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Valve Point Loading Effect in Strained Economic Load Dispatch Using Novel Particle Swarm Optimization Algorithm

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ABSTRACT— Power systems with valve point discontinuities and economic dispatch is resolved using a simple and efficient solution that is based on the particle swarm optimization methodology. It is well known that evolutionary approaches, including GA and PSO, work more effectively for non-convex optimization issues than more established gradient-based methods.

The suggested method's performance has been compared to RGA data for the purpose of validation. On a test system with three generating units, the algorithm's efficacy has been evaluated.

I. INTRODUCTION

The primary purposes of a contemporary system of energy management are economic dispatch. The goal is to lessen the overall price of fuel whilst "meeting" given limitations. It is expressed as an optimization problem. Traditionally, the generators' input-output qualities, referred to as approximation cost functions by functions that are individually quadratic or quadratic below the assumption that generators' Curves of incremental costs that generators' incremental cost curves develop consistently [1]. This premise is false, however, due to the higher order non-linearities and discontinuities of cost functions are a result of the effects of while using fossil fuels to power a unit [2]. It is more realistic to write the cost function instead of a single quadratic function, as a piecewise non-linear function. It is difficult to locate the global minima for the ELD valve point impacts an issue since it is described as an unpolished optimization complicated and non-convex issue feature. Thus, traditional gradient-based optimization techniques are ineffective in these situations and lead to erroneous dispatches. Dynamic programming is a traditional method for using valve point loading to solve the ELD problem. [3] where the best dispatch is chosen after listing every potential option. The issue of dimensionality and excessive examination at each level plagues this approach.

To handle non-convex optimization problems satisfactorily, methods that avoid cost function approximation, while yet requiring minimal computing effort are needed. It is necessary to use a solution approach that does a direct search rather than directly using the incremental cost function to solve the problem. These issues can be solved using dynamic programming techniques. [3]

Using the natural genetics concepts of the laws of evolution and the principle of the fittest, genetic algorithms are strong search engines. They mix assessment of the solution randomized organized information exchange between several strategies to achieve perfection. As no restrictions are placed on the search space throughout the evaluation process, GAs are reliable instruments. These algorithms' capacity to use past data from earlier solutions to boost the performance of subsequent ones is what motivates them. GAs do not have a single point guess restriction because they keep a population of solutions during evaluation [4]. A population-based stochastic search is the PSO and optimization technique that is parallelisable and flexible. Contrary to conventional methods, PSO can readily handle objective functions that are not differentiable [5]. Compared to GA, this approach is less prone to become stuck in local minima. utilizing Each particle that makes up a population signifies a potential remedy for optimization issue, a PSO searches for the best possible solution. Particles move through a multi-dimensional search space by altering their trajectory in the direction of their own best past performance and that of their closest neighbours [6]. The PSO method can produce excellent solutions with stable convergence properties. It is becoming more and more popular as a solution to several power system issues.

The ELD Using a PSO-based approach, the non-smooth cost function issue is resolved in this research.

II. PARTICLE SWARM OPTIMIZATION

The origins of a PSO, a multi-agent search technique, can be found in the haphazard a flock of birds moving in search of food. It is a basic and efficient optimization method that scatters random elements across the problem space. The way that these particles, which are often referred to as swarms, communicate with one another is by building an array based on their relative positions. The fragments modify their locations by evaluating comparative convergence vs the top of the globe. Another name for the updating mode is the particle velocity. Position and velocity are updated heuristically using random generation [7]. Here, the vicinity of a particle determines the effectiveness of global best. The fact that there is such a large neighbourhood typically leads to subpar solutions, hence treating all particles as neighbours does yield decent outcomes. It has been discovered that using a smaller, more tightly knit neighbourhood is more efficient [8]. One approach to evolutionary computing is particle swarm optimization (PSO). [8,9]. It was created by modeling a streamlined social structure, and it successfully dealt with problems involving linear and nonlinear optimization that is ongoing. It is PSO method can produce top-notch solutions faster and with more stability in convergence compared to other stochastic techniques. The as of PSO identified several power system optimization problems and has found a suitable, perfect answer [10].

III.THE EFFECTS OF VALVE POINT LOADING

Due to goal function is discontinuous, non-convex, and generates ripples in heat-rate curves due to the valve-point effects has several minima. For the purpose of accurately describing the impacts of the valve point loading in this research [10,11], the cost function for fuel input and output power for the i^{th}unit is written as i^{th}, where i is the fuel input-power output cost function with rectified sinusoidal function.

IV ELD SOLUTION BASED ON PSO AND USING VALVE POINT LOADING

The PSO method is used in this research to provide a rapid fix for a valve point loading problem with economic dispatch. Consider the standard economic dispatch problem is solved by running a power system with N units, each loaded toP_i, to fullfil a total load demand P_D, including a total of transmission losses P_L . Let F_i the fuel input-power output cost function of each unit be represented by. The equipment must be loaded to reduce the overall cost of gasoline F_T for the N number of producing units, subject to the power balance and unit higher and lower an operating limitations.:

$$\sum_{1=1}^{N} F_i(P_i) \qquad (1)$$

Subject to:

$$\sum_{i=1}^{N} P_i - (P_D + P_L) = 0$$

$$P_i^{min} \leq P^i \leq P_i^{max} \qquad \text{i = 1,2,…,N (2)}$$

For given actual load P_D at all buses, the system loss P_L is a function of active power generation at each generating unit.

Two methods are typically used to calculate system losses. The first is the employment penalty elements, as well as the second is the application of B-coefficients or coefficients for the constant loss formula [12]. The latter is employed in this study and is frequently used by power utilities. This approach expresses transmission losses as a quadratic generational function:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i\ B_{ij}\ P_i \qquad (3)$$

For producing units without valve-point loadings, the fuel cost function is given by

$$F(P_i) = a_i p_i^2 + b_i p_i + c_i \qquad (4)$$

According to [4], the fuel cost function considers producing units' valve-point loadings.

$$F(P_i)=a_iP_i^2 + b_iP_i + c_i + |e_i \times \sin (f_i \times (P_{imin} - P_i))| \qquad (5)$$

Where

$a_{i,}b_i$ $and\ c_i\ fuel\ cost\ coefficients\ are\ the\ fuel\ cost\ i^{th}$ unit, and c_i and f_i

are the i^{th} unit's gasoline cost indices incorporating valve-point effects i^{th}.

The expense of fuel varies more in producing units with multiple valve steam turbines. The heat-rate curves exhibit ripples as a result of the valve-point effects.

Let x and v signify a particle's location and speed in a search space, respectively, A particle's best previous location is noted and denoted by. P^{best}The index of the top particle out of every particle in the group is denoted by the symbol. (g^{best}) [Each particle is aware of both the best value in the group and the best value thus far (P^{best} and g^{best})[13]. Using its present velocity, the distance from P and g best, and the distance from the particle attempts to alter its location in P. Finally, the following formulas can be used to determine each particle's adjusted velocity and position: v_i^{max}

$$v_i^{k+1} = w^* v_i^{k+1} + c_1^* rand_1^*(pbest_i - x_i) + c_2^* rand_2^*(gbest_i - x_i) \qquad (6)$$

$$x_i^{k+1} = x_i + v_i^{k+1}$$

Were

v_i^k: $velocity\ of\ particle\ ^i\ and\ at\ itreation\ ^k$

w : inertia weight parameter

$c_1, c_2 : learing\ factors$

$rand_1, rand_2$: random number between 0 and 1

x_i^k: $position\ of\ particle\ ^i at\ itreation\ ^k$

The inertia weight has a crucial impact in how quickly the PSO algorithm converges. The influence of earlier velocities on the current velocity is controlled by the inertia weight. As a result, this value controls how the particle balances its ability to explore both locally and globally. Good global search is aided by a high inertia weight, but local exploration is made easier by a lower value [14]. As a result, it is standard practice to utilize a higher start investigation and eventually, the weight of inertia lower it while searching progresses in subsequent cycles. Typically, the inertia weight is calculated using the following equation: j^{th}

$$w = w_{max} - ((w_{max} - w_{min})^{*} iter/iter_{max})$$
(8)

Were

$iter$: actual iteration count

$iter_{max}$: most iterations possible

The value of w is typically changed between 0.9 and 0.4. The particle is pulled towards the local best location by constant c_1, whereas the global best position is drawn towards by constant c_2 . These parameters are typically chosen between 0 and 4.

The velocity of Iteration is a procedure that constrained by the highest amount v_i^{max} . Regions between the resolution, or fitness, of the current target and location position are to be searched is determined by the parameter v_i^{max} [15]. This restriction improves local problem space exploration.

Particles may fly past viable solutions if $v_i^{max}$is set too high. Particles may not properly look beyond simple local fixes v_i^{max} is too tiny. In numerous PSO encounters,v_i^{max}

was often set on each variable at 10%–20% of its dynamic range axis. When The PSO methodology has been applied to estimate the optimal generation allocation since the generation cost curves are not smooth. The following actions make up its implementation:

Step (1) The 'dimension' of the issue with ELD is the quantity of online power generators. Between the generators' maximum and minimum operational limitations, the particles are formed at random. The i^{th} particle, for instance, is depicted as follows if there are N units:

$$P_i = (P_{i1} P_{i2} P_{i3} \ldots\ldots P_{iN}) \qquad (9)$$

These initial particles must be workable solutions to the issue that adhere to the operational practical restrictions listed in (2). Step 2: At random generated particle velocities in the range

$$[[-V_j^{max} , V_j^{max}]]$$

The j^{th} generating unit's maximum velocity limit is calculated as follows:

$$V_j^{max} = \frac{P_{j.max} - P_{j.min}}{R} \qquad (10)$$

R is the j^{th} dimension's number of intervals that have been decided upon v_i^{max} was calibrated to be between 10 and 150% of the variable's dynamic range on each axis for each example investigated using the PSO technique. Step 3: Values for each particle's It is necessary to define the evaluation function (fitness function in GA) in order to assess its value. The definition of the assessment process

$$\sum_{i=1}^{N} F_i(P_i) + a\left[\sum_{i=1}^{N} P_i - (P_D + P_L)\right]$$

Here is the punishment parameter; if the power balance condition is not met, the second term penalizes the particle by increasing its cost. When the imperfect cost function caused by valve point consequences are considered, (6) is applied. The initial phrase is derived using the equation (5) for answers where the consequences of the valve point are ignored.

Step (4) These values are established as the particles' initial Pbest values.

Step (5) Gbest, the best value out of all the Pbest values, is found.

Using Eq. (6), new velocities are determined for each particle's dimensions.

Step (7) The position of each particle is updated using Eq. (7).

Step (8) Values for objective functions are determined for modified particle positions [16]. The new value is set to Pbest if it is superior to the existing Pbest.

Step (9) The particle positions indicated by gbest are the best option if the stopping criteria are satisfied. If not, step (3) of the process is repeated.

Result: On a system with three generating units, the PSO algorithm's efficacy for an economical a dispatch method that has the effects of valve point loading is shown [17,18]. In order the outcomes are contrasted with outcomes from the actual coded GA utilising the identical evaluation function and particle techniques in order to assess their performance, solution quality, and convergence effectiveness specification. The software was created on the MATLAB 08.3 platform and evaluated on Pentium 4 personal computers with 1.5 GHz processors and 256 MB of RAM. Although the PSO method's solution quality is greater, it is proven to be sensitive to tuning parameters [19]. Due to the lack of selection and crossover procedures required by this method, PSO also converges more quickly.

A. Results of ELD without the influence of valve points

The best allocation of resources for the three- Unit [1] of the power system was determined using a simple PSO with the power balance and unit operational limitations from (2). The PSO uses the cost function as stated by (3) as its evaluation function. Coefficients of cost and production unit limitations appear in Table I. Coefficients B for assessing losses are listed below [20].

$$[B] = \begin{bmatrix} 0.006760 & 0.000953 & -0.000507 \\ 0.000953 & 0.005210 & 0.000901 \\ -0.000507 & 0.000901 & 0.029400 \end{bmatrix}$$

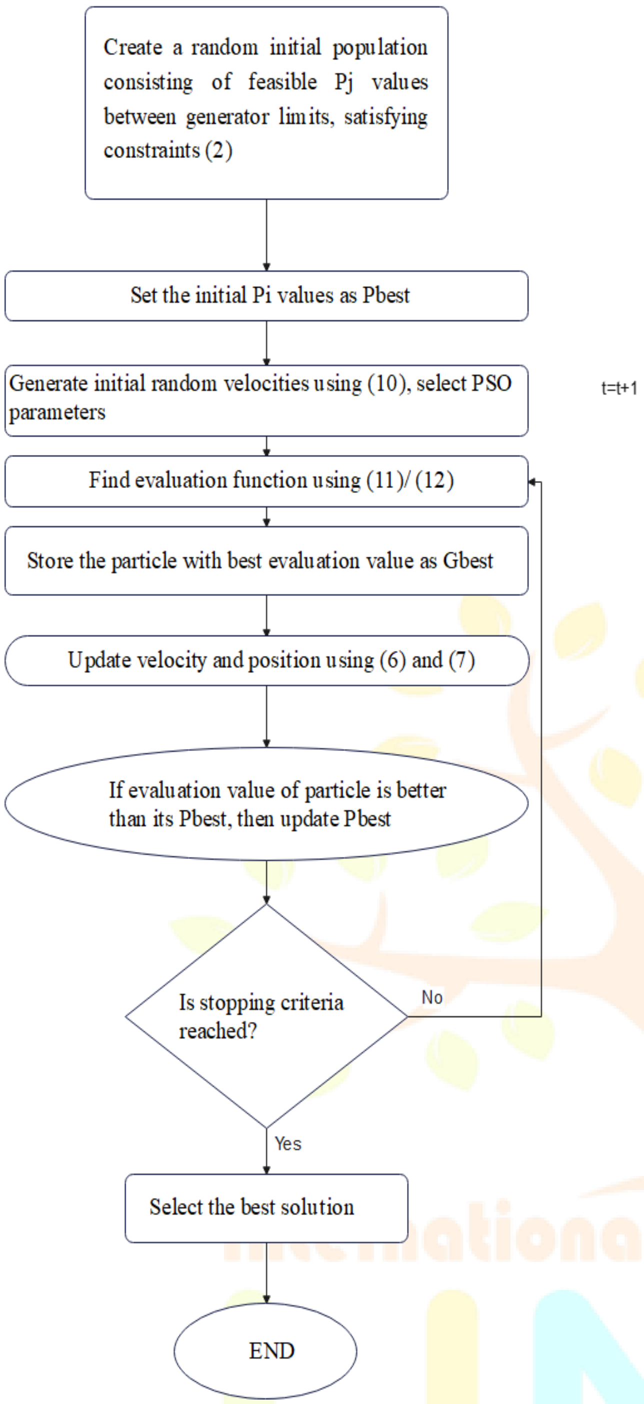

Fig. 1. Flowchart for the ELD proposed PSO algorithm

The steps listed in section IV are used to follow in order to reach the best answer. While PSO method's tuning parameters are mentioned in Table II, the GA parameters are reported in Table III. Results for a system with three generating units operating at three distinct demand levels are compared in Table IV using the traditional lambda iteration approach and actual coded GA [21]. The optimal cost for both the GA and PSO algorithms has been determined as the best outcomes after 100 iterations. It is clear that PSO outperforms GA in terms of locating cost function minima.

B. Results of ELD with VPLE

When a cost factor is not smooth due to valve point effects, the traditional lambda iteration method is ineffective. So, the outcome of the PSO-based strategy is compared to the RGA. The PSO algorithm uses the cost function used as its evaluation function in paragraph (4). The PSO algorithm described in the preceding section is applied in steps 1 through 9 to determine the best price and matching generation allocation [22]. Here, a predetermined as the criterion for comparison, the number of iterations is used GA. Actually, the process of updating Until the decrease in maximal fitness is less than a threshold value for tolerance, the velocity and position are repeated incrementally.

In table V, PSO's efficiency is compared to real coded GA. It is evident that PSO, given the same population size and generations, delivers higher quality solutions than RGA [23]. The effect of population size on PSO solution performance is seen in Table VI. The PSO method is performed for various numbers of iterations for each set until as the population size increases from 20 to 100, convergence occurs [24]. For each set, the best outcomes are noted. With increasing population size, performance progressively increased, but when the population size exceeded 100, the outcomes worsened. Table VI shows the CPU time as well as the ideal cost for the GA and PSO approaches. It is evident that the PSO converges faster than RGA Fig. 2 shows the quick convergence PSO characteristic for ELD with valve point loading.

PSO, like other evolutionary programming-based methods, does not always converge to the same optimal value because of the stochastic nature of the algorithm; nonetheless, it usually always converges to near global solutions.

The identical parameters stated in Table II were used in 50 independent trials, each with a demand level of 700 MW, to show the solution quality and consistency of the used PSO algorithm. In Fig. 3, the best outcomes (least generation cost) from each trial are plotted. The tiny standard deviation of the results obtained can be noted. It is discovered that the ideal cost varies within a narrow range, with an average deviation of around 2% [25].

TABLE I
GENERATORS OPERATIONAL LIMITS AND COST COEFFICIENTS

Variable / Generator	a_i	b_i	c_i	d_i	e_i	P_{imax}	P_{imin}
Unit 1	.00157	7.93	562	300	.032	600	100
Unit 2	.00195	7.86	311	200	.043	400	100
Unit 3	.00483	7.98	79	150	.064	200	50

TABLE II
PSO CHARACTERISTICS

Inertia weight W_{MAX}- W_{MIN}	C_1, C_2	Population size	Generation
0.9-0.4	2,2	100	100

TABLE III

GA PARAMETERS FOR ELD WITHOUT VALVE POINT LOADING

Generation	Population	Crossover Probability	Mutation Probability
100	100	0.9	0.3

TABLE IV

AGENCY ALLOCATION RESULTS WITHOUT VALVE POINT LOADING EFFECT

P_D (MW)	Method	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	PL (MW)	Cost (Rs/hr)
750	Classical	329.6	295.12	142.79	17.56	7451.30
	RGA	367.2	288.66	113.36	19.41	7462.60
	PSO	347.46	322.28	99.01	18	7457.63
850	Classical	377.58	381.29	113.78	22.65	8406.80
	RGA	430.08	321.85	122.06	23.95	8411.62
	PSO	377.58	381.29	113.78	22.65	8414.80
950	Classical	504.12	400	70.97	25.11	93.97.70
	RGA	456.54	380.45	144.35	31.95	9407.00
	PSO	451.2	400	129	30.76	9404.57

TABLE V

PERFORMANCE OF THE PSO IN COMPARISON TO THAT OF THE GA WITH VALVE POINT LOADING

P_D	Method	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	PL (MW)	Cost (Rs/h)
750	PSO	317.97	400.00	50	17.964	7658.61
	RGA	398.79	245.78	125	20.45	7667.50
850	PSO	297.86	380.22	200	28.11	8660.00
	RGA	481.98	245.67	149	26.98	8681.20
960	PSO	600	334.36	50	34.35	9609.30
	RGA	517.65	317.73	147	36.53	9682.00

TABLE VI

THE IMPACT OF POPULATION SIZE ON PSO PERFORMANCE

Demand (MW)	Population Size	Method	Cost (Rs/h)	CPU Time (Sec)
750	20	GA	7465	0.0961
		PSO	7460	0.0632
750	40	GA	7467	0.1061
		PSO	7462	0.0832
750	60	GA	7460	0.112
		PSO	7454	0.0982
750	80	GA	7450	0.117
		PSO	7448	0.101
750	100	GA	7443	0.142
		PSO	7440	0.121

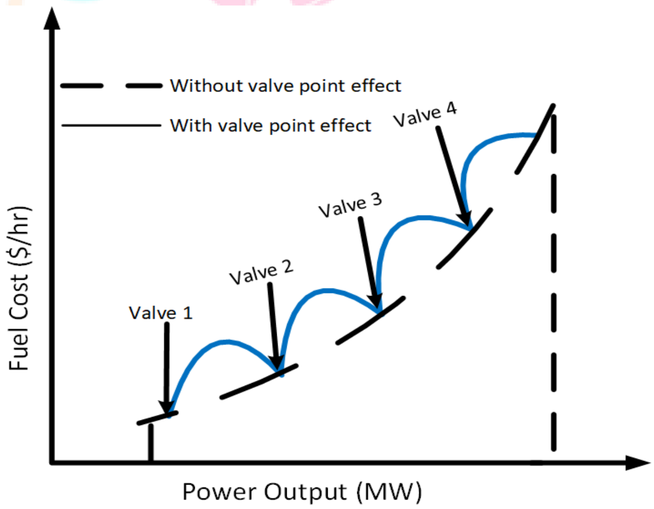

Fig. 2. Valve Point Loading Effect

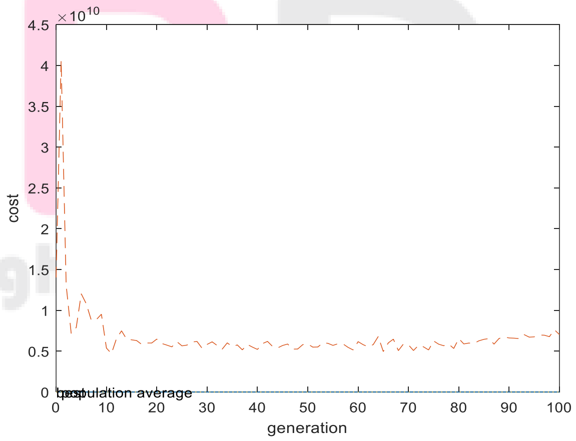

Fig. 3. Valve point loading convergence feature of PSO

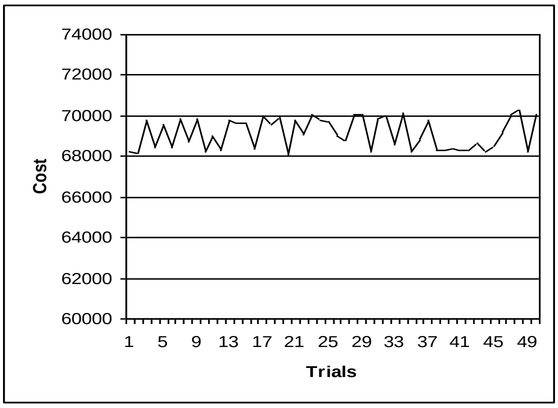

Fig. 4. PSO performance in various tests (Demand PD = 700 MW)

V. CONCLUSION

This study uses a technique based on particle swarm optimization (PSO) is provided to address valve point loading's difficulty with economical dispatch impact. In this instance, the generator cost function is not linear, making task challenging and having many minima. Standard Gradient-based methods are inapplicable non this situation. The stochastic

the use of evolutionary programming PSO and GA, on the other hand, do not necessarily converge to the same minima. However, it is noted that these approaches, because of their simplicity, quickly arrive at solutions that are very close to the global minima. PSO is discovered to deliver good quality solutions in less time than a technique based on RGA. Test findings show that the PSO algorithm can produce results that are nearly universal for all of the studied scenarios, indicating that it Its not excessively dependent on population size and initial population.

The findings acquired by PSO have been demonstrated through the execution of various trials to be relatively Consistent and to exhibit a small standard deviation from the average cost encountered.

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