Power System Optimization using an Adaptive Fuzzy Campus Placement based Optimization Algorithm

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***Abstract*—The use of optimization tools in complex problems is becoming increasingly crucial to overcome the challenging task of achieving efficient results. The Novel Adaptive Fuzzy Campus Placement based Optimization Algorithm (AFCPOA) is a new method for solving optimization problems that is based on campus recruiting process used in universities. In this study, two power system optimization problems, namely, Economic Load Dispatch (ELD) and Optimal Power Flow (OPF) have been tested on IEEE 30 bus test system. The main objective of ELD is scheduling generation units to lower costs while meeting system constraints, whereas OPF decides how to dispatch generating units to meet the demand for power at the lowest possible cost. The proposed method (AFCPOA) is applied on 16 Congress on Evolutionary Computation (CEC) benchmark test functions for validation and subsequently applied to two power system optimization problems ELD and OPF under MATLAB environment. The proposed AFCPOA method shows significant improvement in results compared with other methods for optimization problems.**

***Index Terms*—Particle Swarm Optimization (PSO), Jaya Algorithm (JA), Optimal Power Flows (OPF), Economic Load Dispatch (ELD), Adaptive Fuzzy Campus Placement based Optimization Algorithm (AFCPOA).**

Nomenclature

δ_i Voltage angle of i^{th} bus
δ_j Voltage angle of j^{th} bus
θ_{ij} Admittance angle of i^{th} and j^{th} bus
a_i, b_i, c_i i^{th} Generator cost coefficients
B_{ij} Matrix of loss coefficients
$F(P_G(i))$ Fuel cost of i^{th} generator in $/hr
N_G Number of generator
N_{sh} Number of shunt elements
N_{Tap} Number of Taps
$P_D(i)$ Active power demand of i^{th} generator
$P_G(i)$ Active power generation of i^{th} generator
P_G^{max} Maximum limit of active power generation
P_G^{min} Minimum limit of active power generation
$Q_D(i)$ i^{th} generator reactive power demand
$Q_G(i)$ i^{th} generator reactive power generation
Q_G^{max} Maximum limit of reactive power generation
Q_G^{min} Minimum limit of reactive power generation
S_l Line flow limit of l^{th} line
S_l^{max} Maximum line flow limit of l^{th} line
$T_p(l)$ Tap value of l^{th} branch
$T_p^{max}(l)$ Maximum tap value of l^{th} branch
$T_p^{min}(l)$ Minimum tap value of l^{th} branch
V_i i^{th} Bus Voltage in p.u
V_j j^{th} Bus Voltage in p.u
Y_{ij} Line admittance between i^{th} and j^{th} buses
$Y_{sh}(m)$ Shunt admittance of m^{th} bus
$Y_{sh}^{max}(m)$ Maximum shunt admittance of m^{th} bus
$Y_{sh}^{min}(m)$ Minimum shunt admittance of m^{th} bus
ABC Artificial Bee Colony
BBBC Big Bang and Big Crunch
cgpa Cumulative Grade Point Average
DE Differential Evolution
FA Firefly Algorithm
GA Genetic Algorithm
GWO Grey Wolf Optimization
SD Standard Deviation
TLBO Teaching Learning Based Optimization
WOA Whale Optimization Algorithm
α_i, β_i, γ_i i^{th} Generator cost coefficients

I. Introduction

Power system planning, operation, and control problems have been solved using mathematical optimization (algorithmic) methods over the years. Mathematical formulations of real-world problems are developed under particular assumptions, and even under these assumptions, large-scale power system solutions are not straightforward. On the other hand, because power systems are huge, complicated, and geographically dispersed, there are uncertainties in power system generation. Over the past few years, a wide variety of metaheuristics algorithms have been developed and applied to solve unconstrained and constrained optimization problems given in [1] and [2], respectively. One of the main optimization issues in power systems is Economic Load Dispatch (ELD), which aims to minimize generation costs while respecting operational limitations including environmental effect and system dependability [3]. Complex economic load dispatch issues can be optimally solved with evolutionary programming, particularly when non-convex cost curves and valve-point effects are present [4]. By integrating a dynamic autoregressive moving average (ARMA) model, the best approach enhances economic load dispatch, improving fuel cost accuracy, and achieving a

0.15% reduction in total costs over standard methods [5]. The new enhanced aggrandized class topper optimization algorithm (A-CTO), Gradient-Based Optimizer (GBO), and Search and Rescue optimization algorithm (SAR) were used to address the ELD and Combined Economic and Emission Dispatch (CEED) problems within the power system and were also evaluated on a number of CEC benchmark test functions in [6] and [7]. The Search and Rescue (SAR) optimization algorithm has demonstrated superior performance in minimizing fuel and emission costs for ELD and CEED problems compared to several metaheuristic methods [8]. The incorporation of continuous network flexibility to chance constrained economic dispatch has been shown to improve operational efficiency and mitigate congestion under renewable uncertainties [9]. Optimal power flow (OPF) can be efficiently solved by minimizing costs or losses through the adjustment of control variables, utilizing Newton's method and gradient-based algorithms to meet system constraints [10]. The quick Newton-Raphson approach effectively solves the optimal power flow problem while preserving safe voltage levels and reducing fuel expenses [11]. An improved genetic algorithm is applied to solve the optimal power flow problem, with an emphasis on increasing power system management accuracy and efficiency [12]. Authors of [13]- [14] have implemented the improvised algorithm to reduce the computational hurdles involved in solving the optimal power flow problem in both traditional and market-based power systems to improve efficiency, scalability, and constraint handling. In multi-energy systems, optimal power flow improves efficiency and reduces costs by maximizing energy conversion and dispatch across gas, heating, and electricity networks [15]. Investigation of optimal power flow problem for the IEEE 30 bus test system, taking into account a variety of design variables, with a variety of single and multiple objectives, utilizing several meta-heuristic algorithms, was carried out in [16]- [17].

The purpose of this study is to demonstrate an application of a recently developed optimization algorithm known as AFCPOA in 2023. In section II, the fuel cost minimization as an objective of two power system optimization problems are provided. The proposed AFCPOA method is described in section III. The results and discussions are summarized in sections IV, and conclusions are in section V.

II. Power System Optimization Problem Formulation

The aim of solving the power system optimization problem is to either maximize the desired factors (such as profit, quality power, efficiency, etc.) or minimize undesirable factors (such as energy cost, energy loss, and voltage variations) under some constraints. Long-term planning is accomplished using the simplest planning technique called ELD. In ELD, the majority of system constraints are not taken into account. The OPF problem aims to regulate generation and consumption in order to maximize specific goals, such as reducing the cost of generating power or power loss in the network.

A. Economic Load Dispatch Problem Formulation

Economic Load dispatch is an optimization method that chooses the least expensive generators to meet the total amount of electricity needed within the limits of operation of each generator. The formulation of ELD optimization problem is drawn from [19].

$$Minimize : F(P_G(i)) = \sum_{i=1}^{n_G} c_i + b_i P_G(i) + a_i P_G(i)^2 \quad (1)$$

Such that it satisfies the following equality and inequality constraints,

$$P_D = \sum_{i=1}^{n} P_i - (\sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{j=1}^{n} B_{oj} P_j + B_{oo}) \quad (2)$$

$$P_{G(i)}^{min} \leq P_{G(i)} \leq P_{G(i)}^{max}, i \in N_G \quad (3)$$

B. Optimal Power Flow Problem Formulation

Optimal Power Flow determines the dispatch of generating units to satisfy the electricity demand at the minimum cost while complying with technical limits of the system. The formulation of OPF optimization problem is drawn from [20].

$$Minimize : F(P_G(i)) = \sum_{i=1}^{n_G} \alpha_i + \beta_i P_G(i) + \gamma_i P_G(i)^2 \quad (4)$$

Such that it satisfies the following equality and inequality constraints,

$$P_G(i) - P_D(i) - \sum_{j=1}^{N_b} |V_i||V_j||Y_{ij}| cos(\delta_i - \delta_j - \theta_{ij}) = 0 \quad (5)$$

$$Q_G(i) - Q_D(i) - \sum_{j=1}^{N_b} |V_i||V_j||Y_{ij}| sin(\delta_i - \delta_j - \theta_{ij}) = 0 \quad (6)$$

$$P_{G(i)}^{min} \leq P_{G(i)} \leq P_{G(i)}^{max}, i \in N_G \quad (7)$$

$$Q_{G(i)}^{min} \leq Q_{G(i)} \leq Q_{G(i)}^{max}, i \in N_G \quad (8)$$

$$T_{p(l)}^{min} \leq T_{p(l)} \leq T_{p(l)}^{max}, l \in N_{Tap} \quad (9)$$

$$Y_{h(m)}^{min} \leq Y_{h(m)} \leq Y_{h(m)}^{max}, m \in N_{Sh} \quad (10)$$

$$S_{l(n)} \leq S_{l(n)}^{max}, n \in N_l \quad (11)$$

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N_G \quad (12)$$

III. Adaptive Fuzzy Campus Placement based Optimization Algorithm (AFCPOA)

The authors of this paper have developed a novel Adaptive Fuzzy Campus Placement based Optimization Algorithm (AFCPOA) [22] for solving optimization problems. A cohort of students is slightly adjusted and fitted into the framework of an optimization algorithm after going through tests and recurrent training to obtain the highest knowledge level for project deployment.

TABLE I
COMPARISON OF THE AFCPOA WITH OTHER ALGORITHMS ON THE OPTIMIZATION OF F_{uc}^1 TO F_{uc}^8 BENCHMARK UNCONSTRAINED TEST FUNCTIONS [18] & [1]

F. No	Statistic	GA [1]	PSO [1]	DE [1]	ABC [1]	TLBO [1]	JA [1]	AFCPOA (Proposed)
F_{uc}^1	Mean	-5.66052	-2.08701	-10.1532	-10.1532	-	-	-1.01528
	SD	3.86674	1.17846	0	0	-	-	0.000747
	Best	-	-	-	-	-	-	0
F_{uc}^2	Mean	-5.34409	-1.989871	-10.40294	-10.402941	-	-	-10.4028
	SD	3.517134	1.420602	0	0	-	-	0.000352
	Best	-	-	-	-	-	-	-10.1532
F_{uc}^3	Mean	-186.731	-186.73091	-186.7309	-186.73091	-	-	-185.669
	SD	0	0	0	0	-	-	0.8803207
	Best	-	-	-	-	-	-	-186.651
F_{uc}^4	Mean	1.11E+03	0	0	0	0	0	0
	SD	74.214474	0	0	0	0	0	0
	Best	-	-	-	-	-	0	0
F_{uc}^5	Mean	1.17E+03	0	0	0	-	-	0
	SD	76.5615	0	0	0	-	-	0
	Best	-	-	-	-	-	-	0
F_{uc}^6	Mean	1.48E+02	0	0	0	0	0	0
	SD	74.214474	0	0	0	0	0	0
	Best	-	-	-	-	-	0	0
F_{uc}^7	Mean	-49.9999	-50	-50	-50	-50	-50	-50
	SD	2.25E-05	0	0	0	0	0	0
	Best	-	-	-	-	-	-50	-50
F_{uc}^8	Mean	0.193417	0	0	0	0	-210	-210
	SD	0.035313	0	0	0	0	0	0
	Best	-	-	-	-	-	-210	-210

TABLE II
COMPARISON OF THE AFCPOA WITH OTHER ALGORITHMS ON THE OPTIMIZATION OF G_c^1 TO G_c^8 BENCHMARK CONSTRAINED TEST FUNCTIONS [2]

S.No	Function	Statistic	GA [1]	PSO [1]	ABC [1]	TLBO [1]	JA [1]	AFCPOA (Proposed)
1	G_c^1	Best	-14.44	-15	-15	-15	-15	-15
		Worst	..	-13	-15	-15	-15	-15
		Mean	-14.236	-14.71	-15	-15	-15	-15
2	G_c^2	Best	-0.99	-1	-1	-1.0005	-1.005	-1.0005
		Worst	..	-0.46	-1	-1	-1	-1.005
		Mean	-0.976	-0.764813	-1	-1	-1	-1
3	G_c^3	Best	-30626.053	-30665.539	-30665.539	-30665.5387	-30665.5387	-30665.53867
		Worst	..	-30665.539	-30665.539	-30665.5387	-30665.5387	-30665.53867
		Mean	-30590.455	-30665.539	-30665.539	-30665.5387	-30665.5387	-30665.53867
4	G_c^4	Best	-	5126.484	5126.484	5126.486	5126.486	5126.4967
		Worst	-	5249.825	5438.387	5127.4197	5126.635	5126.9
		Mean	-	5135.973	5185.714	5126.5146	5126.5061	5126.5042
5	G_c^5	Best	-6952.472	-6961.814	-6961.814	-6961.814	-6961.814	-6961.8138
		Worst	..	-6961.814	-6961.805	-6961.814	-6961.814	-6960.3
		Mean	-6872.204	-6961.814	-6961.813	-6961.814	-6961.814	-6961.81
6	G_c^6	Best	31.097	24.37	24.33	24.3101	24.3062	24.3062
		Worst	..	56.055	24.19	26.7483	24.8932	24.4442
		Mean	34.98	32.407	24.493	24.6482	24.3092	24.4797
7	G_c^7	Best	0.75	0.749	0.75	0.7499	0.7499	0.7499
		Worst	..	0.749	0.75	0.7499	0.7499	0.75
		Mean	0.75	0.749	0.75	0.7499	0.7499	0.7499
8	G_c^8	Best	..	961.7150	961.7568	961.7150	961.7150	961.7150
		Worst	..	972.3170	970.3170	961.7150	961.7150	961.7194
		Mean	..	965.5154	966.2868	961.7150	961.7150	961.7163

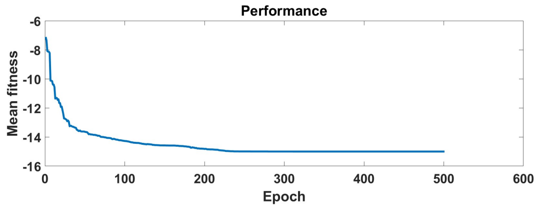

Fig. 1. Convergence plot of Test function G_c^1

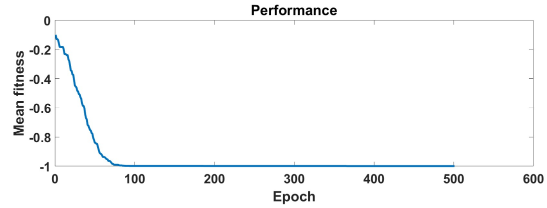

Fig. 2. Convergence plot of Test function G_c^2

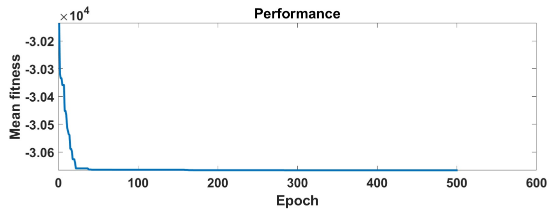

Fig. 3. Convergence plot of Test function G_c^3

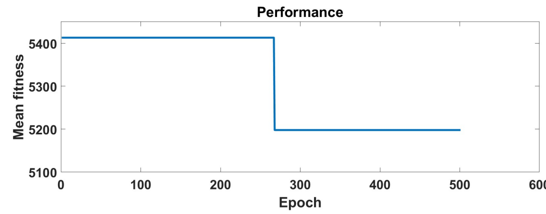

Fig. 4. Convergence plot of Test function G_c^4

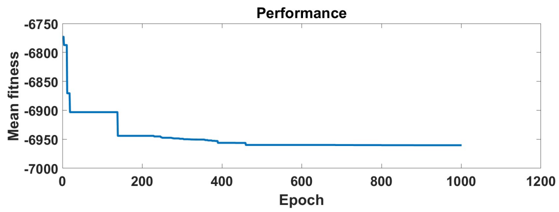

Fig. 5. Convergence plot of Test function G_c^5

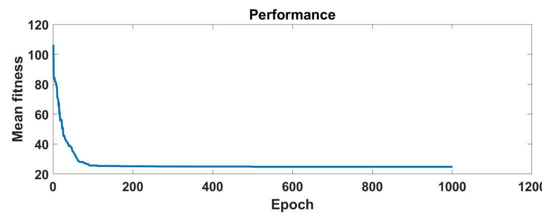

Fig. 6. Convergence plot of Test function G_c^6

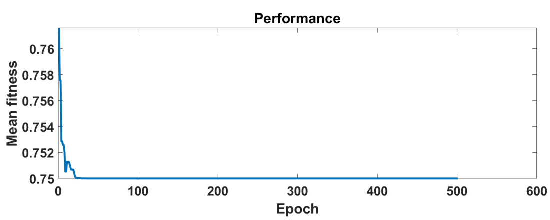

Fig. 7. Convergence plot of Test function G_c^7

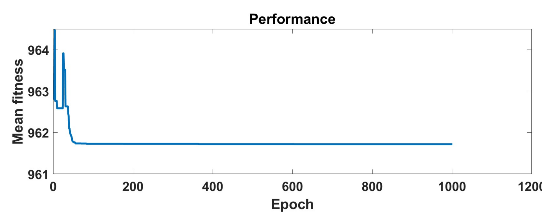

Fig. 8. Convergence plot of Test function G_c^8

TABLE III
COMPARISON OF AFCPOA WITH OTHER ALGORITHMS FOR OPTIMIZING ECONOMIC LOAD DISPATCH PROBLEM ON IEEE 30 BUS TEST SYSTEM

Algorithm	**GA [19]**	**ACO [19]**	**DE [21]**	**FA [21]**	**WOA [19]**	**PSO [19]**	**AFCPOA (Proposed)**
P_G^1 **(MW)**	179.367	177.863	**177.51**	175.07	174.379	176.94	184.174
P_G^2 **(MW)**	44.24	3.8366	48.61	43.29	47.8294	48.71	46.4821
P_G^5 **(MW)**	24.61	20.893	20.91	21.84	21.4578	21.27	19.0438
P_G^8 **(MW)**	19.9	23.1231	12.64	13.63	25.6931	21.09	10
P_G^{11} **(MW)**	10.71	14.0255	12.47	14.43	10.1262	11.83	10
P_G^{13} **(MW)**	14.09	13.1199	12.02	22.24	12.1515	12	12
Fuel Cost ($/hr)	803.699	803.123	803.07	803.96	800.2825	798.43	**761.7114**

TABLE IV
COMPARISON OF AFCPOA WITH OTHER ALGORITHMS FOR SOLVING OPTIMAL POWER FLOW PROBLEM ON IEEE 30 BUS TEST SYSTEM

Algorithm	**Base Case [22]**	**GA [22]**	**BBBC [22]**	**SFLA [22]**	**GWO [22]**	**JA [22]**	**AFCPOA (Proposed)**
P_G^1 **(MW)**	139.36	187.1	176.6	179.19	177.029	178.6	177.0916
P_G^2 **(MW)**	57.56	44.09	44.97	46.67	48.839	47.89	48.6827
P_G^5 **(MW)**	24.56	17.64	26.66	21.3	21.548	21.6	21.7297
P_G^8 **(MW)**	35	14.39	15.84	15.33	21.632	20.98	20.5695
P_G^{11} **(MW)**	17.93	13.01	16.69	13.84	12.1	11.63	13.0765
P_G^{13} **(MW)**	16.91	17.62	12	16.87	12.002	12.45	12.00
Fuel Cost ($/hr)	817.02	806.5	803.942	804.612	803.942	803.4	**801.7101**

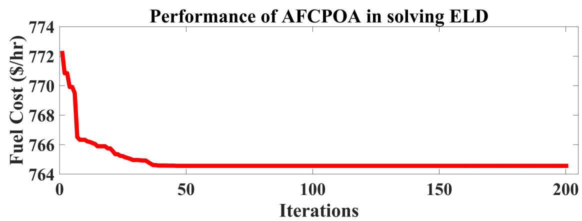

Fig. 9. Convergence plot of ELD problem using AFCPOA

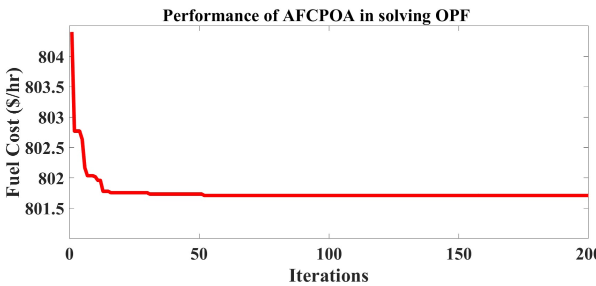

Fig. 10. Convergence plot of OPF problem using AFCPOA

Step 1 - Initialisation : Generate a cohort of candidates with a size of N_p (the population's size) and N_v (the search space's dimension) which fits within the defined set of limits.

Step 2 - Evaluation: A candidate's chances of getting employed rely on their skills and abilities. Subjective measurements based on fitness value are used to increase the algorithm's authenticity. Written test and Interview are the two assessments that are specified. The written test is divided into three sub-components: Cumulative Grade Point Average (cgpa), aptitude, and programming. The interview comprises three sub components: research output, projects, and communication abilities.

$$cgpa = \frac{\mathit{Fitness} - \mathit{min(Fitness)}}{\mathit{max(Fitness)} - \mathit{min(Fitness)}} * (cgpa^{max} - cgpa^{min}) + cgpa^{min} \tag{13}$$

$$Aptitude = Apt^{max}_{score} * \frac{cgpa}{cgpa^{max}} \tag{14}$$

$$Programming = Prog^{max}_{score} * \frac{cgpa}{cgpa^{max}} \tag{15}$$

$$Research = Research_{cf} * Research^{max}_{score} * \frac{cgpa}{cgpa^{max}} \tag{16}$$

$$Project = Project_{cf} * Project^{max}_{score} * \frac{cgpa}{cgpa^{max}} \tag{17}$$

$$Commun = rand * Communication^{max}_{score} * \frac{cgpa}{cgpa^{max}} \tag{18}$$

There is a human uncertainty element that cannot be properly defined when determining a candidate's final written exam score and final interview score. A fuzzy inference engine with a rule base on common sense has been developed for the written test score/ interview score sub components. Here, fuzzy rules were developed using triangular membership functions. The candidate's final score, known as the "caliber score," is a weighted sum of written test and interview scores.

$$Calibre_{score} = 0.6 * Written_{score} + 0.4 * Interview_{score} \tag{19}$$

Step 3 - Probation: During probation, the cohort is divided into trainable and untrainable candidates based on their caliber scores. Initially the trainable candidates who have improved their performance on training will have better knowledge levels. Subsequently, the remaining trainable candidates are further trained to maximize their performance.

$$perturb_{elite} = elite_{candi} + sigmoid(attempt) * \frac{u_{lim} + 2 * u_{lim} * rand}{100} \tag{20}$$

$$perturb_{candi} = candi + (-1 + 2 * rand) * (elite_{candi} - abs(candi)) \tag{21}$$

The algorithm is iterated through **Steps 2** and **Step 3** until it converges. The algorithm's basic concept is to maximize candidates knowledge levels.

IV. Results and Discussions

AFCPOA's performance was evaluated on 16 CEC benchmark test functions and two power system optimization problems using MATLAB -R2022b software [23] on a computer with an Intel (R) Core (TM) i7-3770 CPU clocked at 3.40GHz and 8GB of RAM. The proposed AFCPOA's results of test functions were compared with other algorithms viz. JA, ABC, TLBO, DE, PSO, and GA [1]. The proposed AFCPOA was run 30 times on each benchmark functions and the statistical results were compared with other algorithms for the same number of runs. The comparative results of 8 benchmark unconstrained test functions and 8 constrained bench mark test functions with are tabulated in Table I and Table II, respectively. The convergence plots of constrained test functions are given in Figure 1 to Figure 8. AFCPOA is implemented on IEEE 30 Bus test system to mitigate overall fuel cost by optimizing ELD and OPF. The IEEE 30 Bus test system data is drawn from [19].

A. Economic Load Dispatch problem Results

There are 6 generating units for which the generation can be controlled. The fuel cost coefficients, physical generation limits of generators and loss coefficients are taken from the [19]. The optimization variables are the powers generated from the 6 generators. The physical limits of generators serve as the bounds of optimization space. The 6 generators are expected to support a load of 283.4MW. This serves as an equality constraint. AFCPOA is run with an initial population of 200 for 200 epochs. Figure 9 shows the convergence plot in minimizing the fuel cost. Table III presents a comparison of solution to ELD by AFCPOA with other existing algorithms in the literature. It can be seen that the AFCPOA has the lowest overall fuel cost for generating at 761.7114 $/hr in comparison with other methods.

B. Optimal Power flow problem Results

The IEEE 30 Bus test system data (line and bus data) including control variables (active power generation limits), constraints, and fuel cost coefficients, are taken from [20]. Table IV compares the numerical results of the proposed method to the OPF problem's solution utilizing various optimization algorithms. The total fuel cost results obtained by proposed method is better than other existing methods. AFCPOA technique has the lowest overall fuel cost for generation at 801.7101 $/hr in comparison with other methods. The cost-variation convergence plot based on AFCPOA is given in Figure 10.

V. Conclusions

This study tested the performance of the proposed AFCPOA in solving unconstrained and constrained benchmark test functions. Two power system optimization problems, namely, economic load disptach and optimal power flow problems were solved using AFCPOA method. The possibility of obtaining global optimal solution is very high vis-à-vis other optimization methods. The performance of AFCPOA in comparison with other meta heuristic optimization algorithms is quite significant. In further studies, the proposed method can be applied to several optimization problems in different areas of engineering.

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