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NON-CONVEX ECONOMIC LOAD DISPATCH WITH ADAPTIVE ACCELERATED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

Economic Load Dispatch (ELD) is essential for efficient power system operation. The objective is to satisfy demand at minimum cost while meeting operational constraints. Valve-point effects and multiple constraints make the problem nonlinear and nonconvex. These features limit the performance of conventional optimization methods. This paper proposes an advanced metaheuristic method called Adaptive Accelerated Particle Swarm Optimization (AAPSO). The approach combines dynamic adaptation of classical PSO parameters with an additional acceleration term. This strategy improves the balance between global exploration and local exploitation. It reduces premature convergence and enhances stability and accuracy in highly multimodal and constrained ELD problems. The proposed method was tested on standard 5-, 13-, and 40-unit systems with valve-point effects. Results show that AAPSO consistently achieves lower generation costs around 19,15% compared to other techniques and recent metaheuristic algorithms. All generator limits and power balance constraints are strictly satisfied. Convergence curves demonstrate fast convergence, robustness, and strong ability to avoid local optima.



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I. INTRODUCTION

Nowadays, electrical energy is a fundamental pillar of nations' economic, industrial, and technological development [1]. Indeed, the rise of modern technologies and improved living standards is inextricably linked to the availability of reliable, continuous, and affordable electrical energy [2-4]. Globally, electricity is considered one of the main drivers of growth due to its central role in all productive sectors and critical infrastructure [5]. In this context, ELD is a key field of research in the operation of electrical networks [6]. Its main objective is to meet energy demand while minimizing the overall cost of production and ensuring optimal management of available resources [7]. This optimization is based on the appropriate allocation of the power generated by the various power plants, thereby reducing energy losses, limiting fuel consumption, and consequently decreasing the cost per kilowatt-hour [8]. An electric power system generally consists of a limited number of power plants supplying a large number of consumers through an interconnected network [9]. A fundamental characteristic of electricity is that it is generated simultaneously with its consumption, which requires constant adjustment between supply and demand [10]. Thus, the active and reactive power of generators must be continuously regulated, while respecting their operating limits, to respond to load variations at the lowest possible cost [11]. However, the safe and reliable operation of the transmission network must comply with a set of operational constraints, such as line transit limits, transformer capacities, permissible voltage levels, and frequency stability [12]. Exceeding these thresholds can lead to instability phenomena that could compromise the security of the electrical system [13].

In this context, the issue of economic energy distribution has become increasingly important, particularly in a context marked by rising fuel costs and the deregulation of electricity markets [14]. The aim is to determine the optimal active and reactive power of generators, within their constraints, in order to meet demand while minimizing total operating costs [15]. This problem is generally formulated as the Optimal Power Flow (OPF) problem. However, the nonlinear and highly constrained complexity of this problem, accentuated by the integration of decentralized production, often makes the application of conventional optimization methods inflexible or ineffective [16]. Metaheuristic methods appear as promising alternatives for solving ELD problems [17]. Particle Swarm Optimization (PSO) has established itself as one of the most effective metaheuristics for handling constrained non-linear and multi-modal optimization problems, particularly in the context of ELD [18]. Classical PSO, based on a mathematical model of cooperative swarm behavior, has notable advantages such as a simple algorithmic structure, a small number of control parameters, and ease of implementation. However, despite its proven performance, this classic version can suffer from limitations related to premature convergence and insufficient exploration of the search space [19]. To overcome these shortcomings, numerous adaptive and modified variants of PSO have been developed in the literature, based on dynamic parameter adjustment, the introduction of hybrid strategies, or the integration of advanced strategies, as shown in Table 1.

Table 1: Comparative table of recent PSO algorithms for the nonconvex ELD problem.

Ref	Algorithm	Remarks
[18]	PSO	Simple to implement, but sensitive to premature convergence and local optima if the parameters are not correctly adjusted.
[19]	Iteration PSO	IPSO improves convergence and avoids local minima thanks to the Iteration Best index, albeit with a slightly longer processing time.
[20]	Adaptive PSO	Adaptive PSO dynamically adjusts parameters, improving convergence while maintaining algorithmic simplicity, but moderate convergence.
[21]	Modied PSO	MPSO incorporates an attractive factor, improving overall convergence and efficiency for ELD problems, but with high complexity.
[22]	Hybrid differential evolution and PSO	HDEPSO improves overall convergence and reduces costs, at the expense of slightly increased computational complexity.
This Work	Adaptive Accelerate PSO	AAPSO combines parametric adaptation and acceleration, improving convergence and robustness for complex ELD problems.

Source: Authors (2026).

The main objective of this work is to study and optimize power distribution in electrical networks by solving the non-convex ELD problem through minimization of the active power generation cost function. To do this, the AAPSO optimization method is applied to solve the optimal power flow problem. The results obtained are evaluated on standard test networks and compared with several metaheuristic algorithms from the literature, considering the effect of the valve. This work is structured as follows: The first section presents the mathematical formulation of the ELD problem. The second section is devoted to the proposed optimization method, as well as its operating principle and adaptive mechanism. The third section presents the simulation results obtained using the proposed AAPSO method, accompanied by a comparison with existing methods reported in the literature. Finally, the last section concludes this work with a conclusion.

II. MATHEMATICAL FORMULATION OF THE ELD PROBLEM

The ELD problem focuses on determining the optimal power output of committed generating units to minimize the total fuel cost while respecting operational and physical constraints. The problem is mathematically represented by a nonlinear objective function combined with equality and inequality constraints [23].

II.1 OBJECTIVE FUNCTION

For a system comprising n generating units, the overall fuel cost can be expressed as the sum of the individual generator cost functions. In its conventional quadratic form, the fuel cost of each unit is given by:

$$F_{\text{total}} = \sum_{i=1}^n F(P_i) = \sum_{i=1}^n (a_i P_i^2 + b_i P_i + c_i) \quad (1)$$

Where P_i denotes the active power output of the i th generator, and a_i , b_i , and c_i are the corresponding cost coefficients.

II.2 VALVE-POINT LOADING EFFECTS

In practical systems, valve-point effects introduce ripples in the fuel cost curve, making it non-smooth and more challenging to optimize. This is typically modeled as

$$F_{\text{total}} = \sum_{i=1}^n \left(a_i P_i^2 + b_i P_i + c_i + e_i \left| \sin \left(f_i (P_i^{\min} - P_i) \right) \right| \right) \quad (2)$$

Where e_i and f_i are the valve-point coefficients, and $P^{\min}$ represents the minimum output limit of the i unit.

II.3 OPERATIONAL CONSTRAINTS

II.3.1 Power Balance Constraint

The sum of generated powers must satisfy the system demand P_D while accounting for transmission losses P_L :

$$\sum_{i=1}^n P_i - P_D - P_L = 0 \quad (3)$$

Transmission losses are often represented using the B -coefficient formulation:

$$P_L = \sum_{i=1}^n \sum_{j=1}^n P_i B_{ij} P_j + \sum_{i=1}^n B_{i0} P_i + B_{00} \quad (4)$$

Where B_{ij} , B_{i0} , and B_{00} are loss coefficients determined by the network configuration.

II.3.2 Generator Output Limits

Each generator must operate within its rated minimum and maximum output:

$$P_i^{\min} \leq P_i \leq P_i^{\max}$$

II.3.3 Ramping Rate Constraints

Sudden changes in generator output are restricted by ramp-up (UR_i) and ramp-down (DR_i) limits relative to the previous output P_i^0 :

$$P_i - P_i^0 \leq UR_i, \quad P_i - P_i^0 \leq DR_i$$

II.3.4 Prohibited Operating Zones

Some generators have forbidden operating ranges, known as Prohibited Operating Zones (POZ), where operation is not permitted. For a generator with prohibited zones, the permissible intervals are:

$$P_i \in \begin{cases} [P_i^{\min}, PL_{i,1}] \\ [PU_{i,k-1}, PL_{i,k}], \\ [PU_{i,pzi}, P_i^{\max}] \end{cases}, \quad k = 2, 3, \dots, pzi,$$

Where $PL_{i,k}$ and $PU_{i,k}$ denotes the lower and upper bounds of the k th prohibited interval. In summary, the ELD problem is a nonlinear and, in the presence of valve-point effects, nonconvex optimization problem. It is constrained by power balance, generator limits, ramping capabilities, and prohibited zones. This mathematical representation forms the foundation for evaluating the performance of optimization algorithms in solving realistic ELD scenarios [24].

III. ADAPTIVE ACCELERATED PARTICLE SWARM OPTIMIZATION

PSO is a population-based metaheuristic inspired by the collective dynamics of social groups, such as bird flocks and fish schools [25]. In PSO, each particle represents a candidate solution whose position is updated iteratively based on its own experience and that of the swarm. While classical PSO is simple and often effective, its performance can degrade when applied to non-convex, highly multimodal problems, such as economic dispatch with valve-point effects [26]. To overcome these limitations, an Adaptive Accelerated PSO (AAPSO) framework is proposed. AAPSO incorporates both adaptive parameter control and an additional acceleration term, designed to balance exploration and exploitation dynamically.

III.1 PRINCIPLE AND ADAPTIVE MECHANISM OF AAPSO

The inertia and learning parameters of the PSO technique are fixed, which can lead to slow convergence or trapping in local optima, while AAPSO introduces an adaptive and accelerated mechanism. This process can dynamically adjust the inertia and learning coefficients based on the convergence state of the swarm. This adaptation improves the balance between global exploration and local exploitation promoting faster and more accurate convergence to the optimal solution. As a result, AAPSO demonstrates an increased ability to effectively track dynamic variations in the optimization problem, making it particularly suitable for real-time applications and complex nonlinear systems. To enhance the balance between exploration and exploitation, the AAPSO algorithm employs time-varying parameters [27]. The inertia weight $w(It)$ and the acceleration coefficients $c_1(It)$ (cognitive) and $c_2(It)$ (social) evolve linearly over iterations as follows:

$$w(It) = w_{\max} - \frac{w_{\max} - w_{\min}}{\text{MaxIt}} It \quad (5)$$

$$c_1(It) = c_{1,\text{initial}} - \frac{c_{1,\text{initial}} - c_{1,\text{final}}}{\text{MaxIt}} It \quad (6)$$

$$c_2(It) = c_{2,initial} + \frac{c_{2,final} - c_{2,initial}}{MaxIt} It \quad (7)$$

Where It is the current iteration, $MaxIt$ is the maximum number of iterations, w_{max} and w_{min} are the initial and final inertia weights, and $c_{1,initial}$, $c_{1,final}$, $c_{2,initial}$, $c_{2,final}$ are the initial and final cognitive and social acceleration coefficients, respectively. The inertia weight decreases over time to transition the swarm from global exploration to local exploitation. Simultaneously, the cognitive coefficient $c_1(It)$ is reduced, weakening individual particle influence, while the social coefficient $c_2(It)$ is increased, strengthening convergence toward the global best. This adaptive evolution dynamically balances diversification and intensification throughout the optimization process.

III.2 PRINCIPLE OF ACCELERATION TERM

An additional velocity-dependent acceleration term is incorporated to capture second-order effects, akin to momentum in optimization dynamics. The velocity update equation is formulated as:

$$v_i(t+1) = w(t) v_i(t) + c_1(t) r_1 \circ (p_{best} - x_i(t)) + c_2(t) r_2 \circ (g_{best} - x_i(t)) + \alpha(t) (v_i(t) - v_i(t-1)) \quad (8)$$

Where x_i and v_i denote the position and velocity of particle i , p_{best} is the personal best, g_{best} is the global best, r_1 and r_2 are vectors of uniformly distributed random numbers in $[0, 1]$, and $\circ$ denotes component-wise multiplication. The time-varying acceleration coefficient $\alpha(t)$ decreases over iterations to ensure numerical stability and controlled convergence.

III.3 CONSTRAINT HANDLING AND FEASIBILITY

For the economic dispatch problem, particle positions must satisfy generator limits and meet the total load demand exactly. After each update, candidate solutions are repaired: values violating bounds are clipped, and the vector is scaled proportionally to maintain the total generation equal to the load. This approach preserves feasibility and prevents oscillatory behavior that can occur when particles are repeatedly forced back into admissible regions [28]. The flowchart of the algorithm is illustrated in Figure. 1.

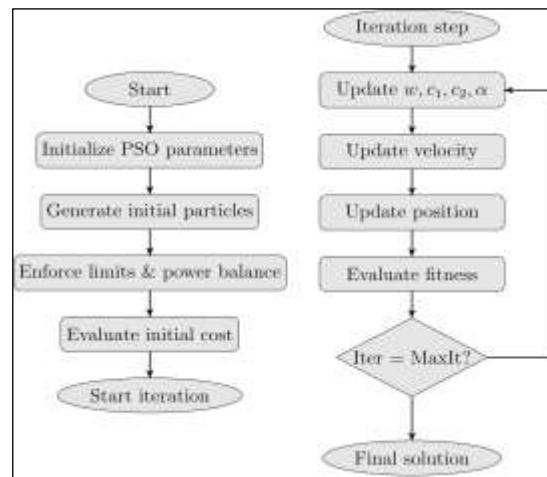


Figure 1: Flowchart of the proposed AAPSO method.
Source: Authors (2026)

IV. COMPARATIVE RESULTS ON THE STANDARD TEST SYSTEM

This section presents the performance evaluation of the proposed AAPSO on IEEE bus systems of small, medium, and large scales (5-, 13-, and 40- unit systems), with comparisons to established ELD solution methods [29]. The primary objective of AAPSO is to minimize the total fuel cost while satisfying generator constraints and power demand. The algorithm was implemented in MATLAB R2016b on a laptop equipped with an Intel Core i5 (10th generation) processor and 8 GB RAM. Optimization was performed using 50 search agents over 500 iterations. The approach was evaluated under various operating conditions, including systems with valve-point loading effects.

IV.1 CASE1: 5-UNIT SYSTEM WITH VALVE-POINT LOADING EFFECTS

For the 5-unit system with a power demand of 730 MW (Appendix A), Table 2 presents the comparative fuel costs and generator outputs.

Table 2: Economic dispatch results for the 5-unit system with valve-point effect.

Method	Fuel Price (Rs/h)	Demand (MW)	G1	G2	G3	G4	G5
GA [30]	2412.54	730	218.02	109.01	147.52	28.38	227.03
PSO [30]	2252.57	730	229.52	125.00	175.00	75.00	125.48
BAT [30]	2412.71	730	218.03	109.01	147.54	28.38	272.04
APSO [30]	2140.97	730	225.38	113.02	109.41	73.11	209.07
SMA [31]	2034.97	730	229.52	102.98	112.68	75.00	209.82
AAPSO	1950.66	730	220.97	94.57	150.73	30.56	233.73

Source: Authors (2026).

The proposed AAPSO achieves the lowest fuel cost of **1950.6552 Rs/h**, demonstrating its superior efficiency over SMA and other conventional approaches. The convergence curve in Figure 2 confirms rapid and stable convergence.

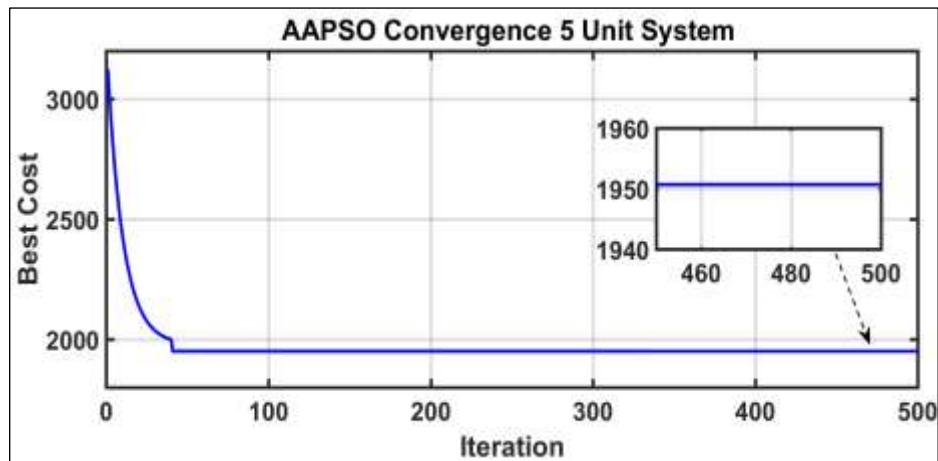


Figure 2: Convergence curve of AAPSO for ELD (5-unit system) with valve-point loading effect.
Source: Authors (2026).

IV.2 CASE 2: 13-UNIT SYSTEM WITH VALVE-POINT LOADING EFFECTS

Table 3 presents the economic dispatch results of the 13-unit system considering valve-point effects (Appendix B). The proposed AAPSO method achieves the lowest fuel cost among all compared techniques, demonstrating superior convergence performance.

Table 3: Economic dispatch results of a 13-unit system with valve-point effect.

Method	GWO [32]	JAYA [32]	NGWO [32]	EP-SQP [33]	SA [33]	GA [33]	PSO-SQP [33]	CJAY A [33]	GWOII [32]	GWOI [32]	GA-SA [33]	CPSO [34]	SMA [31]	AAPSO
FP	24231.18	24220.75	24185.45	24266.44	24970.91	24418.99	24261.05	24178.80	24198.47	24244.69	24275.71	24211.56	24177.24	24171.33
RPD	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00	2520.00
G1	647.38	628.32	631.00	628.31	668.40	627.05	628.32	628.32	630.98	645.56	628.23	682.32	628.32	628.28
G2	306.40	299.20	297.94	299.17	359.78	359.40	299.05	299.20	300.80	306.95	299.22	299.83	298.04	299.17
G3	309.61	306.91	299.93	299.05	358.20	358.95	298.97	299.20	302.75	306.54	299.17	299.19	298.92	298.82
G4	175.14	159.73	157.93	159.64	104.28	158.93	159.47	159.73	159.67	168.70	159.12	159.70	159.72	159.65
G5	66.88	159.73	159.64	159.66	60.36	159.73	159.14	159.73	161.03	162.50	159.95	159.64	159.69	159.72
G6	162.75	159.73	159.23	158.44	160.64	159.72	159.72	159.72	159.73	197.17	158.85	159.67	159.72	159.71
G7	174.31	109.87	159.76	159.87	162.12	159.39	159.54	159.73	159.12	167.14	156.17	159.69	159.42	159.71
G8	61.23	159.73	159.66	159.73	163.03	158.89	158.85	159.73	110.43	160.89	159.93	159.65	159.69	159.70
G9	175.14	159.73	159.18	159.67	161.12	110.19	159.78	159.73	120.12	186.11	159.86	159.78	159.72	159.72
G10	116.76	114.81	76.88	114.03	159.17	77.27	110.92	110.04	116.89	116.81	110.78	114.42	76.29	74.71
G11	116.76	114.81	160.50	114.03	75.00	75.00	110.92	114.80	117.07	116.81	75.00	114.76	114.17	77.32
G12	99.92	92.01	86.09	87.59	159.55	86.54	91.66	91.99	94.09	91.06	92.62	91.64	55.00	91.86
G13	108.56	55.00	94.19	87.59	159.56	85.54	91.66	91.99	88.69	66.51	92.62	91.64	91.03	91.62
Ploss	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	0.00	0.00

Source: Authors (2026).

Figure 3 illustrates the convergence of AAPSO, which rapidly reaches optimal solutions and maintains stable performance across iterations.

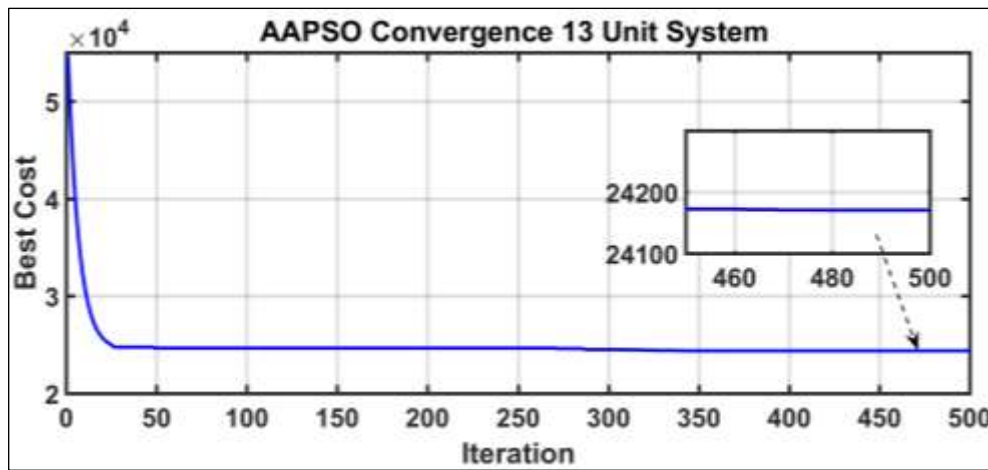


Figure 3: Convergence curve of AAPSO for ELD (13-unit system) with valve-point loading effect.
Source: Authors (2026).

IV.3 CASE 3: 40-UNIT SYSTEM WITH VALVE-POINT LOADING EFFECTS

The 40-unit system parameters are detailed in Appendix C. The results are summarized in Table 4.

Table 4: Economic dispatch results of a 40-unit system with valve-point effect.

Meth od	GWO [32]	NGWO [32]	PSO-LRS [32]	IGA [32]	NPSO [32]	GWOII [32]	CJAYA [32]	GWOI [32]	SMA [31]	AAPSO
FP	122602.37	121881.81	122035.79	121915.93	121704.73	122430.74	122581.85	122678.91	121658.66 56	121593.69 07
RPD	10500	10500	10500	10500	10500	10500	10500	10500	10500	10500
G1	109.0947	111.3177	111.9858	110.97	113.9891	107.6544	114	109.7268	112.35251 88	111.2487
G2	112.0471	112.7551	110.5273	110.88	113.6334	109.2161	111.6651	111.7342	112.46889 84	113.9998
G3	115.4584	118.6377	98.5560	98.17	97.5500	94.7874	119.9876	119.2197	97.491499 56	120
G4	179.8333	183.3649	182.9622	178.85	180.0059	182.3441	188.2606	181.6041	179.74155 79	179.7409
G5	46.1649	91.8097	87.7254	87.78	97	86.9731	96.9763	89.8836	93.717059 17	93.8271
G6	83.1571	104.3697	139.9933	140	140	109.1907	139.9488	125.1816	139.99945	140
G7	261.6345	297.6533	259.6628	260.37	300	259.4910	264.0949	265.0775	260.43619 78	300
G8	292.4025	289.4349	297.7912	286.83	300	284.1803	299.9814	290.2216	289.743	285.0376
G9	284.7149	298.4044	284.8459	285.14	284.5797	285.1526	284.9042	285.2586	296.0535	284.8931
G10	132.9049	129.35	130	204.86	130.0517	129.3500	130.0908	134.9231	130.0189	130.0638
G11	101.6726	241.9702	94.6741	165.98	243.7131	317.4787	94.0011	167.9983	168.7887	168.8001
G12	319.8174	166.9113	94.3734	167.75	169.0104	157.3563	94	183.6314	168.7212	94.008
G13	215.0746	214.849	214.7369	214.31	125	300.6095	125.1028	219.5396	125.0003	125.0173
G14	394.9259	215.669	394.1370	305.65	393.9662	305.0848	394.2529	394.9259	394.2872	304.5668
G15	398.1829	305.69	483.1816	393.66	304.7586	395.3099	484.1262	212.7154	304.59194 05	394.2842
G16	304.1546	394.6479	304.5381	394.60	304.5120	203.9544	304.5950	484.5572	394.3118	394.288
G17	490.0842	494.7618	489.2139	489.22	489.6024	489.6721	490.8265	494.3478	489.29146 08	489.2796
G18	493.2515	493.1559	489.6154	489.25	489.6087	492.3490	489.3438	491.2367	489.881	489.2996
G19	511.4229	512.7416	511.1782	511.23	511.7903	514.3882	51.3775	514.3755	511.2385	511.3174
G20	511.9422	520.8929	511.7336	510.69	511.2624	511.7323	512.1395	514.3755	511.2866	511.3079
G21	532.3762	526.1137	523.4072	524.74	523.3274	532.2046	523.6621	522.6016	523.3004	523.3604
G22	532.2484	532.1443	523.4599	525.52	523.2196	527.3193	523.3534	523.6988	523.2929	523.3971
G23	530.7732	536.8421	523.4756	522.98	523.4707	527.3193	524.9677	523.6988	523.3215	523.3963
G24	526.1112	524.4669	523.7032	522.22	523.0661	539.9336	524.2850	536.1385	523.2599	523.3735
G25	524.4545	525.2461	523.7854	523.26	523.3978	526.6306	522.9279	523.5451	523.3046	523.4462
G26	523.4934	529.3289	523.2757	523.32	523.2897	524.8658	523.2298	524.0780	523.2675	523.3024
G27	11.5028	9.95	10	10	10.0208	9.95	10	14.8568	10.00489	10.0666
G28	9.9541	9.95	10.6251	10	10.0927	9.95	10.0047	21.0962	10	10.0489
G29	10.3272	9.95	10.0727	10	10.0621	9.95	10	13.1286	10.00001	10.011
G30	91.6019	88.4106	51.3321	88.86	88.9456	90.3385	97	88.5089	92.73674	97
G31	188.8475	188.9088	189.8048	162.30	189.9951	159.6875	190	188.0180	189.9981	190

G32	165.2531	188.8126	189.7386	177.94	190	188.9923	189.9503	166.2968	190	190
G33	188.9197	186.9624	189.9122	160.18	190	173.1974	190	182.0808	190	190
G34	189.2968	195.0897	199.3258	166.54	165.9825	189.6808	169.8860	164.9636	195.8292	200
G35	180.4605	171.5047	199.3065	164.80	172.4153	192.1671	199.8549	172.6948	200	200
G36	184.2698	176.1085	192.8977	170.68	191.2978	157.5027	199.9896	191.0765	200	200
G37	89.6748	89.5297	110	108.17	109.9893	104.4095	109.9712	108.8942	89.89076	110
G38	90.1485	89.3589	109.8628	100.68	109.9521	86.74132	109.9977	100.8804	91.73751	90.326
G39	57.0464	109.3222	92.8751	109.34	109.8733	100.2970	109.9871	27.8744	109.9905	110
G40	514.3622	512.5412	511.6883	511.28	511.5671	512.43873	511.2250	511.7717	511.2371	511.2917

Source: Authors (2026)

The proposed AAPSO achieves the minimum fuel cost of **121593.69 Rs./h**, outperforming all compared methods, while satisfying all system constraints. The convergence curve in Figure 4 indicates that AAPSO efficiently reaches optimal solutions.

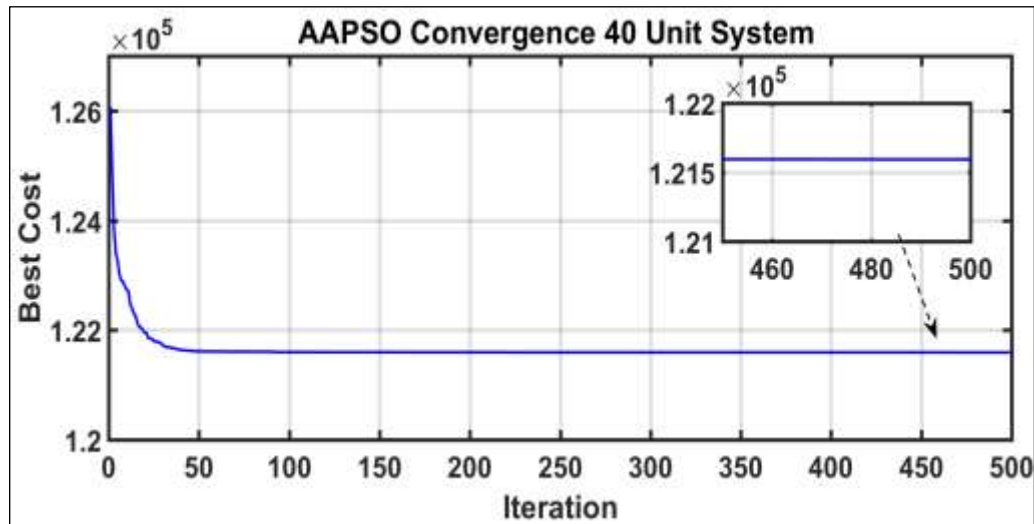


Figure 4: Convergence curve of AAPSO for ELD (40-unit system) with valve-point loading effect.

Source: Authors (2026).

V. CONCLUSION

This article studied economic load dispatch (ELD) in electrical networks, formulated as a nonlinear, non-convex optimization problem with valve effects and multiple operational constraints. To overcome the limitations of conventional methods, an advanced metaheuristic approach, Adaptive Accelerated Particle Swarm Optimization (AAPSO), was proposed. AAPSO combines the dynamic adaptation of conventional PSO parameters with an additional acceleration term, thereby improving the balance between global exploration and local exploitation. This enhances the stability of optimization for highly multi-modal and constrained ELD problems, thereby limiting premature convergence. Tests on standard systems of various sizes, including valve-point effects, show that AAPSO consistently achieves better quality solutions in terms of production cost while respecting all constraints. Compared to recent metaheuristics, it offers faster convergence, superior robustness, and a better ability to avoid local optima. These results confirm the potential of AAPSO as a reliable and effective tool for non-convex ELD problems. Future prospects include its extension to dynamic ELD formulations, integrating renewable energies and associated uncertainties.

VI. AUTHOR'S CONTRIBUTION

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Appendix A

Table 5: Five-Units Test System Data (Load = 730 MW).

Unit	P_{min} (MW)	P_{max} (MW)	a (\$/MW ² h)	b (\$/MWh)	c (\$/h)	d (\$/h)	e (1/MW)
G1	50	300	0.0015	1.8	40	200	0.035
G2	20	125	0.0035	1.8	60	140	0.040
G3	30	175	0.0012	2.1	100	160	0.038
G4	10	75	0.0080	2.0	25	100	0.042
G5	40	250	0.0010	2.0	120	180	0.037

Source: [29].

Appendix B

Table 6: Thirteen-Units Test System Data (Load = 2520 MW).

Unit	P_{min} (MW)	P_{max} (MW)	a (\$/h)	b (\$/MW)	c (\$/MW ²)	d (\$/MW)	e (1/MW)
G1	0	680	550	8.10	0.00028	300	0.035
G2	0	360	309	8.10	0.00056	200	0.042
G3	0	360	307	8.10	0.00056	200	0.042
G4	60	180	240	7.74	0.00324	150	0.063
G5	60	180	240	7.74	0.00324	150	0.063
G6	60	180	240	7.74	0.00324	150	0.063
G7	60	180	240	7.74	0.00324	150	0.063
G8	60	180	240	7.74	0.00324	150	0.063
G9	60	180	240	7.74	0.00324	150	0.063
G10	40	120	126	8.60	0.00284	100	0.084
G11	40	120	126	8.60	0.00284	100	0.084
G12	55	120	126	8.60	0.00284	100	0.084
G13	55	120	126	8.60	0.00284	100	0.084

Source: [29]

Appendix C

Table 7: Forty-Units Test System Data (Load = 10500 MW).

Unit	P_{min} (MW)	P_{max} (MW)	a (\$/h)	b (\$/MW)	c (\$/MW ²)	d (\$/MW)	e (1/MW)
G1	36	114	94.705	6.73	0.00690	100	0.084
G2	36	114	94.705	6.73	0.00690	100	0.084
G3	60	120	309.54	7.07	0.02028	100	0.084
G4	80	190	369.03	8.18	0.00942	150	0.063
G5	47	97	148.89	5.35	0.01140	120	0.077
G6	68	140	222.33	8.05	0.01142	100	0.084
G7	110	300	287.71	8.03	0.00357	200	0.042

G8	135	300	391.98	6.99	0.00492	200	0.042
G9	135	300	455.76	6.60	0.00573	200	0.042
G10	130	300	722.82	12.9	0.00605	200	0.042
G11	94	375	635.20	12.9	0.00515	200	0.042
G12	94	375	654.69	12.8	0.00569	200	0.042
G13	125	500	913.40	12.5	0.00421	300	0.035
G14	125	500	1760.4	8.84	0.00752	300	0.035
G15	125	500	1728.3	9.15	0.00708	300	0.035
G16	125	500	1728.3	9.15	0.00708	300	0.035
G17	220	500	647.85	7.97	0.00313	300	0.035
G18	220	500	649.69	7.95	0.00313	300	0.035
G19	242	550	647.83	7.97	0.00313	300	0.035
G20	242	550	647.81	7.97	0.00313	300	0.035
G21	254	550	785.96	6.63	0.00298	300	0.035
G22	254	550	785.96	6.63	0.00298	300	0.035
G23	254	550	794.53	6.66	0.00284	300	0.035
G24	254	550	794.53	6.66	0.00284	300	0.035
G25	254	550	801.32	7.10	0.00277	300	0.035
G26	254	550	801.32	7.10	0.00277	300	0.035
G27	10	150	1055.1	3.33	0.52124	120	0.077
G28	10	150	1055.1	3.33	0.52124	120	0.077
G29	10	150	1055.1	3.33	0.52124	120	0.077
G30	47	97	148.89	5.35	0.01140	120	0.077
G31	60	190	222.92	6.43	0.00160	150	0.063
G32	60	190	222.92	6.43	0.00160	150	0.063
G33	60	190	222.92	6.43	0.00160	150	0.063
G34	90	200	107.87	8.95	0.00010	200	0.042
G35	90	200	116.58	8.62	0.00010	200	0.042
G36	90	200	116.58	8.62	0.00010	200	0.042
G37	25	110	307.45	5.88	0.01610	80	0.098
G38	25	110	307.45	5.88	0.01610	80	0.098
G39	25	110	307.45	5.88	0.01610	80	0.098
G40	242	550	647.83	7.97	0.00313	300	0.035

Source: [29].