).c_1.r_1.\left(pbest_{id} - x_{id}^t\right) + (1-r_2).c_2.(1-r_1).\left(gbest_{gd} - x_{id}^t\right) \quad (46)$$

All the numbers involved in the equation are uniformly distributed random numbers and *sign* is a sign function which is defined as

$$sign(r) = \begin{cases} -1 & (r \leq 0.05) \\ 1 & (r > 0.05) \end{cases} \quad (47)$$

Sudden change in direction of a bird is incorporated by a craziness operator which ensures that the particle would have a predefined craziness probability to maintain the particles diversity. Resultantly the crazed velocity is given by

$$v_{id}^t = v_{id}^t + p(r_4)sign(r_4)v_d^{craziness} \quad (48)$$

where $v_d^{craziness}$ is a random parameter selected uniformly within the range $\left[v_d^{\min}, v_d^{\max}\right]$; $p(r)$ and $sign(r)$ are defined as

$$p(r) = \begin{cases} 1, & (r \leq P_{cr}) \\ 0, & (r > P_{cr}) \end{cases} \quad (49)$$

$$sign(r) = \begin{cases} 1, & (r \geq 0.5) \\ -1, & (r < 0.5) \end{cases} \quad (50)$$

where P_{cr} designates a predefined probability of craziness. The suggested CRAZYPSO shows superior performance as compared to other optimization techniques. Reference [163] advocated exactly the same idea of CRAZYPSO for the solution of the automatic generation control (AGC) problem. The problem involves a two area thermal power system taking into consideration governor dead-band nonlinearity. In the strategy, the evaluation of the control, however, is considered as an optimization problem.

A modified PSO (MPSO) algorithm was suggested in [164] and [165] for handling constrained ELD problems (with VPL effects) considering 6 and 15 unit systems with higher order general cost polynomials. In addition to basic constraints, constraints like MF options, POZ, etc. are considered. By fixing the values of the parameters, namely the inertia weight factor and the acceleration coefficients involved in the PSO velocity equation or changing their values according to the mechanisms proposed in the standard PSO, handling the constrained ELD problems bearing multi-fuel higher order cost polynomials becomes difficult. For example, in standard PSO, in case if $gbest = pbest_i = x_i$ and assuming the current position x_i a local minimum, then the direction of velocity remains the same during the next iterations. Enough iterations have to be performed in order to jump from the local minimum thus slowing the convergence. In the proposed MPSO, an additional third (random) part called "promising part" (embedded with cognitive and social parts) is introduced for calculating the velocity vector, which assists in jumping from the local minimum quickly to ensure fast convergence. Randomness of PSO also reduces. In addition, the constraints are handled using the penalty method in MPSO. MPSO shows promising results than that of GA and PSO.

In [166], an improved version of coordinated aggregation-based PSO (CA-PSO) [131] called (ICA-PSO) was developed for working out the constrained ELD problem with VPL effects. Conventional CA-PSO suffers from the drawbacks that not only the particles do not consider the cognitive operator (the ability of retaining memory of its best position achieved thus far) but also they do not organize their search adaptively thus exhibiting poor convergence characteristics. The proposed ICA-PSO eliminates the drawbacks in CA-PSO and incorporates various mechanisms to ensure the improved convergence. It takes into account the cognitive operator by retaining a memory of its *pbest*. As a result, a particle is captivated by those particles having achieved better position than its own. More specifically, at iteration-t, the velocity of particle-i having lesser achievement than particles-j is regulated by means of coordinators multiplied by weighting factors, i.e.,

$$v_i^t = \underbrace{\left(x_j(t) - x_i(t)\right)}_{\text{particle-}i\text{ coordinator}} \times \underbrace{\left(\frac{f(x_j) - f(x_i)}{\sum_l \left(f(x_l) - f(x_i)\right)}\right)}_{\text{weighting factor } \omega_{ij}} j, \quad l \in T_i \quad (51)$$

where T_i denotes the set of particles-j with better achievement than particle-i. In addition, improved CA-PSO's ability of selecting the number of search intervals adaptively, varying the population size adaptively, and searching accuracy for particles up to two digit points, result in the improved convergence characteristics. When tested on power systems having 6, 13, 15, and 40 thermal units, ICA-PSO ensures minimum fuel cost than that of other optimization techniques.

In order to deal with large-scale ELD problem considering various constraints such as POZ, RRL, transmission losses, and VPL effects, an advanced parallelized PSO algorithm with modified stochastic acceleration factors (PSO-MSAF) was suggested in [167]. In proposed PSO-MSAF, a set-up of parallel computing platform consisting of average-performance computers with a manger passing on the different values of acceleration parameters c_1, c_2 and the upper and lower limits of each of the random numbers r_1 and r_2 to each of the workers is initialized. The algorithms, thus, are run simultaneously on multiple machines in such a way that they use different bounded values of the stochastic acceleration factors. The results produced by these workers are subsequently compared and the best result is selected as the final optimal solution. In the paper, architecture of the

PSO-MSAF is highlighted in detail. Accomplishing this prevents the particles from premature convergence especially while figuring out the ED problems involving a sizeable number of thermal units. Through the set-up, extenuation of the burden of multimodality and heavy computation is accomplished with ease. Moreover, the performance of the proposed algorithm is further enhanced by introducing a penalty parameterless constraint handling strategy capable of handling power balance (equality), POZ and RRL. When solved the three ED problems consisting of 3, 15 and 40 generating units though PSO-MSAF, it shows better convergence properties than other techniques like, GA, asynchronous parallel PSO (PAPSO), etc.

Reference [168] suggested variable acceleration coefficients based PSO (VACPSO) method which incorporated the idea of the partitioning of the cognitive component into its good and bad experience components and TVAC simultaneously into the classical PSO to enhance the exploration capability with less computational burden while solving an ELD problem taking into account POZ and VPL effects. On the solution of two power systems comprising 3 and 4 thermal generating units with nonlinear characteristics, it has been inferred that VACPSO shows promising results than that of the other calculus-based and metaheuristic optimization approaches.

In [169], four different metaheuristic algorithms, namely classical PSO (CPSO), PSO with TVAC (PSO_TVAC), DE, and BFO are compared in the form of solution quality, convergence characteristics thus convergence speed, etc. while applying them to NCED problem taking into account VPL effects, POZ and RRL. For the sake of comparison, the algorithms are tested on three test systems having 3, 13 and 40 thermal units. Results show that PSO_TVAC takes less convergence time as compared to other algorithms.

An effective PSO algorithm with social weight called ESWPSO was suggested in an IEEE conference paper [170] to handle the ELD problems considering the network transmission losses. VPL effects are not taken into consideration. In ESWPSO, the exploitation and the exploration characteristics are improved by introducing a social weight factor into the velocity update formula which then takes the following form:

$$v_{id}^{t+1} = \omega.v_{id}^{t} + c_1.r_1().\left(pbest_{id} - x_{id}^{t}\right) + c_2.(1-\omega).\left(gbest_{gd} - x_{id}^{t}\right) \quad (52)$$

The extremum disturbance operator is then introduced in ESWPSO to find high quality solutions by generating random points in promising area. When demonstrated on two power system cases considering 6 and 15 generating units, ESWPSO ensures higher quality solutions as compared to other metaheuristic methods.

In the extended version [171], however, the VPL effects are considered in the ELD problems. Through the mathematical treatment, the effect of inertia weight on the convergence speed is highlighted. In order to deal with equality constraint (real power equation), an additional random correction operator is introduced. When tried to solve the EDVPL and EDVPLMF problems consisting of 15 and 10 generating units respectively, hybrid SWPSO shows promising results than that of IGA_MU and MPSO.

In [172], a variant of PSO named an iteration PSO (IPSO) was proposed to solve constrained ED problems without VPL effects (although considered the other realistic constraints such as RRL, generation limitation, POZ, and transmission losses). In IPSO, in order to enrich the searching behavior, improve solution quality, and increase the convergence rate, a new index called "*iteration best*" is consolidated into the original velocity equation of PSO. The velocity update formula for IPSO method bearing the new index is calculated by

$$v_{id}^{t+1} = \omega.v_{id}^{t} + c_1.r_1().\left(pbest_{id} - x_{id}^{t}\right) + c_2.r_2().\left(gbest_{gd} - x_{id}^{t}\right) + c_3.r_3().\left(I_{best,d}^{t} - x_{id}^{t}\right) \quad (53)$$

with

$$c_3 = c_1\left(1 - \exp\left(-c_1 \times iter\right)\right) \quad (54)$$

Here $I_{best,d}^{t}$ represents the best value of evaluation function attained by any particle in iteration t and the exponentially-changing weighting parameter for the stochastic acceleration term c_3 is responsible for pulling each particle towards $I_{best,d}^{t}$ [173]. When tested on two power systems consisting of 6 and 15 units, IPSO outperforms the other optimization techniques like classical PSO, chaotic PSO, hybrid GAPSO, etc. In [174], Abdullah *et al.* employed exactly the same concept of a new index named "*iteration best*" as in IPSO to solve the practical ED problem. Here, however, VPL effects are considered. When tested on two power systems consisting of 3 and 13 units, IPSO shows superior results than that of PSO. Abdullah *et al.*, in another paper [175], introduced the idea of *rbest* (a novel best neighbor particle) rather than *Ibest* in traditional PSO's velocity formula to eliminate the premature convergence problem while dealing with the ELD problem involving POZ and RRL constraints. The novel variant of PSO involving *rbest* was given the name modified PSO (MPSO). The randomly selected parameter *rbest* obtained from the best position of another neighbor particle *pbest* diversifies the particle movement (to avoid premature convergence) by sharing extra information with each particle. MPSO is then amalgamated with TVAC (MPSO-TVAC) to keep balance in exploration and exploitation capabilities. When tested on various test cases, MPSO-TVAC offers promising results. In [176], an improved version of IPSO named a modified iteration PSO (MIPSO) incorporating two new indices named, "*iteration best* 1" and "*iteration best* 2" into the velocity equation rather than one index as was in IPSO was suggested while solving the ELD problem with VPL effects. MIPSO further enhances the searching behavior and solution quality and avoids itself from being trapped into local optimum. The updated velocity of MIPSO method incorporating the new indices is calculated by

$$v_{id}^{t+1} = \omega.v_{id}^t + c_1.r_1().\left(pbest_{id} - x_{id}^t\right) + c_2.r_2().\left(gbest_{gd} - x_{id}^t\right) + c_3.r_3().\left(I_{best1,d}^t - x_{id}^t\right) + c_4.r_4().\left(I_{best2,d}^t - x_{id}^t\right) \quad (55)$$

To ensure the feasibility and efficiency of MIPSO, it is administrated to four test systems possessing 3, 6, 13 and 15 thermal units respectively and gives minimum mean cost as compared to other metaheuristic optimization techniques.

Ivatloo *et al.* utilized the idea of the integration of TVAC and index-based IPSO in his work successfully. In [177] and [178], iteration PSO with TVAC (IPSO-TVAC) method inheriting salient features of both TVAC-PSO and IPSO methods simultaneously was proposed to handle the constrained nonconvex ED problem considering the VPL effects. On one hand, IPSO suggests the addition of a new index called "*iteration best*" to the original velocity equation to ameliorate searching behavior thus to avoid premature convergence. On the other hand, TVAC are employed to enhance the solution quality. As a result, the velocity update formula takes the form.

$$v_{id}^{t+1} = \omega.v_{id}^t + \left(\left(c_{1f} - c_{1i}\right)\frac{iter}{iter_{\max}} + c_{1i}\right) \cdot r_1().\left(pbest_{id} - x_{id}^t\right) + \left(\left(c_{2f} - c_{2i}\right)\frac{iter}{iter_{\max}} + c_{2i}\right).r_2().\left(gbest_{gd} - x_{id}^t\right) + \left(c_1\left(1 - \exp\left(-c_1 \times iter\right)\right)\right).r_3().\left(I_{best1,d}^t - x_{id}^t\right) \quad (56)$$

Velocity term involving the constriction factor is considered while calculating the position of the particle. The feasibility of IPSO-TVAC is investigated by applying it to a 6, 13, and 40 unit test systems. IPSO-TVAC is found to exhibit better convergence characteristics than that of other optimization techniques.

The idea of time-varying acceleration coefficients (TVAC) based PSO was also utilized efficiently in [179] for tackling ED problems with VPL effects. The solution of two test systems consisting of 6 generating units with 26 buses and 46 transmission lines and 15 generating units through TVAC-PSO validates its feasibility and effectiveness. Reference [180] efficiently made use of TVIW with constriction factor and TVAC in PSO while dealing with various nonconvex nonlinear ELD problems with VPL effects. The particles were not made crazy, i.e., the current velocity term was not set to zero. When tested on various power systems, PSO-TVAC shows promising results than that of other optimization techniques. Reference [181] also employed TVAC based PSO (TVAC-PSO) for the solution of ELD problem without VPL effects. Through TVAC, convergence rate is enhanced by well-exploring the search space. The effectiveness and feasibility of TVAC-PSO is validated by applying it to solve power system possessing 3 and 6 generating units. TVAC-PSO exhibits better convergence characteristics than that of PSO.

Reference [182] suggested an intelligent PSO (INPSO) to enrich the social behavior by incorporating an additional novel index named "another particle best position ($pbest_{ap}$)" into the PSO's velocity update formula for the quick fix of NCED problem considering the VPL effects. The additional behavior shares information among the particles facilitating them to direct themselves toward global solution. The particle's velocity adopts the following form.

$$v_{id}^{t+1} = \omega.v_{id}^t + c_1.r_1().\left(pbest_{id} - x_{id}^t\right) + c_2.r_2().\left(gbest_{gd} - x_{id}^t\right) + c_3.r_3().\left(pbest_{ap} - x_{id}^t\right) \quad (57)$$

with

$$c_3 = c_{3\max} - \left(c_{3\max} - c_{3\min}\right)\left(\frac{iter}{iter_{\max}}\right) \quad (58)$$

Evaluation of $pbest_{ap}$ is executed through the proposed diversity-based judgment mechanism while preserving the population diversity. DSM fine-tunes the solutions obtained through INPSO with less computational expense and ensures local optimization. When solved two power systems containing 13 and 40 generating units through INPSO-DSM, INPSO-DSM comes up with solutions of better quality as compared to PSO, PSO-IW and INPSO.

Reference [183] suggested a modernistic differential PSO (DPSO) algorithm in order to eliminate the inherited problem in the form of getting trapped at local minima faced by traditional PSO while figuring out an ELD problem taking into consideration the VPL effects and POZ. In DPSO, the experience of a randomly selected particle from the swarm designated as a target particle is enumerated in the PSO's velocity formula. The velocity update formula with additional term incorporating the scaled difference between the target particle and the selected particle (trying to avoid from trapping in local minima) is expressed by

$$v_{id}^{t+1} = \omega.v_{id}^t + c_1.r_1.\left(pbest_{id} - x_{id}^t\right) + c_2.r_2.\left(gbest_{gd} - x_{id}^t\right) + c_3.r_3.\left(x_{ld}^t - x_{id}^t\right) \quad (59)$$

where the parameter $l \in [0, n]$ corresponds to the expert particle with respect to target particle i. DPSO demonstrates better convergence characteristics in comparison to PSO when tested on a 10 unit power system.

E. SIMULTANEOUS VARIATIONS IN INERTIAL, AND COGNITIVE AND SOCIAL COMPONENTS

Many researchers introduced simultaneous variations in inertial, and cognitive and social components to strengthen the performance of PSO. In [184], four pre-existing variants of PSO have been applied separately to the ELD problem containing 13 generating units with VPL effects to ensure both exploration and exploitation. Network transmission losses are neglected. Firstly, a standard PSO with TVIW and fixed acceleration coefficients for the cognitive and social components is applied. Secondly, in adaptive PSO (APSO), the highly fitted particle is made slower than lowly fitted particle by selecting different values of inertia weight for each particle according to its rank in order to ensure convergence. The detailed procedure of adaptive mechanism to handle constraints is well-highlighted. Thirdly, in order to avoid from premature convergence, chaotic PSO (CPSO) methods amalgamating PSO with AIWF, and CLS based on the logistic equation is utilized. Lastly, in new PSO (NPSO), the search space is efficiently explored by partitioning the PS's cognitive into its good and bad experience components. For the typical design example, APSO shows better convergence characteristics than that of other PSOs.

Reviews and comparison of the performance of various PSO variants including classical PSO (with constriction factor and TVIW), PSO with chaotic inertia weight (PSO_CIW), PSO with chaotic acceleration coefficients (PSO_CAC), and PSO with TVAC (PSO_TVAC) with a traditional solver, i.e., the General Algebraic Modeling System (GAMS) while working out the MAED problem were presented in [185]. CIW and CAC are made chaotic using the well-famous logistic map. The objective function of MAED involves the minimization of not only the total fuel cost function but also the cost function associated with tie line power flow. When tested on four test cases having generating units with various equality and inequality constraints, PSO_TVAC shows promising results than that of the other PSO variants. Although the performance of PSO_TVAC matches well in accuracy with GAMS but takes almost 100 times more computational time.

In [186], another modified form of PSO named a stochastic weight trade-off PSO (SWT_PSO) was introduced to preserve the balance between (global) exploration and (local) exploitation through trading off stochastic weights amongst previous velocity momentum, cognitive and social components while solving the NCED problem. In classical PSO, the weighting coefficients for cognitive and social components are generated independently. Here, relative generation of the two weights is accomplished through adopting the idea presented in [187], i.e., if one random parameter possesses a large value, the other should keep a small value, or vice versa. Similarly, trade-off among the three components involved in PSO's velocity equation is accomplished by assigning stochastic weights to them in such a way that both exploitation and exploration characteristics are ensured. Diversity of a swarm member (thus the global search capability) is further enhanced by reversing the direction of certain particles initially moving in the opposite direction of a feasible region through "lethargy" factor. When tested on four different power systems involving nonconvex cost functions, SWT_PSO shows outstanding results as compared to other optimization techniques.

In [188], an improved version of PSO named adaptive acceleration coefficients (AAC) based PSO (AAC-PSO) was proposed in order to solve ELD problem without the VPL effects. In AAC-PSO, in order to best-manage the exploration and exploitation characteristics, exponentially-varying adaptive inertia weight and acceleration coefficients are introduced and are defined by:

$$\omega = \omega_{\max}.\exp\left(-\alpha_\omega \times iter\right) \tag{60}$$

$$c_1 = c_{1i}.\exp\left(-\alpha_c \times iter \times k_c\right) \tag{61}$$

$$c_2 = c_{2i}.\exp\left(-\alpha_c \times iter \times k_c\right) \tag{62}$$

where

$$\alpha_c = -\left(\frac{1}{iter_{\max}}\right).\ln\left(\frac{c_{2i}}{c_{1i}}\right) \tag{63}$$

$$k_c = \frac{F_m - gbest}{F_m} \tag{64}$$

Here, by following the same pattern as described in (63), α_ω is determined on the basis of $\omega_{\max}$ and $\omega_{\min}$. k_c is calculated on the basis of *gbest* and *pbest*. F_m designates the mean value of the best positions with respect to all particles. When demonstrated on two power systems containing 6 and 15 thermal units, AAC-PSO shows better convergence characteristics than that of conventional PSO.

Jadoun *et al.* contributed tremendously to solve NCED problem by introducing various modified versions of inertial and cognitive and social components in PSO. In [189], a dynamically controlled PSO (DCPSO) method was suggested to tackle the NCED problem of large dimensions.In the proposed method, the TVIW (regulates only the initial velocity component) and the statically-controlled (assume constant values) acceleration coefficients are controlled dynamically by acquainting new exponential functions. The performance of the cognitive component is enriched by adding the preceding experience into it whereas the social component with the RMS experience ensures-well the global optimal solution. An altered control equation administrating the particl's velocity dynamically by recommending suitable exponential constriction functions ζ_1 and ζ_2 related to the acceleration coefficients and an exponential decaying function ω_e related to the inertia weight is expressed by

$$\begin{aligned} v_{id}^{t+1} &= \omega_e.v_{id}^t + \zeta_1.c_{1b}.r_1().\left(\frac{pbest_{id} - x_{id}^t}{\Delta t}\right) \\ &\quad + (1-\zeta_1).c_{1p}.r_2().\left(\frac{x_{id}^t - ppreceding_{id}}{\Delta t}\right) \\ &\quad + \zeta_2.c_2.r_3().\left(\frac{gbest_{gd} - x_{id}^t}{\Delta t}\right) \\ &\quad + \zeta_2.c_2.r_4().\left(\frac{grms_{gd} - x_{id}^t}{\Delta t}\right) \end{aligned} \tag{65}$$

where

$$\omega_e = \exp\left(-\underbrace{\left(\frac{iter}{iter_{\max}}\right)}_{\eta} \times \log_e \underbrace{\left(\frac{\omega_{\max}}{\omega_{\min}}\right)}_{k_w}\right) \tag{66}$$

and

$$\zeta_1 = \exp\left(-\mu_1 \eta\right) \tag{67}$$

$$\zeta_2 = k\exp\left(-\mu_2 \eta\right), \quad k = \zeta_1 c_{1b}/\zeta_2 c_2; \tag{68}$$

The newly introduced dynamic exponential functions for the inertial, cognitive and social components into the particl's updated velocity equation ensure better exploration and exploitation to a larger extent. Simulation results validate the effectiveness of DCPSO.In PSO with time varying operators suggested in [190], rather than considering the preceding experience $ppreceding_{id}$, the poor experience $ppoor_{id}$ is added to the cognitive component to ameliorate its performance. For the sake of controlling the acceleration coefficients dynamically, new exponential constriction functions ζ_1 and ζ_2 are introduced. In addition, TVIW is modulated by introducing a new truncated sinusoidal function. The velocity update formula is now expressed by

$$\begin{aligned} v_{id}^{t+1} &= \omega.v_{id}^{t} + \zeta_1.c_{1b}.r_1().\left(\frac{pbest_{id} - x_{id}^{t}}{\Delta t}\right) \\ &\quad + (1-\zeta_1).c_{1p}.r_2().\left(\frac{x_{id}^{t} - ppoor_{id}}{\Delta t}\right) \\ &\quad + \zeta_2.c_2.r_3().\left(\frac{gbest_{gd} - x_{id}^{t}}{\Delta t}\right) \end{aligned} \tag{69}$$

where

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min})\cos^2\left(\frac{\theta}{2}\right), \quad 0 \le \theta \le \pi \tag{70}$$

with

$$\begin{aligned} \theta &= X \times iter + Y \\ &= \left(\frac{\pi}{iter_{\max} - iter_{\min}}\right) \times iter + \left(\frac{-\pi \times iter_{\min}}{iter_{\max} - iter_{\min}}\right) \end{aligned} \tag{71}$$

The amendments in inertial weight and acceleration coefficients control the movement of the particles in such a way that the new PSO ensures better exploration and exploitation characteristics. When tried to solve three standard test systems consisting of 13, 40 (with VPL effects), and 40 (with VPL effects and POZs) generating units, the proposed PSO algorithms shows superior convergence characteristics. Employing almost the same idea of using the improved cognitive component of velocity update formula, in [191], Jadoun *et al.* suggested an improved PSO (IPSO) for the solution of large dimensional multi-constraints MAED problem. In the proposed IPSO, rather than partitioning the cognitive component into the best and worst experience, the cognitive component is partitioned into the best and preceding experience of the particle to ensure global exploration during initial iterations. Through the constriction factor, the strength of the social component is made weaker during initial iterations. The local exploitation during later iterations is ensured through the social component. The suggested velocity update formula takes the form

$$\begin{aligned} v_{id}^{t+1} &= \omega.v_{id}^{t} + c_{1b}.r_1().\left(\frac{pbest_{id} - x_{id}^{t}}{\Delta t}\right) \\ &\quad + c_{1p}.r_2().\left(x_{id}^{t} - ppreceding_{id}\right) \\ &\quad + C.c_2.r_3().\left(\frac{gbest_{gd} - x_{id}^{t}}{\Delta t}\right) \end{aligned} \tag{72}$$

In addition, exponential inertia weight factor described in (66) is employed. When tested on a four areas, 40 generators test system, IPSO shows promising results as compared to the other methods.

In [192], the performance of PSO algorithm involving the constriction factor was studied empirically while applying it to solve the NCED problem taking into consideration the VPL effects. The (traditional) idea of velocity clamping is introduced by

$$v_{id}^{t+1} = \begin{cases} v_{id}^{t+1}, & \text{if } v_{id}^{t+1} < v_i^{\max} \\ v_i^{\max}, & \text{if } v_{id}^{t+1} > v_i^{\max} \end{cases} \tag{73}$$

where

$$v_i^{\max} = \frac{\left(P_{i,\max} - P_{i,\min}\right)}{\delta}, \quad \text{where } 1/\delta \in [0,1] \tag{74}$$

In order to comprehensively inspect the effects of four parameters, namely the price penalty factor (ppf), the controller associated with the velocity clamping scheme (δ), the acceleration constants (c_1 and c_2) and the limits (lower and upper) of the inertia weight (ω) through the computer simulation results, separate experimental setups are established. Following the guidelines outlined in the paper, time consumed in picking the parameters values can be saved.

In [193], the classical PSO (CPSO) considering constriction factor and TVIW individually as well as simultaneously and the three improved versions of PSO algorithms (IPSOs) were employed to tackle the ELD problem with transmission losses. However, VPL effects are not taken into consideration. In case of the first IPSO, both the position and the velocity of the particles are updated whereas in case of the second IPSO, only the velocity is updated (not the position) when a particle attains the global position during the search. This results in the reduction of the search area of the swarm and oscillation of the particles in less computational time (thus faster convergence). In the third version of IPSO, the position of the particles whose current position is better than its *pbest* is not renewed. This results in the best fitness evaluation. For the comparison purposes, 20 trial runs are selected. When demonstrated on ELD problem having IEEE 5, 14, 30 bus systems, the improved PSO algorithms give optimum fuel cost than that of CPSO. PSO (itself) and its variants, namely PSO with constriction factor approach (PSOCFA), PSO with inertia weight factor approach (PSOIWA), and PSO with CF and IW approaches (PSOCFIWA) were employed to tackle the ELD problem neglecting the transmission losses and VPL effects [194], the ELD problem with POZ constraint [195], the ELD problem with RRL constraint [196], and the ELD problem with POZ and RRL constraints [197]. Convergence behavior of PSO and its variants is compared while solving the ELD problem consisting of a fifteen-unit system.

Reference [198] suggested a modified PSO (MPSO) algorithm which incorporated the *pbest* and *gbest* based varied inertia weight factor ω and acceleration coefficients c_1 and c_2 into PSO to figure out ELD problem with transmission losses but neglecting VPL effects. The varied ω, and c_1 and c_2 are calculated by (75) and (76):

$$\omega_i^t = \omega_{\min} + \frac{F_{pbest}^{t-1} \times \left|F_1^{t-1} - F_{pbest}^{t-1}\right|}{F_1^{t-1} \times \left|F_1^{t-1} - F_{gbest}^{t-1}\right|} \tag{75}$$

$$c_{1,i}^t = \sqrt{\frac{F_i^{t-1}}{F_{pbest}^{t-1}}}, \quad c_{2,i}^t = \sqrt{\frac{F_i^{t-1}}{F_{gbest}^{t-1}}}; \tag{76}$$

The velocity and position are then updated. When tested on a 3 thermal generating unit system, MPSO shows better performance than that of a conventional method and PSO.

In [199], pros and cons of the various modified already-suggested versions of PSO applied to solve constrained ED problems were presented. In addition, an improved PSO called IPSO utilizing the newly introduced exponential inertia weight factor and acceleration coefficients for the social and cognitive parts was suggested for the resolution of ELD problem with VPL effects in order to exploit better exploration and exploitation characteristics. The suggested inertial weight and acceleration coefficients are defined by (77) and (78) respectively.

$$\omega = \frac{1}{(1 + \exp(-\alpha \times F(G_t))^n)} \tag{77}$$

$$c_i = 1 + \frac{1}{(1 + \exp(-\alpha \times F(G_t))^n)}, \quad i = 1, 2 \tag{78}$$

where $F(G_t)$ designates the tth iteration of the global optimum fitness n whereas α calculated by $\alpha = 1/F(G_t)$ is required to be predefined. When applied to a thermal system consisting of 3 generating units, IPSO algorithm shows better convergence characteristics than that of other optimization techniques.

F. VARIATIONS IN RANDOM NUMBERS

In standard PSO, generation of both the random variables (one for the cognitive part and the other for the social part) is accomplished through the uniform probability distribution within the range [0, 1]. It has been observed that both exploration and exploitation characteristics of the PSO algorithm can be enhanced while keeping the same parameters through the other probability distribution functions (PDFs) such as Gaussian, Cauchy, exponential, etc. Random numbers can also be generated using chaotic sequences. A review of the PSO algorithm involving variations in random numbers is presented in this subsection.

Reference [200] suggested the use of Gaussian probability distribution (GPD) and/or chaotic sequences for the generation of random numbers in PSO approach rather than using the uniform probability distribution while solving constrained ED problem without VPL effects having 15 and 20 generating units with constraints in the form of RRL and POZ. Random numbers generated through the GPD and/or chaotic sequences in the interval $[-1, 1]$ are mapped into the interval [0, 1]. The use of chaotic sequences in PSO assists in escaping from local optima, while the GPD may ensure faster convergence in local search. Famous logistic map used in the paper for the generation of the chaotic sequences is defined as

$$cx_i^t = \mu cx_i^{t-1}\left(1 - cx_i^{t-1}\right), \quad 0 \leq \mu \leq 4; \tag{79}$$

where t represents the sample number, and μ is a control parameter. Various types of PSO may be constructed by generating the random numbers for the cognitive and social parts on the basis of GPD and/or chaotic sequences. The new PSO approaches are summarized in Table 2.

TABLE 2. Various variants of PSO on the basis of random numbers.

Random Variables	PSO Type	PDF and/or Chaotic Sequences
r_1, r_2	Type 1 (Standard PSO)	uniform → cognitive uniform → social
	Type 2	Gaussian → cognitive uniform → social
	Type 3	uniform→ cognitive Gaussian→ social
	Type 4	Gaussian → cognitive Gaussian → social
	Type 5	uniform → cognitive chaotic → social
	Type 6	chaotic → cognitive uniform→ social
	Type 7	Gaussian → cognitive chaotic → social
	Type 8	chaotic → cognitive Gaussian → social

In addition, a two-step based constraint handling strategy is proposed. In the first step, determination of the decision variable vectors (solutions) lying within user-defined upper and lower bounds is accomplished. The second step involves rewriting the total fuel cost function. The PSO and its variants are applied to work out two test systems considering 15 and 20 thermal generating units involving nonlinear VPL effects and are found to show promising performance in comparison to other heuristic methods.

The same authors Coelho *et al.* in another paper [201] suggested the generation of the random variables used in the velocity update formula through chaotic sequences based on Hénon map rather than based on logistic map, to enhance the convergence rate thus the resulting precision while solving the ED problem considering the VPL effects. Hénon map is described by

$$cx_i^t = 1 - a.cx_i^{t-1} + z_i^{t-1}, \quad z_i^t = b.cx_i^{t-1}; \tag{80}$$

To be specific, setting $a = 1.4$ and $b = 0.3$ gives the output values of z in the range [0.3854, 0.3819] which are then are normalized in the range [0, 1]. The novel proposed chaotic PSO after ensuring fast convergence is then embedded with an implicit filtering (IF) local search method to fine-tune the final solution obtained thus for. Simulation results validate the workability and efficacy of the proposed hybrid approach when demonstrated on a test system consisting of 13 thermal units. Just like the work of Coelho *et al.*, Hardiansyah in another paper [202] proposed a modified PSO (MPSO) technique which employed GPD (with zero mean and variance of one) for the generation of random number for the cognitive part and Cauchy probability distribution (CPD) for the generation of random number for the social part, both in the interval [0, 1], in velocity update equation while solving the ELD problems with VPL effects. This introduces new diversification and intensification strategy into the particles thus preventing them from converging prematurely. When demonstrated on four test problems, MPSO provides better convergence properties than that of HPSO-TVAC and PSO-TVIW.

Reference [203] endorses the idea of enhancing further the search capability and guaranteeing a high probability of achieving the high quality solution without significantly impairing the convergence speed and the simplicity of the structure of PSO through the Gaussian random variables (both for the cognitive and social parts) rather than uniform random variables as in the case of standard PSO in the velocity update formula. Classical PSO utilizing the Gaussian random variables was given the name a modified PSO (MPSO) which was then used for the solution of NCED problems. The Gaussian random variables handle well the amount of perturbation added to the velocity vector, thus assisting the approach in escaping from local optima. In this way, the diversity of the population is maintained throughout iterative process thus guaranteeing a high probability of achieving the better solution. MPSO shows better convergence characteristics in comparison to other forms of PSO involving time-varying coefficients.

The Trelea PSO (Trelea-PSO) method was suggested in [204] to solve the NCED problem considering the VPL effects and MF options. In Trelea-PSO, particle's velocity equation is updated by setting the random numbers to the expected values of 1/2 along with the other modifications. Choosing these values of random numbers simplifies the velocity equation and thus enhances the convergence speed. In the paper, the inertia weight factor is set to 0.729 and the acceleration coefficients are given the value of 1.494. Trelea-PSO outperforms the other metaheuristic optimization techniques when tested on a power system consisting of 10 units with multiple fuels, and multiple fuels and loading effects.

In [205], another improved version of PSO called democratic PSO (DPSO) originally developed by Kaveh and Zolghadr [206] was employed to solve ELD problem with VPL effects. In DPSO, in order to incorporate the "democratic" effect of particles swarm upon the movement (in solutions space) of a certain particle, an additional supplementary term $c_3.r_3.d_{id}^t$ (see (81)) is introduced into the velocity update formula which is now given by

$$v_{id}^{t+1} = \omega.v_{id}^t + c_1.r_1().\left(pbest_{id} - x_{id}^t\right) + c_2.r_2().\left(gbest_{gd} - x_{id}^t\right) + c_3.r_3().d_{id}^t \quad (81)$$

Introduction of d_{id}^t factor calculated in [206] facilitates the particles in the swarm to get additional information and to allow a few of the low performant particles to manipulate the movement of the swarm in order to enhance the PSO exploration capability. The performance of DPSO is further improved (the resulting algorithm is called DPSO-Sine) by replacing the uniformly distributed random numbers with the chaotic sequences (generated through chaotic Sine map) based random numbers which are defined by

$$cr_i^{t+1} = \frac{a}{4}\sin\left(\pi \times cr_i^t\right), \quad i = 1, 2, 3, \ a \in [0, 4]; \quad (82)$$

When demonstrated on two power systems possessing 13 and 40 thermal generating units, DPSO and DPSO-Sine offer promising results than that of PSO algorithm and other metaheuristic optimization techniques.

In [207], the improved PSO (IPSO) suggested for the dynamic nonconvex ELD problem uses the concept of randomly-dimensioned velocity vector of PSO. More specifically, the velocity is made randomized by selecting the components of the random number vectors independently. Doing so enhances the chances of attaining better global solution. Experimental results validate the efficacy of the suggested variant of PSO.

G. CONSTRAINTS HANDLING STRATEGIES

Economic dispatch problem is essentially a constrained optimization problem with heavy constraints in the form of equalities and inequalities. Owing to the canonical version of PSO, it does not provide a mechanism for tackling heavily-constrained practical dispatch problems. Suffered from a high computation cost, a traditional, convenient and easily-implementable penalty function method (where constraints are penalized) is usually employed to convert constrained dispatch problems into the unconstraint ones. In penalty function method, in order to tackle constraints, actually a suitable penalty function corresponding to each of the equality and inequality constraints involved in the ED problems is incorporated into the fitness function. To handle constraints even well, various constraints handling methods are suggested in the literature. Some methods preserve the feasibility of solutions and some distinguish well the feasible and unfeasible solutions. In addition, hybrid methods are also proposed. In this subsection, a review of PSO and its modified versions to tackle the heavy constraints in dispatch problems is presented.

In a modified PSO (MPSO) suggested in [208], a mechanism is proposed to work out the equality and inequality constraints involved in the ED problems during the modification of each individual's search. The conventional PSO's inherited dynamic process remains unaltered during the process of the application of the constraint treatment mechanism. In order to satisfy the equality constraint, a random variable in the form of a generator output during each iteration is enumerated as a slag generator whose value is computed on the basis of the difference between the total generation (excluding the slag generator) and the total system demand. Regarding the inequality constraints, the next position of a particle (individual) calculated by the PSO algorithm results in violating the inequality constraints. The violation of the inequality constraints is avoided by setting the position of a particle to its minimum or maximum value depending on the velocity assessed. In addition, the convergence speed is accelerated in MPSO by reducing the dynamic search-space based on the distance between the *gbest* and the inequality boundaries. Transmission network losses and POZ are ignored. When demonstrated on two test cases involving 3 and 40 generators to validate its effectiveness, MPSO ensures minimum cost as compared to other optimization techniques. Following exactly the same mechanism suggested by Park *et al.* in [208], [209] suggested an efficient PSO to solve ED problem with 2 and 3 generating units without VPL effects, and 3 generating units with VPL effects. Efficient PSO shows promising results than that of NM, IEP, and MHNN. In [210], an efficient PSO (EPSO) algorithm suggested to solve two ED problems, one with convex cost functions and the other one with nonconvex cost functions (considering VPL effects), also utilized the same idea (proposed by [208]) of constraint handling mechanism to tackle equality and inequality constraints and reduced dynamic search-space to ensure fast convergence. Transmission network losses are considered to make the dispatch problem more realistic. EPSO exhibits better convergence properties than that of other soft computing techniques.

Reduction of the search space (excluding the infeasible domain) was also ensured through PSO based new constraint-preserving method (NCPM) [211] in order to boost the probability of finding the global minima while solving a (multi-area) nonconvex ED (NED) problem with VPL effects. Traditionally, all infeasible solutions are eliminated through the well-famous rejecting strategy adopted by classical feasible-solutions methods. NCPM, however, adopts some auspicious ways for generating feasible solutions efficiently. In NCPM, steps involving the initialization of randomly generated particles while satisfying constraints, updating the modified position and velocity considering constraints, updating the *pbest* and *gbest*, space reduction strategy and stopping criteria are clearly highlighted in the paper. Simulation results reveal that NCPM algorithm offers promising results in the form of convergence speed and computation time than that of the other evolutionary techniques such as PSO and EP with the rejecting strategy.

Rather than adopting the penalty function method (as it suffers from various limitations such as a careful fine tuning of the price penalty factors, authenticate estimates of the degree of penalization, etc.) to handle equality and inequality constraints effectively, feasibility-based rules to take up inequality constraints (generator capacity limits, etc.) and heuristic strategies with priority list based on probability to deal with equality constraints (the power balance equation, etc.) are suggested in the improved PSO (IPSO) [212]. Accomplishing this facilitates the population to approach the feasible region quickly. Like always, while handling constraints, the inherited dynamic process in PSO is kept preserved for all individuals in swarm. Unlike the traditional PSO, the constraint-handling strategy adopted in the paper does not need setting of any additional parameters, thus lessening the burden of fine-tuning of penalty factor to ameliorate the optimization efficiency. The feasibility-based rules pass on information to PSO to tackle inequality constraints on finding *pbest* and *gbest*. When demonstrated on three power systems, computer results authenticate the workability and efficiency of the proposed IPSO method.

In order to avoid from the problem of premature convergence in PSO, an improved PSO handling well both the equality and inequality constraints and improving the aspect regarding the initialization of swarm was suggested in [213] to tackle the ELD problem, however, without VPL effects. Actually, in the improved PSO, both the equality (power balance equation) and inequality (generator capacity limits) constraints are penalized through penalty price factor and are included in the overall objective function to be minimized. This is how the constraints are handled. When two power systems possessing 3 and 5 thermal units are assessed, the improved PSO displays better convergence characteristics.

An improved chaotic PSO (ICPSO) algorithm [214] integrating PSO, Logistic map based chaotic mutation (to avoid premature convergence), and enhanced heuristic strategies (to handle various constraints) was proposed to work out ELD problem with VPL effects. Moreover, the effects of two crucial parameters (inertia weight factor and chaotic mutation) on the ICPSO performance are also investigated. Inspired from the work of Yuan *et al.* [212], feasibility-based rules based an enhanced constraint-handling strategy is devised to deal with the complex inequality constraints effectively whereas the equality constraints are resolved through the heuristic strategies without enforcing any restrictions. The ELD problem involves the adjustment of the outputs of thermal units at each iteration while fulfilling the inequality and equality constraints. In addition, rather than using the TVIW, the velocity of a particle is updated by using the inertia weight factor given by

$$\omega = (\omega_{\max} - \omega_{\min}) \times \exp\left(-\beta \times iter\right) + \omega_{\min} \tag{83}$$

where β is the shrink factor that decides the varying velocity of ω. Initially, a large ω makes ICPSO explore globally, while at a later stage, a small ω makes the algorithm explore locally. When computed two power systems possessing 10 and 30 thermal units, the ICPSO algorithm shows its feasibility and effectiveness over other metaheuristic techniques.

In [215], Wang *et al.* also proposed a chaotic self-adaptive PSO (CSAPSO) algorithm to resolve ELD problem taking into consideration the VPL effects and transmission losses. This time, a randomness adjustment strategy based enhanced constraint-handling strategy is suggested to handle linear and nonlinear constraints. In the proposed strategy, the complex inequality constraints are treated first while ensuring the feasible outputs of generating units. Then, the equality constraints are tackled in feasible region while guaranteeing that the already-satisfied inequality constraints are not violated again. In order to ameliorate the precision of PSO, the velocity of particles including the constriction factor is updated dynamically as

$$v_{id}^{t+1} = C\left[\omega.v_{id}^{t} + c_1.r_1.\left(pbest_{id} - x_{id}^{t}\right) + c_2.r_2.\left(gbest_{gd} - x_{id}^{t}\right)\right] \quad (84)$$

with

$$C = \begin{cases} C_{\max} - (C_{\max} - C_{\min}).2^{\frac{(f(gbest^{Gen}) - f(gbest^{Gen-d}))}{\varepsilon}}, & \text{if } iter > d \\ C_{\max}, & \text{if } iter \leq d \end{cases} \quad (85)$$

Here ε and d are constant factors. ω is calculated using (83). To avoid the premature convergence, CLS based on the Tent chaotic map described by

$$cx^{t} = \begin{cases} cx^{t-1}/0.7 & \text{for } 0 \leq cx^{t} < 0.7 \\ 10.cx^{t-1}.(1 - cx^{t-1})/3 & \text{for } 0.7 \leq cx^{t} \leq 1 \end{cases} \quad (86)$$

is incorporated into the evolution procedure of PSO. When tested on three power systems, CSAPSO ensures better solution in feasible time as compared to other metaheuristic algorithms.

In [216], an improved PSO utilizing the concept of feasible region adjustment (FRA) mechanism to meet both the equality and inequality constraints simultaneously was recommended to tackle an ED problem with VPL effects and RRL, however, neglecting P_{Loss}. Usually while fulfilling the inequality constraints, the equality constraints are violated by the solutions. As soon as the power generation deviates from the demand, FRA strategy is invoked. In addition, TVIW and TVAC are employed to ensure better exploration and exploitation characteristics. The proposed algorithm demonstrates its feasibility when applied to a 6 generating unit containing power system.

Usually the constraints are penalized, for their tackling, in the penalty function method (pfm). To facilitate the readers, other advantageous constraint handling approaches other than the pfm for handling equality (power balance equation (PBE)) and inequality (generator capacity limits (GCL), RRL, etc.) are summarized in Table 3.

TABLE 3. Other constraints handling strategies.

Constraint	Mechanism/Strategy/Concept	Ref.
Equality (PBE)	By selecting loading of any one of the units as independent and replacing its current value by a value calculated through a specific formula	[104]
Equality (PBE)	Through the concept of a *reference* generator	[101]
Inequality (GCL)	A position check strategy (a repair algorithm)	
Equality (PBE)	Through the concept of a *slag* generator	[208],
Inequality (GCL)	By setting a particle's position to its minimum or maximum value depending on the velocity assessed (position check strategy)	[209], [210]
Linear	New constraint-preserving method (NCPM)	[211]
Inequality (GCL and RRL)	Feasibility-based rules	[212], [214]
Equality (PBE)	Priority list (probabilistic)-based heuristic strategy	
Linear and nonlinear	A randomness adjustment strategy based enhanced constraint-handling strategy	[215]
Equality (PBE) and GCL and RRL	Feasible region adjustment (FRA) mechanism	[216]
Equality (PBE) and POZ and RRL	A penalty parameterless constraint handling strategy	[167]
Equality (PBE)	A random correction operator	[171]
Equality and inequality	An adaptive mechanism	[184]
Equality and inequality	A two-step based constraint handling strategy where the first step involves determining the decision variable vectors lying within user-defined bounds and the second step rewriting the F_T.	[200]
Equality (PBE)	An equality handling method which devises that the difference between total generating power and demand should be evenly shared among units except the one approaching its generating limit.	[217]
Equality and inequality	By following the rule: "a viable particle is preferred to an unviable one".	[223]
Equality and inequality	A heuristic handling mechanism (operator) to modify infeasible solutions	[224]

H. VARIATIONS IN POSITION FORMULA

Till now, review of PSO algorithms involving variations in various components of velocity update formula has been presented. Many researchers suggested amendments in PSO position formula to enhance the algorithm performance.

In order to attain better solution quality, [217] suggested four modified versions of PSO which explored the vicinity of particle's best position (not the current position) found so far while solving the ED problems with VPL effects. Traditional PSO ensures optimal solution by searching a new position around the current position. Based on the observation that a particle considers *pbest* (the best solution a particle found so far) as the experience acquired by it in past time, the position updating formula of a new PSO called personal best-oriented PSO (PPSO) may be expressed as

$$x_{id}^{t+1} = v_{id}^{t+1} + pbest_{id} \quad (87)$$

The position formulas of three other variants of PSO derived by combining the newly developed PPSO position equation and the original PSO position equation are summarized in Table 4.

In addition, a straightforward equality constraint treatment method is also proposed in the paper. The proposed algorithms show their supremacy over other evolutionary optimization techniques when applied to two test cases possessing 13 and 40 generating units.

Rather than using the (unconstrained) fitness function obtained through penalty factor approach to guide search direction, [218] proposed that the feasibility of particles can

TABLE 4. PSO variants and their corresponding formulas.

Position Formula	PSO Variant
$x_{id}^{t+1} = v_{id}^{t+1} + 0.5 \times \left(pbest_{id} + x_{id}^{t} \right)$	Mean PPSO (MPPSO)
$x_{id}^{t+1} = v_{id}^{t+1} + r.pbest_{id} + (1-r).x_{id}^{t}$	Adaptive PPSO (APPSO)
$x_{id}^{t+1} = \begin{cases} x_a, & \text{if } f(x_a) \le f(x_b) \\ x_b, & \text{if } f(x_b) \le f(x_a) \end{cases}$	Decisive PPSO (DPPSO)
$x_a = v_{id}^{t+1} + x_{id}^{t}$	
$x_b = v_{id}^{t+1} + pbest_{id}$	

be checked through some constraints such as generator operation constraints, RRL, POZ, etc. Usually during the process of renewing the memories (*pbest* and *gbest*), all the particles only keep track of feasible solution leaving infeasible particles to have no role in guiding a particle to fly in the next iteration. Superior exploration characteristics can be achieved by declaring all initial particles as feasible particles after adjusting constraints not fulfilling the constraints in form of equalities and inequalities. The particles traverse the searching space while keeping their randomly generated initial power within the specified power limits. A particle which loses global or local search capability is called as an "inactivity" one. The velocity of such a particle approaches zero near position *gbest*. This happens only when the generated power exceeds the margin boundary and therefore some constraints are violated. The inactivity particles are made capable of possessing optimal global searching capacity by modifying them with their current optimal value during each iteration on the basis of the difference between the fitness values of the particle *pbest* and *gbest*, ΔF, calculated by

$$\Delta F_i = \frac{\left(F_i - F_g\right)}{\min\left\{\left|F_i\right|, \left|F_g\right|\right\}} \tag{88}$$

where F_i and F_g represent the fitness values associated with the particle *pbest* and *gbest* respectively. For ΔF_i less than predetermined threshold value, an inactivity particle should adjust itself using its current optimal value at each iteration. Once the inactivity particle is modified using PSO's cognitive feature, then the modified position is set according to (89).

$$x_{id}^{t+1} = a \times r() + gbest_{gd}, \quad a = 0.5; \tag{89}$$

When assessed on a power system possessing 6 thermal units, the proposed algorithm shows better calculation precision than that of other optimization techniques.

A new PSO named moderate random search PSO (MRPSO) proposed in [219] ensured improved exploration without affecting exploitation by updating the particle's position equation only while solving the practical ED problem with VPL effects and RRL constraints. There was no need of updating the velocity of the particle. MRS strategy incorporated with PSO only uses a position update equation given by [220]

$$x_{id}^{t+1} = p_d + \alpha\gamma\left(mbest_{id} - x_{id}^{t}\right) \tag{90}$$

where

$$p_d = r_0 pbest_{id} + (1 - r_0)\, gbest \tag{91}$$

$$mbest = \sum_{i=1}^{S} \frac{pbest_{id}}{S} \tag{92}$$

Here S denotes the population size; p_d attractor controls the main moving direction of particles; r_0 represents the uniformly distributed random variable; *mbest* designated as the mean best position refers to the step size for the advancement of particles and enhances the diversity and the exploration ability of particle; $\gamma = (r_1 - r_2)/r_3$ represents the random property of the MRPSO; α like ω controls the convergence rate of MRPSO. In addition, weight improved PSO (WIPSO) adopting TVAC and a new (modified) TVIW was also proposed to ensure better global solution. A new (modified) TVIW is defined as

$$\omega_{new} = \omega_{\min} + \left(\omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter\right) \times r_3() \tag{93}$$

MRPSO shows better convergence characteristics as compared to WIPSO and constriction factor based classical PSO (CPSO). In another paper Singh and Kumar [221], employed the same MRPSO algorithm for the resolution of a multiobjective combined economic emission dispatch (CEED) problem without VPL effects. When tested on a 6 generating unit system, MRPSO shows promising performance than that of WIPSO and CPSO. The concept of MRPSO was also utilized in [222] to work out both convex and nonconvex ELD problems (without the transmission losses) having 6 and 10 unit systems. MRPSO shows better convergence characteristics than that of standard PSO, and PSO with TVAC and natural exponent inertia weight (NEIW).

In [223], various modifications were suggested in standard PSO to realize a fast constrained PSO (fast-CPSO) algorithm which was then used for solving smooth and nonsmooth ED problems. In the proposed fast-CPSO, firstly, each particle's position is updated randomly using a Gaussian distribution with mean calculated by $(pbest + gbest)/2$ to bias the particle to exploit its personal best positions and standard deviation computed by

$$par_i = N\left(\frac{pbest_{id} + gbest}{2}, \left|pbest_{id} - gbest\right|\right) \tag{94}$$

Secondly, constraints are handled using a very simple scheme that follows the rule: "a viable particle is preferred to an unviable one". Thirdly, in order to avoid from the problem of premature convergence, a concept of bi-population (where the entire population is portioned into only two static and independently-evolved subpopulations) is incorporated into the fast-CPSO. The two subpopulations do not share any information between them. Exploring the search space through two swarms independently enhances the chances for the particles not to get trapped in local optima. Fourthly, to surmount the problem of potential stagnation (arises on scrutinizing the vicinity of the global optimum), a shake mechanism is brought in. When tested on five power systems involving cost functions with convex and nonconvex characteristics, fast-CPSO shows promising results than that of other metaheuristic techniques.

A control parameter-free improved bare-bones PSO (BBPSO) with a local searcher called directionally chaotic search (DCS) was suggested in [224] to tackle the nonconvex dynamic ED problem with VPL effects. In the hybrid algorithm, the basic level search is carried out through the improved BBPSO which may direct the particles to advance to optimal regions, while DCS acts as a fine-tuner to bring to light optimal solution. Unlike the traditional PSO, BBPSO does not employ the particle velocity. Rather it uses a Gaussian sampling, a function of *pbest* and *gbest*, to update the particles' positions in a random way [225]:

$$x_{id}^{t+1} = G\left(\frac{pbest_{id} + gbest_{gd}}{2}, \left|pbest_{id} - gbest_{gd}\right|\right) \quad (95)$$

An alternative of BBPSO designated as BBExp [225] is expressed as

$$x_{id}^{t+1} = \begin{cases} G\left(\frac{pbest_{id}+gbest_{gd}}{2}, \left|pbest_{id} - gbest_{gd}\right|\right), & U < 0.5 \\ pbest_{id}, & \text{otherwise} \end{cases} \quad (96)$$

It has been observed that using the above formula ensures 50% chance of jth dimension of a particle to change to corresponding *pbest*. Hence BBExp biases toward exploiting its personal best positions. In addition, an adaptive disturbance factor is introduced into the improved BBPSO to further avoid premature convergence by happening the *pbest* of a particle to be close or equal to *gbest*. A new genetic operator are also incorporated into the improved BBPSO to enhance its search capability. Moreover, a heuristic handling mechanism for constraints is introduced to modify infeasible particles.

In [226], an extended version of PSO named E-PSO algorithm was proposed to resolve the ED problem considering the continuous nonlinear cost curves. In E-PSO, rather than applying solely the diversification process (where the particles tend to visit space which has not yet been explored to find the optimal position leaving no space unnoticed around the best position) during the exploration process just like as in case of classical PSO, the concept of intensification process of the particles displacement (where the particles advance toward the search space near the solution area when there is a requirement (not necessarily all the time)) suggested by K. Tchomté *et al*. is also implemented. Combination of both the diversification and intensification processes for the particles during the exploration of search space ensures higher quality solutions. A novel position update formula incorporating both the processes of a particle is then suggested. When tested on a 6 unit generation system, E-PSO shows its effectiveness as compared to the standard PSO.

An improved PSO (IPSO) suggested in [227] while solving the ELD problem with VPL effects utilizes position updating strategies where the particle in the population updates the position according to *pbest* with a large probability in the beginning, and according to *gbest* with a large probability in the later stage of iteration to augment the diversity of population and the convergence speed respectively. The position update formula is expressed by

$$x_{id}^{t+1} = \begin{cases} x_{id}^{t} + 2.r_1().\left(pbest_{id} - x_{id}^{t}\right), & \text{if } r < \gamma \\ x_{id}^{t} + 2.r_2().\left(gbest_{gd} - x_{id}^{t}\right), & \text{else} \end{cases} \quad (97)$$

where γ signifies the decision probability. Moreover, a mutation operator after position updating is incorporated in IPSO to further boom the population diversity and prevent the premature convergence. The position update formula now takes the following form

$$x_{id}^{t+1} = x_{iL} + r() \times (x_{iU} - x_{iL}) \quad (98)$$

where x_{iL} and x_{iU} represent the lower and upper limit of search space respectively. When tested on power systems possessing 13 and 40 generating units, IPSO shows promising results than that of PSO and BBPSO.

I. QUANTUM MECHANICS BASED PSO

Many researchers have incorporated the quantum mechanics theories into the classical PSO algorithm in order to improve its exploration and exploitation characteristics. In this regard, nearly a decade ago, *Sun et al*. proposed quantum behaved versions of PSO [228], [229] utilizing the pertinent features of both PSO and Schrödinger equation and potential field distribution based quantum mechanics. From onwards, many researchers utilized the idea of quantum mechanics based PSO for the resolution of constrained ELD problem.

Based on potential field distribution i.e., the harmonic oscillator potential well (HQPSO), [230] suggested a quantum-inspired PSO called QPSO to solve an ED problem possessing 13 generating units with nonconvex fuel cost function taking into consideration the VPL effects. Unlike PSO where the state of each of the particles is associated deterministically with its position vector x and velocity vector v which assists in determining the trajectory of the particle, in QPSO, an appropriate time-dependent Schrödinger equation is employed to determine the state of a particle probabilistically. In other words, rather than following a determined trajectory by a particle as in the case of Newtonian mechanics, in quantum mechanics all particles move under quantum-mechanical rules. Accomplishing this enhances the dynamicity of a particle, thus resulting in better convergence characteristics. Application of attractive potential field eventually assists in pulling all particles to the location defined by local attractors. QPSO shows promising performance than that of PSO and other methods.

In [231], inspired from the theory of both quantum mechanics and PSO, a modified quantum-behaved PSO (QPSO) method was proposed to resolve the ED problem neglecting the VPL effects. Classical PSO algorithm may not guarantee to be global convergent. Trajectory analysis reveals that the convergence of PSO algorithm may be ensured if each particle converges to its local attractor ρ_{id}^t defined at the coordinates as [232]:

$$\rho_{id}^t = \varphi_d^t \times pbest_{id}^t + \left(1 - \varphi_d^t\right) \times gbest_d^t \tag{99}$$

where $\varphi_d^t = c_1 \times r_1/(c_1 \times r_1 + c_2 \times r_2)$. For $c_1 = c_2$, φ_d^t reduces to a uniformly distributed random number. In addition, population diversity is enhanced through the integration of differential mutation (DM) operator from DE algorithm with QPSO, thus ameliorating the global quality solutions of the algorithm. The resulting QPSO-DM algorithm demonstrates its feasibility when compared with QPSO, PSO, GA, and DE while solving the power systems possessing 6, 15, and 40 thermal units.

In [233], another version of the quantum-behaved PSO named QPSO integrating the PSO algorithm and quantum computing theory was proposed for unfolding the nonconvex ELD problem, however, considering VPL effects. The superposition characteristic for making a single particle present several certain probability states (superposition of many states) to potentially increase population diversity, and the probability representation of quantum methodology for making particle state be presented according to a certain probability, are combined into PSO algorithm. For the sake of realizing the update operation of particles, the quantum rotation gates are used. A particle is coded by qubit for QPSO. Accomplishment of the superposition characteristic and probability representation of quantum methodology into PSO helps QPSO to acquire satisfactory solution. Two power systems bearing 3 and 13 generating units are solved through QPSO to validate its effectiveness.

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In [235], another kind of hybrid quantum mechanics inspired PSO named HQPSO was reported to solve a nonlinear constrained ELD optimization problem. However, this time VPL effects are taken into consideration. In HQPSO, the positions and velocities of the particles are redefined in a more diverse manner, thus ensuring the exploration of more search space. Actually, a multi-population-based scheme is introduced where the particles are refined within multiple populations to avoid the particles from trapping in local optima. In the scheme, the total fixed number of generations are partitioned into several sub-generations as well, thus imposing no extra computational burden on HQPSO. Another socio-cognitive component is brought in the velocity update formula in order to incorporate the multi-population scheme. Correspondingly, the local attractor then takes the form:

$$\rho_{id}^t = \varphi_{1d}^t.pbest_{id}^t + \varphi_{2d}^t.ibest_d^t + \varphi_{3d}^t.gbest \tag{100}$$

where $\varphi_{id}^t = c_i r_i/(c_1 r_1 + c_2 r_2 + c_3 r_3)$, $i = 1, 2, 3$; $\sum_{i=1}^{3} c_i \leq 5$ such that $c_1 > c_2 > c_3$. HQPSO shows improved convergence characteristics when applied to work out four test cases containing 6, 10, 13 and 40 thermal generating units.

Reference [236] suggested a new quantum mechanics based PSO called quantum PSO (QPSO) for the solution of the ELD problems possessing 13 and 40 generating units with VPL effects. Instead of representing the particle by its velocity vector v_i and position vector x_i (as they cannot determined simultaneously according to uncertainty principle), in QPSO, a particle is represented by a wave function $\Psi(x, t)$ and moves according to

$$x_i^{t+1} = \begin{cases} p + \beta.\left|Mbest_i - x_i^t\right|.\ln(1/u), & \text{if } k \geq 0.5 \\ p - \beta.\left|Mbest_i - x_i^t\right|.\ln(1/u), & \text{if } k \leq 0.5 \end{cases} \tag{101}$$

where

$$p = (c_1.pbest_{id} + c_2.gbest_{id})/(c_1 + c_2) \tag{102}$$

$$Mbest_i = \frac{1}{N}\sum_{i=1}^{N} pbest_i \tag{103}$$

Here *Mbest* designates the mean best position; c_1, c_2, u, and k are the uniformly distributed random numbers in the range [0, 1]; β is called the contraction-expansion (CE) coefficient and assists in controlling the convergence speed. QPSO ensures stronger search capability with fewer parameters. QPSO outperforms the other metaheuristic methods when applied to figure out ELD problems. In [237], the enhanced exploitation and exploitation characteristics have been achieved even with fewer parameters (one control parameter) in an extended version of QPSO called species-based QPSO (SQPSO) when assessed to tackle the ELD problems with VPL effects, POZ, and RRL. It is a well-known fact that recognizing the best-fit particle as a leader of subpopulation tremendously influences the *lbest* type of PSO operation. This is what almost the same idea in the form of "speciation concept" presented in [238] is adopted in QPSO to determine the best particle and its neighborhood. Simulation results reveal that convergence characteristics of SQPSO improves tremendously as compared to QPSO when tried to solve various ELD problems. Reference [239] utilized exactly the same idea of QPSO [236] for the solution of an ELD problem consisting of 3 generating units without the network transmission losses and VPL effects.

In all the above mentioned references dealing the quantum mechanics based PSOs, the solved ED problems do not consider multiple fuel options although they have or not considered the VPL effects. In [240], an improved but modified version of QPSO named SQPSO combining QPSO with a selective probability operator (involved during the update mechanism while calculating the local attractor) was proposed for the solution of ED problems considering both the MF options and VPL effects. In SQPSO, the position of a particle is updated using the information of *gbest* and the whole swarm's *pbest*. The newly introduced selective probability operator balances the global and local searching abilities and enhances the diversity of QPSO through the use of recombination operator to maintain the best solution and by exchanging information among individuals in the whole swarm. SQPSO exhibits better convergence characteristics than that of QPSO, PSO and DE.

In order to enhance the global search capability, [241] suggested a Q-learning quantum-behaved PSO (QPSO) algorithm for the resolution of the ELD problems considering the transmission losses. Valve point effects are neglected. Through the enhanced Q-learning method, an agent earns accumulatively without a discount. Generation of a set of n new particles on the basis of income from each particle is accomplished through the Boltzmann distribution. When demonstrated on three test systems containing 6, 15 and 40 thermal units, QPSO shows promising results as compared to other metaheuristic techniques.

Reference [242] tackled well the relatively complex ELD problem bearing cubic cost function, however, neglecting the VPL effects through a quantum computing inspirited PSO (QPSO) approach. Transmission losses are taken into consideration. QPSO incorporates the well-established quantum concepts such as quantum bit (qubit) denoting the particle and quantum rotation gate into PSO to make it more effective. In addition, concept of self-adaptive probability selection is also implemented. To augment population diversity, chaotic sequences based mutation is also introduced. When tried to work out power systems possessing 3 and 5 generating units, QPSO ensures superior quality solution in comparison to GA and PSO.

J. VARIATIONS IN SWARM POPULATION

In [243], a modified PSO (MPSO) was proposed to handle the premature convergence problem faced by standard PSO while solving ED problem assuming nonconvex cost functions considering both equality and inequality constraints. This is accomplished by controlling the diversity of a small population. Rather than generating all the n particles randomly as in case of PSO, in MPSO, one-third of the n particles are generated randomly and remaining two-third of the n particles are generated by using (104) and (105).

$$X^t_{i+n/3d} = X^t_{id} + r\left(X^t_{\max d} - X^t_{id}\right) \tag{104}$$

$$X^t_{k+n/3d} = X^t_{kd} - r\left(X^t_{kd} - X^t_{\min d}\right) \tag{105}$$

where $d \in 1, 2, \ldots, m$ represents the dimension of the particle; $i \in 1, 2, \ldots, n/3$ and $k \in 1, 2, \ldots, n/3$ represent the two-third of n; $X^t_{\min d}$ and $X^t_{\max d}$ represent the minimum and maximum values related to dth particle; r is a random variable. The positions and velocities of one-third originally generated and then two-third newly generated diversified particles (individuals) are updated using the original PSO equations. By efficiently controlling the random numbers linearly in the interval [0, 1] and diversifying the population, exploration and exploitation of the search space are enhanced in MPSO. On comparison, MPSO outperforms PSO and guaranteed convergence PSO (GCPSO).

In [244], a catfish PSO algorithm was introduced to handle the ED problem including VPL effects. In catfish PSO, each particle among the randomly initialized swarm in search space is updated on the basis of *pbest* and *gbest*. As the original particles get stagnated and cause the premature convergence problem, 10% of them bearing worst fitness values are replaced by catfish particles. For the numerical results, population size is set to 40 whereas acceleration coefficients are given the value of 2. When employed on three different test systems containing 3, 13, and 40 generating units, catfish PSO offers better convergence characteristics than that of PSO.

In one of the variants of PSO called local PSO, more precisely Lbest PSO, adjustment of each particle's velocity is made on the basis of *pbest* and the best performance attained so far rather than considering the whole population. The velocity update formula for Lbest PSO is thus expressed by

$$v^{t+1}_{id} = \omega.v^t_{id} + c_1.r_1().(pbest_{id} - x^t_{id}) + c_2.r_2().(lbest - x^t_{id}) \tag{106}$$

Lbest PSO suffers from the problem of premature convergence as it employs only *lbest* information. In [245], the concept of dynamically varying sub-swarms (DVS) [246] was introduced into Lbest PSO to enhance Lbest PSO's performance. When tested on DED problems (with VPL effects) having 5, 10, and 110 units, LPSO_DVS validates its effectiveness.

An improved version of PSO called a dynamic double population PSO (DDPSO) algorithm was proposed in [247] to deal with the ELD problem considering network transmission losses neglecting, however, the VPL effects. In DDPSO, the evolutionary strategy not only learns from the successful experience but also gains valuable information from the previous failure experience to update the velocity and position of the particles. When tested on an IEEE 30 node system possessing 6 units, DDPSO outperforms the PSO.

PSO algorithm with an efficient population utilization strategy (EPUSPSO) was suggested in [248] for dealing with ELD problem considering transmission losses but neglecting the VPL effects. Through EPUS, particles are made effective to locate the optimal point. The solution-sharing strategy suggests that particles are added or eliminated according to the fitness value of global optimal solution. If the fitness value does not update for the two consecutive generations, a particle is added to the population, otherwise, a particle with lower fitness value is discarded. For the sake of resetting all dimensions of individual particles' current positions, search range sharing strategy is also introduced. The proposed method improves its accuracy and the convergence speed in this way. When tested on three different ELD problems having 3, 13, and 40 generating units, EPUSPSO validates its supremacy over PSO.

K. RANDOM DRIFT PSO

In [249], another modified version of PSO named the random drift PSO (RDPSO) approach inspirited from the metal conductors' free electron (placed in an external electric field) model was proposed to solve ED problems without the VPL effects to boost the global exploration capability of the algorithm. In RDPSO, it is assumed that the direction of the movement of the particle toward its local focus resembles to the drift motion of an electron in a metal conductor placed in an external electric field. By free electron model, an electron exhibits not only the drift motion but also the thermal motion which appears to be a random movement while careening towards the location of the minimum potential energy. Achieving minimum potential energy by an electron is equivalent to minimizing problem's evolution function. Incorporating the superposition of the thermal VR_{id}^{t} as well as drift motion VD_{id}^{t} into the particle's velocity equation, i.e., $v_{id}^{t} = VR_{id}^{t} + VD_{id}^{t}$ not only reduces the computing cost of the algorithm but also ameliorates the global search ability. When solved various power systems through RDPSO, RDPSO outplays the other metaheuristic techniques and gives less generation cost.

Reference [250] claimed that the performance (efficacy) of RDPSO can be further ameliorated by embodying a crossover operation pursued by a greedy selection process while introducing the personal best position of the particles instead of the mean best position in the velocity update formula. The resulted improved RDPSO (IRDPSO) algorithm dealt efficiently well the highly nonconvex and continuous ELD problems with VPL effects, POZ, MF options, RRL, etc. Laborious work in the form of tuning the algorithm parameters on the basis of the dynamics of the considered optimization problem is enlightened by amalgamating a self-adaption mechanism with IRDPSO (ST-IRDPSO). When tested on five power systems bearing 6, 10, 13, 40, and 140 generating units, ST-IRDPSO and IRDPSO outshine RDPSO with regard to convergence characteristics.

L. MULTI-AGENT BASED PSO

In [251], a novel multi-agent based hybrid PSO algorithm named HMAPSO integrating the PSO algorithm with the deterministic search, the Multi-agent system (MAS), and the bee decision-making process was exercised to resolve the ED problem taking into consideration the VPL effects but neglecting the MF options and POZ. In HMAPSO, the whole search area partitioned into different fragments is traversed by different agents. The agent finds the best solution in its corresponding fragment through modified Nelder–Mead (NM) method and shares the solution with other agents through bee waggle dance. Consensus method borrowed from honey bee swarms then selects the best solution to ensure high-quality solution reliably with the faster convergence characteristics in a reasonably good computation time. When tested on two test cases having 13 and 40 generators respectively, HMAPSO is found more accurate and robust in exploring the global optimum point than its counterparts like GA and PSO.

In order to converge the agents to the global optimal solution quickly and accurately, in [252], also MAS based PSO (MAPSO) was suggested for working out the ELD problem with VPL effects. In MAS, ability of the agents to communicate, exchange information, and interact with other systems in the partitioned population search space eases in attaining goals in the form of locating the optimal point quickly and accurately. When applied to three different ELD problems having 3, 13 and 40 generating units, MAPSO offers better convergence characteristics than that PSO.

M. PSO WITH KALMAN FILTER

Reference [253] applied Kalman-particle filter (KF-PF) to the nonsmooth ELD state estimation problem (with VPL effects and POZ) that had already been optimized through PSO in order to avoid the solution from being trapped in local optima. PSO integrated with KF-PF was given the name PSO-KF-PF in which the best solution attained through PSO is further processed through KF and PF to ensure the most optimal results. KF-PF was found more efficient than KF and PF alone. When demonstrated on a test system possessing 6 and 40 thermal units, the proposed algorithm validates its feasibility and effectiveness.

In [254], an efficient self-adaptive chaos and Kalman filter-based PSO algorithm (SCKF-PSO) was employed to deal with nonconvex ELD problems with VPL effects and POZ. In the proposed algorithm, the deterministic position of the particles as in case of PSO is made estimated using the estimation strategy of Kalman filter, giving more directions to particles to select. The better position among the ones predicted through Kalman filtering algorithm and PSO is chosen for the next iteration. This enhances the population diversity and reduces the number of iterations necessary to attain the better solution without affecting final solution's quality. Meanwhile, self-adaptive chaos sequences based on Tent equation are applied to the global best and worst particles, respectively, to avoid from premature convergence problem. When tested on 3 different ELD problems, SCKF-PSO shows promising results than that of C-PSO, K-PSO, and PSO.

N. COMPREHENSIVE LEARNING PSO

In comprehensive learning PSO (CLPSO), particles refurbish their velocities on the basis of the best performance of all individuals. In [255], CLPSO utilized its robust exploration and exploitation capabilities to direct the solution process's random trajectory toward the global optimum region while solving NCED problem with transmission losses and POZ. CLPSO outshines PSO and DE with regard to convergence characteristics when applied to two power systems with 6 and 15 generating units.

Reference [256] made efficient use of the concept of parallel computing to accelerate the convergence speed of comprehensive learning PSO (CLPSO) algorithm applied to deal with computationally intensive constrained ED problem considering VPL effects. Two different parallelism approaches, namely a coarse-grained and a fine-grained parallelism implemented through Graphics Processing Units (GPUs) evaluate, in parallel, the fitness value associated with each particle to intensify the computational power of CLPSO. CLPSO with GPU consumes extremely less time in resolving the large-scale ED problems having 9, 18, 36, and 72 units.

O. OTHER MISCELLANEOUS PSOs

Many researchers improve the performance of standard PSO by incorporating some slight changes in the basic structure of PSO. In [257], in order to avoid individuals from searching areas outside the problem's constraints region and to avoid from premature convergence, a modified version of PSO [258] was presented to tackle the constrained nonconvex ED problem with POZ. However, VPL effects are not considered. The proposed modified PSO, essentially a parallel population-based search method, updates both the original velocity and position of particles by restricting themselves within the search space. When tested on a 15 unit system with 4 units having POZ, the modified PSO outperforms both the conventional methods and the Hopfield neural network (HNN) method.

In [259], a novel adaptable optimization algorithm called modified PSO (MPSO) incorporating various modified operators, such as neighborhood magnifying operator and mutation operator into classical PSO to ensure optimal global search was suggested for working out the complicated nonconvex ED problems considering the VPL effects. The global convergence property (independent of the initialization) of MPSO is proved using the stochastic analysis theorem while presenting a sufficient condition for convergence. When applied to various test cases already solved through other optimization techniques like evolutionary programming (EP) and quadratic programming (QP), MPSO shows the better results than that of them.

In [260], another modified PSO (MPSO) was proposed for solving convex and nonconvex ED problems without considering the VPL effects. In the proposed MPSO, a particle updates its flying velocity and position not only according to its own and the best one as is the case in basic PSO but also according to other particles in the group. Rendering this enhanced study behavior not only enhances the chances of finding the global optimum efficiently but also decreases the impact of the initial position of the particles. Simulation results ensure the efficiency, feasibility and effectiveness of MPSO when compared with the conventional numerical method, evolutionary programming (EP) approach and the classical PSO approach.

In [261], based on virus theory of evolution, an improved discrete PSO algorithm called virus-evolutionary PSO (VEPSO) algorithm was recommended for the resolution of ELD problem with VPL effects. VEPSO's two swarms, namely a particle swarm and a virus swarm represent a set of candidate solutions and a substring set of the particle swarm, respectively. VEPSO utilizes two virus infection operators for infection and transduction of a virus. In the co-evolutionary process, partial genetic information in the particle swarm is propagated by a virus through these operators which improve the horizontal search ability of PSO algorithm. VEPSO validates its effectiveness and feasibility during the application to a test system bearing 13 thermal units.

In [262], a novel θ-PSO algorithm was suggested to tackle the constrained nonconvex ELD problem considering VPL effects, transmission losses, RRL, and POZ. θ-PSO algorithm works on the basis of the 'phase angle vector', generates a solution of high quality in less computation time, and achieves stable convergence quickly. Replacing the increment of velocity by the increment of phase angle and deciding the position by the mapping of the phase angle, θ-PSO is described in vector notation by

$$\Delta\theta_{id}^{t+1} = \omega.\Delta\theta_{id}^{t} + c_1.r_1.\left(\theta_{best,id}^{t} - \theta_{id}^{t}\right) + c_2.r_2.\left(\theta_{gbest,gd}^{t} - \theta_{id}^{t}\right) \tag{107}$$

$$\theta_{id}^{t+1} = \theta_{id}^{t} + \Delta\theta_{id}^{t+1}, \quad \text{with } \theta_{id}^{t}, \Delta\theta_{id}^{t} \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right] \tag{108}$$

where θ_{id}^{t} and $\Delta\theta_{id}^{t}$ represent the phase angle and the increment in phase angle of particle i in iteration t. In θ-PSO, searching process reduces to a small region in θ-phase thus making the search of the allowable region more precisely. During simulations, the inertial weight factor and the acceleration coefficients are kept fixed. When demonstrated on power systems possessing 6, 13, 15, and 40 thermal units, θ-PSO surpasses the other metaheuristic techniques with regard to computational efficiency and solution quality.

In [263], orthogonal vectors (OVs) generated by the d particles having possible solution in the d-dimensional search space based a novel stochastic orthogonal PSO (OPSO) algorithm was proposed for the solution of ED problem considering POZ but neglecting the VPL effects. The particles are guided to rush in one direction toward global minimum through the OVs which are generated and updated in each iteration. All this is accomplished by introducing a new topology called "Orthogonal Particle Formation (OPF)" inside the swarm. When tested on a 15 generating units system, OPSO shows high quality solution, robustness, and convergence as compared to other optimization methods.

Reference [264] recommended the Q-learning-based PSO (QSO) algorithm borrowing the salient feature of both PSO and Q-learning for tackling the constrained NCED problem with VPL effects. Q-learning approach is one the reinforcement learning methods which stores the Q-values in a lookup table. In QSO, each particle mimics the behavior of *gbest* in the swarm. Finally, selection of the (global) best individual is carried out on the basis of its accumulated performance rather than its momentary performance at each iteration. When tested on various systems, QSO displays outstanding performance in comparison to other metaheuristic techniques

In [265], an improved attractive and repulsive PSO (ARPSO) was suggested for the solution NCED problem with VPL effects. In ARPSO, both the exploration and exploitation characteristics of a particle are enhanced through observing a diversity factor whose value changes from 0 to 1. At each iteration, distance of each particle to the *gbest* changes, so does the diversity. Particles lying close to *pbest* bear small values of diversity. ARPSO is further improved (PARPSO) by incorporating a penalty factor into it. Introduction of penalty factor enhances the capability of global search by making each particle repulsive from *gworst*. When demonstrated on a power system possessing 40-units, PARPSO ensures optimum fuel cost as compare to basic PSO (BPSO), added penalty PSO (PPSO), and attractive and repulsive PSO (ARPSO).

V. ALREADY-CONDUCTED PSO BASED SURVEYS

A very brief survey and summary about the application of the state-of-art PSO algorithm to resolve the complex ED problem was presented in [266]. Advantages and disadvantages of PSO are also highlighted. The paper may serve as a starting point for those who want to gain an insight into PSO and its application to ED problems. Similarly, a survey of PSO applied to various electric power optimization problems such as (real power) ED, reactive power dispatch (QPD), optimal power flow (OPF), unit commitment (UC), transmission and generation planning, maintenance scheduling, state estimation, model identification, load forecasting, control, and others was also presented in [267] till 2007. As a number of power system applications are considered for the survey purpose, applicability of PSO to these applications is reviewed limitedly. The survey also covers both recent advancements and further research tendencies of the area in detail. Constraint handling methods based on preference of feasible solutions over infeasible ones, penalty functions, and multiobjective optimization concepts are comprehensibly highlighted.

In [268], a survey of PSO applied to various applications in electric power systems including ED, QPD and power losses reduction, OPF, power system controller design, neural network training, and other electric power system areas such asthe process of feeder reconfiguration, UC problem, identification of the autoregressive moving with exogenous variable (ARMAX), etc. was reported. However, the paper gives very limited notions about the solution of the practical ED problems through PSO and its modified forms.

A comprehensive literature review of PSO algorithm till 2009 applied to ED problem had also been presented in [269]. The ED problem has been constructed well considering all the operational and system constraints. However, the review includes both all-thermal and hydrothermal cases. Surely a number of modifications in PSO came into existence afterwards that needed to be addressed.

Another ‘limited’ review about PSO tackling the ED problem till the start of year 2013 has also been proposed in [270] to felicitate the engineers. This shows the significance and popularity of PSO. An analysis of various modified and hybrid forms of PSO ranging from inertia weight PSO (IWPSO) to crazy particle PSO (CRPSO) applied to solve the NCED problem was presented in [271]. A survey on PSO and its variants used for the solution of NCED problems was also conducted by [272]. The survey, however, covers around about only a dozen of papers. In [273], an attempt had also been made to summarize the application of PSO to the constrained complex nonlinear ED, combined emission ED (CEED), and emission controlled economic dispatch (ECED) resulted from the identification of emission dispatch (EMD) problems. A ‘limited’ summary of the application of PSO to the single-objective dispatch problems was also presented in [274]. The summary points out some very few variations in PSO to improve its performance. The survey, however, cannot be called a complete and comprehensive survey. In the paper, the constraints associated with the ED problem are well-described.

VI. CONCLUSION

Metaheuristic optimization techniques and their variants may solve the convex and nonconvex ELD problems efficiently as these methods do not need to have the information about the derivative of the cost function irrespective of the fact that they may not guarantee the global optimal solution. The PSO method among the metaheuristic techniques has been extensively used, as the reviews and number of citations suggest, to figure out the dispatch problems. However, in order to deal with constrained convex and nonconvex ELD problems, various modifications in the basic structure of PSO are suggested in the literature. This part of the paper provides a detailed and comprehensive review of PSO and its modified versions applied solely to work out the practical ELD problems. A unique survey on each of the modifications made to PSO is presented in a separate subsection. The comprehensive review has been presented in such a way that that a reader may easily grasp the concept of PSO (effects of the variations of coefficients involved in the velocity and position equations on the performance). A more elaborative and detailed survey has been presented as compared to those already mentioned in the paper. The paper may act a good initial point for those who want to solve dispatch problems using PSO. Owing to the availability of a large number of papers about PSO and its modified versions, a review of hybrid forms of PSO (hybridization of PSO with advanced calculus-based and other metaheuristic techniques) have not been considered as it may lengthen the paper. A thorough-survey of the hybrid forms of PSO to handle-well the ED problems is going to be presented in part II of the paper.

Future work may involve the application of all the suggested improved versions of PSO to other complex, constrained, and multiobjective power system problems. The problems include CEED, ECED, the dispatch problem involving (distributed) renewable energy resources, power system controller design, maintenance scheduling, model identification, load forecasting, etc.

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