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Evolutionary Based Optimal Power Flow Solution For Load Congestion Using PRNG

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Abstract *- This paper presents a solution for optimal power flow by considering the random nature of load variations in a regulated electricity network. The algorithms are based on an evolutionary approach. Namely, Improved Learner Performance-based Behaviour algorithm (ILPB), Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO), and Harris Hawks Algorithm (HHO) are attempted to identify the best solution under random load variations. The concept of a pseudo-random number generator is used to represent the variations in load. The IEEE-30 and IEEE-118 bus standard systems are considered in addition to the practical 62-bus Indian utility system to evaluate the performance of the algorithms. The systems are assessed with different objectives such as total fuel cost, total active power losses, total voltage deviation, and voltage stability index to achieve the optimal solution for the power flow problem. The purpose of all algorithms is to obtain the optimal solution by minimizing the fitness functions. Based on the optimal value of the solution and convergence characteristics of the test systems, the effectiveness and robustness of the algorithms are compared under random load conditions and definite raise and fall-off load conditions.*

Keywords: *Grey Wolf Optimization; Harris Hawks Optimization; Improved Learner Performance-based Behaviour algorithm; Optimal power flow; Whale Optimization Algorithm*

I. INTRODUCTION

The optimal Power Flow (OPF) problem is mathematically formulated in the 1960s by Carpentier[1], and significant dedicated attempts have been concerned with finding a decisive solution to the problem. In the near future, the majority of the power system networks are associated with renewable energy sources and electric vehicles. The arrival of renewable energy sources, electrical vehicles, hybrid AC-DC grid systems, energy storage systems, different generating stations, uncertainty in load conditions, and numerous interconnections has made the power system more complex, robust, complicated, non-linear, non-convex, unregulated, and unpredictable structure [2]. The study of power systems addresses the security, operation, and planning problems. The mainly concentrated problem of power systems is optimal power flow [3]. A solution to the OPF problem gives a solution to economic dispatch, unit commitment, and reactive power dispatch. OPF problem is drafted with both balanced and imbalanced constraints. The power flow equations form the balanced constraints. The bounds of dependent and independent variables form the imbalanced constraints [4]. The dependent variables (control variables) are the generator's active power at the reference bus, voltages at the PQ bus, the generator's reactive power at all PV buses, and apparent power flow in transmission lines. The independent variables (decision variables) are the generator's active power at all PV buses except the reference bus, voltages at all PV buses, compensator's reactive power, and online tap settings transformers. Obtaining a solution to the OPF problem is very difficult for engineers using conventional methods such as Newton-Raphson and Lagrangian method, Linear and quadratic programming, Interior point, and Gradient methods [5-7]. The traditional techniques are not much efficient in getting the solution for systems with non-differential, non-convex, discrete, continuous, complex objective functions and constraints.

To overthrow the complication of conventional methods, artificial intelligent searching methods are used to solve the OPF problem. Artificial intelligent searching algorithms are categorized as inspired evolutionary algorithms, physics-inspired algorithms, human-inspired algorithms, and nature-inspired algorithms. Evolutionary inspired algorithms to solve OPF problems are Genetic Algorithm (GA), Evolutionary Programming (EP), Differential Evolution Algorithm (DE), Differential Search Algorithm (DSA), Backtracking Search Algorithm (BSA, Improved Evolutionary Algorithm (IEA) and so on. Physics inspired algorithms for solving OPF problems are Colliding Bodies Optimization Algorithm (CBOA), Improved Colliding Bodies Optimization Algorithm (ICBOA), Opposition Based Gravitational Algorithm (OBGA), Gravitational Search Algorithm (GSA), Black-Hole based Optimization Algorithm (BHOA), Simulated Annealing (SA)and so on.,. Human inspired algorithms to solve OPF problems are Biogeography Based Optimization (BBO), Imperialist Competitive Algorithm (ICA), The League Championship Algorithm (TLCA), Teaching Learning Based Optimization (TLBO), Tabu Search (TS), and so on., Nature-inspired algorithms for OPF problem are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Moth Flame Algorithm (MFA), Moth Swarm Algorithm (MSA), Glow Worm Swarm Optimization (GWSO), Krill Herd Algorithm (KHA), Shuffled Frog Leaping Algorithm (SFLA)and so on., [8].

In this paper, the existing Learner Performance Behavior-based algorithm (LPB) [9] is improved by implementing simulated binary crossover instead of arithmetic crossover and named as Improved Learner Performance Behavior algorithm (ILPB). The proposed ILPB is used to solve the optimal power flow problem in the power systems. The ILPB algorithm resembles the process of learners getting admissions into different departments in different institutions for graduation from different high school education. The performance behavior of the learners is unusual during college study when compared with school study. The performances of the learners are made more effective for college study with the help of adding some factors to the school study procedure. Multiple groups of the population are formed with learners based on the CGPA score. By forming populations based on CGPA, it causes a good balance between exploration and exploitation. The first and foremost step in ILPB is the creation of an initial population randomly. Next, a percentage of the population is separated from the initial random population based on the divide probability (dp) value. Next is to form two groups from the separated population based on the fitness value. The subpopulation with the highest fitness is named as good population group (GP), and the sub-population with the lowest fitness is named as Bad population group (BP). High priority is given to the individuals that are present in a good population group to enter the optimization process. At last, new individuals are generated by applying crossover (SBX) and mutation operators. The performances of the individuals are improved by SBX and mutation operators.

In this paper, evolutionary inspired algorithm ILPB - Improved Learner Performance-based Behaviour algorithm (ILPB) and nature-inspired algorithms WOA, GWO, and HHO are used to determine the solution for OPF problem with balance and imbalanced constraints. The solution to the OPF problem is to think about reducing total fuel cost, decreasing active power loss, improving voltage profile, and enhancing voltage stability limit. The solution for the OPF problem with random load conditions and definite raise and the fall-off in load conditions are addressed in this paper by considering various EAs viz., ILPB, WOA, GWO, and HHO.

This paper is structured as Section-I with Introduction and importance of OPF, Section-II with the formulation of OPF problem along with the fitness functions and respective constraints, Section-III describes different EAs, Section-IV reports the results of EAs, and Section-V concludes the findings of research and future scope.

II. PROBLEM FORMULATION

The OPF problem can be arithmetically described as $\min F(x,u)$ exposed to

$$g_j(x,u) = 0 \qquad j = 1,2,3, \dots\dots\dots\dots m \quad (1)$$

$$h_j(x,u) \leq 0 \qquad j = 1,2,3, \dots\dots\dots\dots p \quad (2)$$

F is the fitness function that is to be optimized, x is a vector of dependent variables (state variables), u is a vector of independent variables (control variables), g_j is balanced constraints, h_j is imbalanced constraints, m is the number of balanced constraints, p is the number of imbalanced constraints.

The vector of state variables, x in the power system, can be represented as

$$x = [P_{G1}, V_{L1} \dots, V_{LN}, Q_{G1}, \dots Q_{GN}, S_{TL1} \dots, S_{TLN}] \quad (3)$$

P_{G1} is the real power of slack bus (reference bus), V_L is the voltage of load bus (PQ bus), Q_G is reactive power of generator bus (PV bus), S_{TL} is apparent power flow in the transmission line, LN is number of load buses, GN is number of generator buses, TLN is number of transmission lines

The vector of control variables, u in the power system, can be represented as

$$u = [P_{G2}, ., P_{GN}, V_{G1}, ., V_{GN}, Q_{C1}, ., Q_{CN}, T_1, ., T_{TN}] \quad (4)$$

P_G is the output power of all generators except the reference bus, V_G is the voltage of all generator buses, Q_C is the injected reactive power of shunt compensator, T is tap settings of the transformer, CN is the number of shunt compensators, TN is the number of transformers.

A. Objective Functions

1). Total Fuel Cost: The first fitness function is to reduce the total fuel cost, which is communicated as

$$TFC = \sum_{i=1}^{GN} F_i(P_{Gi}) = \sum_{i=1}^{GN} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \quad (5)$$

F_i is fuel cost of i^{th} generator, a_i, b_i, c_i is the cost coefficients of i^{th} generator

2). Total Active Power Losses: The second fitness function is to decrease the total active power loss expressed as:

$$TAPL = \sum_{i=1}^{TLN} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}) \quad (6)$$

G_{ij} is the conductance of the transmission line,δ_{ij} is the phase difference between voltages.

3). Voltage Profile Improvement: The third fitness function is to improve voltage profile by minimizing the total voltage deviations of load buses from the specified voltage, which is expressed as:

$$TVD = \sum_{i=1}^{LN} |(V_i - 1)| \quad (7)$$

4). Voltage Stability Enhancement:

The fourth fitness function is to enhance the stability of the power system by minimizing the voltage stability index (L) value, thereby keep the system far away from voltage collapse. The fitness function is indicated as:

$$VSI = \min(L_{max}) = \min(\max(L_n))\,; n = 1,2,.,L \quad (8)$$

B. Constraints

1). Equality constraints:

$$Generation - Demand - Losses = 0 \quad (9)$$

$$P_{Gi} - P_{Di} - |V_i|\sum_{j=1}^{BN}|V_j|(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}) = 0 \quad (10)$$

$$Q_{Gi} - Q_{Di} - |V_i|\sum_{j=1}^{BN}|V_j|(G_{ij}sin\delta_{ij} - B_{ij}cos\delta_{ij}) = 0 \quad (11)$$

P_{Gi} is generated active power at i^{th} bus, Q_{Gi} is generated reactive power at i^{th} bus, P_{Di} is active load demand at i^{th} bus, Q_{Di} is reactive load demand at i^{th} bus, G_{ij} is conductance between i^{th} bus and j^{th} bus, B_{ij} is susceptance between i^{th} bus and j^{th} bus, δ_{ij} is the phase difference between voltages of i^{th} bus and j^{th} bus, V_i is the voltage at i^{th} bus, V_j is the voltage at j^{th} bus.

2). Inequality constraints:

Generator active power, $P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}$ (13)

Generator bus voltages, $V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}$ (14)

Generator reactive power, $Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}$ (15)

Transformer tap settings, $T_i^{min} \le T_i \le T_i^{max}$ (16)

Shunt VAR compensator, $Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}$ (17)

Apparent power in transmission lines, $S_{Li} \le S_{Li}^{min}$ (18)

The voltage at load bus, $V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}$ (19)

III. EVOLUTIONARY ALGORITHMS

A. Improved Learner Performance-based Behaviour algorithm (ILPB):

In the proposed ILPB algorithm, a population P has randomly generated that consists of graduate learners who want to apply for graduate studies in different departments of an institution. Every department has been specified with a minimum CGPA score for eligible learners to be admitted into a particular department. The operators divide probability ‘dp’ is considered as the range specified by the department, through which the population is partitioned into R, and S. S is the population of learners that are eligible for admission in a particular department. The study behavior of graduate learners is different from the study behavior of school learners. Graduate learners are partitioned into high learners and low learners. High learners are having high CGPA than the specified range, whereas the low learners are those having a low specified range of CGPA. Now, the fitness of each individual present in S is calculated, and the individuals are sorted in decreasing order of their fitness value. Divide the population into the high population (HP) consisting of individuals with high fitness and low population (LP) consisting of individuals with low fitness. The highest fitness value of individuals present in HP and LP is evaluated. The fitness of individuals present in the R population is also calculated. If the fitness of the individual present in R is lesser than or equal to the highest fitness value of the individual present in LP, then move the individual from R to LP. If the fitness of the individual present in R is lesser than or equal to the highest fitness value of the individual present in HP, then move the individual from R to HP. Otherwise, if the fitness of the individual present in R is superior to the highest fitness value of the individual present in HP, then move the individual to perfect population PP. The learners having higher CGPA score is preferred more than the learners having lower CGPA for admitting to a particular department. The number of learners specified by the departments is chosen from the PP and HP. If the number of learners is less than the specified number of learners for the departments, then the institute will decide to allot the learners from the low population. In order to perform SBX crossover and arithmetic mutation, choose an individual from PP if it is not empty otherwise, select from HP if it is not empty. If both PP and HP are empty, then select the individual from LP. After accepting the graduate learners, i.e., individuals by the department, the performance behavior of graduate learners needs to be improved. The performance of the graduate learners is improved by seeking help from others, self-study, or working groups. In this algorithm, simulated binary crossover and mutation are implemented for improving the performance behavior of the individual. The role of the crossover operator is to make the individual exchange the study behavior with others. Thus, the individual contains study behavior that is different from the original study behavior of the learners. The study behavior of the individuals is updated randomly or at a specific rate by using a mutation operator. The simulated binary crossover [10] is expressed as eq.20 and eq.21

$$NL_i^{(1,\ t+1)} = 0.5[(1+\beta_{qi})L_i^{(1,\ t)} + (1-\beta_{qi})L_i^{(2,\ t)}]$$
$$NL_i^{(2,\ t+1)} = 0.5[(1-\beta_{qi})L_i^{(1,\ t)} + (1+\beta_{qi})L_i^{(2,\ t)}] \quad (20)$$

$$\beta_{qi} = \begin{cases} (2u_i)^{\frac{1}{\eta_c+1}} & ;\ u_i \le 0.5 \\ [\frac{1}{2(1-u_i)}]^{\frac{1}{\eta_c+1}} & ;u_i > 0.5 \end{cases} \quad (21)$$

where $L_i^{(1,\ t)}$ & $L_i^{(2,\ t)}$ are the solutions of learner-1 & learner-2, $NL_i^{(1,\ t+1)}$ & $NL_i^{(2,\ t+1)}$ are the solutions of new learner-1 & new learner-2, u_i are random numbers between 0 and 1, η_c is distribution index.

The pseudo-code for ILPB is given below:

```
Initial population (P) is created randomly
Specify the parameters of ILPB
While stopping condition is not satisfied
        Split P into R and S based on the dp value
        Calculate fitness of individuals S
        Sort in descending
        Divide population S based on fitness as HP & LP
        Calculate highest fitness (HF) of  HP and LP
        Calculate the fitness (F) of individuals in R
        If FP < HFLP, Move it from R to LP
        Else if FP< HFHP, Move it from R to HP
        Else, Move to Perfect population (PP)
```

While K < N
If PP is not empty, Select it from PP
Else if HP is not empty, Select it from HP
Else, Select it from LP
Increment K
End while
Perform simulated binary crossover
Perform mutation
Check for stopping criteria
If stopping criteria is not satisfied,
go to splitting the population
Else, stop the process by obtaining a solution
End while
Obtain optimal solution

B. Whale Optimization Algorithm (WOA):

The whale optimization algorithm (WOA) is another kind of artificial intelligent algorithm based on the hunting nature of whales. The algorithm involves two phases, namely, exploitation and exploration for the searching of prey [11]. The location of each whale is renovated by bubble net attacking strategy in exploitation, whereas in exploration, each whale renews its position by selecting a random search agent. Bubble net attacking is a strategy of shrinking, encircling the prey in a spiral-shaped movement established on the identified best solution[12].

C. Grey Wolf Optimization (GWO):

The Grey Wolf Optimization (GWO) algorithm is developed by Mirjalili et al. in 2014 [13], which is based on the hunting structure of grey wolves in nature. GWO simply follows the directorship ranking for a searching solution. Alpha (α), beta (β), delta (δ), and omega (Ω) are the arrangements in the directorship ranking that are considered as the best solutions [14]. The steps involved in the GWO algorithm are as follows [15]: GWO starts with the initialization of search agents (grey wolves) with random values. After initialization, the top most solutions are structured based on the leadership hierarchy as α, β, δ in encircling. The fitness values are computed for the leader wolves (α, β, δ). After computing the fitness value, check the stopping condition. If stopping criteria is satisfied, the optimal global solutions are displayed and stop the process. Otherwise, the algorithm follows to hunting, attacking, and exploration stages. In the hunting stage, renew the position of current search agents (α, β, δ).In the attacking stage, determine the fitness value of the current search agents. If the fitness value is not convinced, rearrange the search agents based on directorship ranking in the exploration stage. After exploration, once again, fitness values for new search agents are computed and check for the stop criteria[16].

D. Harris Hawks Optimization (HHO):

Harris hawk's optimization (HHO) algorithm is developed by Heidari et al. [17]. It addresses optimal solutions for various optimization problems based on the hunting nature of Harris hawks. The hunting process involves detecting, surrounding, advancing, and invading the prey[18]. Exploration and exploitation are the two main phases in HHO. There is an intermediate phase, which defines the transformation between exploration and exploitation. The first phase includes foreseeing, searching, and discovering the prey. The second phase contains the initial energy (E_0) and the escaping energy of the prey (E). The transformation between exploration and exploitation hinges on the escaping energy of the prey (E). Depend on the magnitude of |E|, start the exploration phase if $|E| \geq 1$; otherwise exploiting phase if $|E| < 1$. In the exploitation phase, based on the value of |E|, once again, the hawks decide to apply a soft if $|E| \geq 0.5$) or hard besiege if $|E| < 0.5$to capture the prey from a certain space[19].

IV. RESULTS & DISCUSSIONS:

The effectiveness of EAs is tested with random as well as definite raising and fall-off load conditions on the standard IEEE-30 bus system, IEEE-118 bus system, and practical 62-bus Indian utility system. The performances of the EAs are investigated by random varying load conditions using Pseudo-Random Number Generator (PRNG) and definite raise and fall-off load conditions. The simulation results are carried out with AMDA Ryzen 5 processor having 64-bit Windows 7 OS with 8 GB RAM. The simulation is performed in MATLAB 2013b along with MATPOWER 7.0b. The number of population or search agents is seized to 50, and the maximum number of iterations is 200.

For better results of ILPB, the crossover probability, crossover index, mutation index have been changed individually and simulated for 25 individual trail runs. The crossover probability has been changed from 0.75 to 0.95 with an increase of 0.02. The crossover index has been replaced with an interval of 0.5 from 1 to 5. The mutation index has been increased from 10 to 20 with an interim of 2. Finally, ILPB has performed effectively by considering crossover probability as 0.88, crossover index at 3, and mutation index at 18.

Considering the random nature of load variations, the concept of pseudo-random number generator (PRNG) [20] has been implemented in the test systems by using the following expression:

$$R_{n+1} = (xR_n + y)\ mod\ M, n \geq 0 \qquad (22)$$

where, $R_0 is\ the\ initial\ value (0 \leq R_0 < M)$,
$x\ is\ the\ multiplier\ (0 \leq x < M)$,
$y\ \ is\ the\ increment\ (0 \leq y < M)$,
$M\ is\ the\ modulus\ M > 0$,
$R_n\ is\ the\ sequence\ of\ the\ pseudo\ random\ number$

A. Standard Test System-1: IEEE-30 Bus System

The standard test system-1 is composed of 6 generator buses and 24 load bus having 41 branches with 4 online tap changing transformers and 9 reactive power compensators. It is connectedwith21 active loads among 24 load buses, 25 decision variables with a total connected load of (283.4+j 126.2) MVA. The voltage magnitude at the generator bus is bounded to [0.95, 1.1] p.u. The limit of tap settings of online tap changing transformers is [0.9, 1.1] p.u. The limit of shunt capacitors is [0,5] MVAR.

The comparison of the best value of each objective function for standard test system-1with different EAs is given in Table-I. The best value for all objective functions is obtained by using ILPB. ILPB is converged for the raise 25% load and fall-off load of 50%. The first objective function (TFC) is not converged for load greater than 15% raise with WOA and HHO. Above 25% load raise and below 50% fall-off load, all EAs are not giving convergence solution for OPF problem.

The best values of the first objective function (TFC) with variable load condition for standard test system-1using different EAs is shown in Fig.1. For -50% load change, the best value 345.2318 $/hr is obtained by using ILPB, and the worst value 345.2523 $/hr is obtained by using HHO. For +15% load change, the best value 968.1498 $/hr is obtained from ILPB, and the worst value 968.3786 $/hr is obtained from GWO. For +20% and +25%, the objective function is not converged by using WOA and HHO.

The best values of the second objective function (TAPL) with variable load condition for standard test system-1 using different EAs is shown in Fig.2. For -50% load change, the best value 1.1288 MW is obtained by using ILPB, and the worst value 1.1449 MW is obtained by using WOA. For +25% load change, the best value, 6.9791 MW, is obtained from ILPB, and the worst value, 7.0149 MW, is obtained from HHO.

The best values of the third objective function (TVD) with variable load condition for standard test system-1 using different EAs is shown in Fig.3. For -50% load change, the best value 0.4773 p.u is obtained by using ILPB, and the worst value 0.4865 is obtained by using HHO. For +25% load change, the best value 0.5368 p.u is obtained from ILPB, and the worst value of 0.5492 p.u is obtained from HHO.

The best values of the fourth objective function (VSI) with variable load condition for standard test system-1 using different EAs is shown in Fig.4. For -50% load change, the best value 0.0604 p.u is obtained by using ILPB, WOA & HHO, and the worst value 0.0605 is obtained by using GWO. For +25% load change, the best value 0.1590p.u is obtained from ILPB, and the worst value 0.1593p.u is obtained from WOA & HHO.

Table I: Comparison of the best value of each objective function for standard test system-1with load variation using different EAs

Load Variation	EAs	TFC	TAPL	TVD	VSI
-50 %	**ILPB**	**345.2318**	**1.1288**	**0.4773**	**0.0604**
	WOA	345.2383	1.1449	0.4859	0.0604
	GWO	345.2469	1.1346	0.4797	0.0605
	HHO	345.2523	1.1415	0.4865	0.0604
-40 %	**ILPB**	**420.6105**	**1.6126**	**0.4705**	**0.0729**
	WOA	420.6182	1.6306	0.4737	0.0732
	GWO	420.6363	1.6205	0.4770	0.0730
	HHO	420.6359	1.6272	0.5060	0.0731
-30 %	**ILPB**	**507.3688**	**2.2920**	**0.4656**	**0.0857**
	WOA	507.3922	2.3138	0.4752	0.0857
	GWO	507.3884	2.3115	0.5090	0.0857
	HHO	507.4042	2.3168	0.4832	0.0857
-20 %	**ILPB**	**601.7954**	**2.7285**	**0.4926**	**0.0983**
	WOA	601.8329	2.7492	0.4970	0.0990
	GWO	601.8272	2.7445	0.5124	0.0985
	HHO	601.8902	2.7739	0.4968	0.0988
-10 %	**ILPB**	**700.0150**	**3.0988**	**0.4946**	**0.1114**
	WOA	700.0578	3.1294	0.5359	0.1116
	GWO	700.0885	3.1081	0.5102	0.1114
	HHO	700.0979	3.1236	0.6230	0.1116
Normal load condition	**ILPB**	**802.1448**	**3.6487**	**0.5279**	**0.1248**
	WOA	802.2270	3.6687	0.5383	0.1249
	GWO	802.2899	3.6648	0.5362	0.1249
	HHO	802.2337	3.6681	0.5442	0.1248
+05 %	**ILPB**	**855.4127**	**4.0111**	**0.5271**	**0.1313**
	WOA	855.4986	4.0324	0.5403	0.1315
	GWO	855.5293	4.0317	0.5466	0.1313
	HHO	855.6311	4.0419	0.5636	0.1315
+10 %	**ILPB**	**910.6807**	**4.4714**	**0.5368**	**0.1384**
	WOA	910.7851	4.4896	0.5534	0.1385
	GWO	910.7514	4.5288	0.5548	0.1385
	HHO	910.8064	4.5017	0.5381	0.1384
+15 %	**ILPB**	**968.1498**	**5.0280**	**0.5443**	**0.1449**
	WOA	968.2131	5.0447	0.5771	0.1452
	GWO	968.3786	5.0955	0.5456	0.1450
	HHO	968.2800	5.0484	0.5923	0.1451
+20 %	**ILPB**	**1029.5633**	**5.9471**	**0.5347**	**0.1522**
	WOA	*NC*	5.9822	0.5721	0.1524
	GWO	1029.7956	6.0083	0.5400	0.1529
	HHO	*NC*	5.9683	0.5393	0.1523
+25 %	**ILPB**	**1096.0174**	**6.9791**	**0.5368**	**0.1590**
	WOA	*NC*	7.0119	0.5488	0.1593
	GWO	1096.2891	7.0005	0.5369	0.1591
	HHO	*NC*	7.0149	0.5492	0.1593

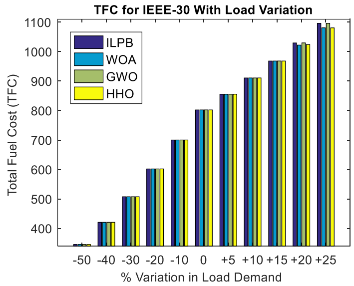

Fig.1: TFC with variable load for standard test system-1

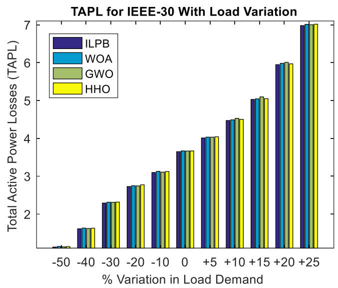

Fig.2: TAPL with variable load for standard test system-1

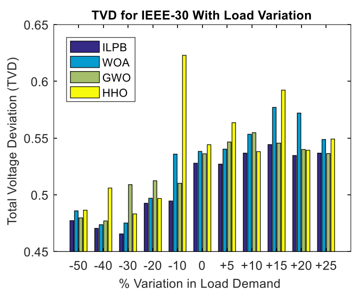

Fig.3: TVD with variable load for standard test system-1

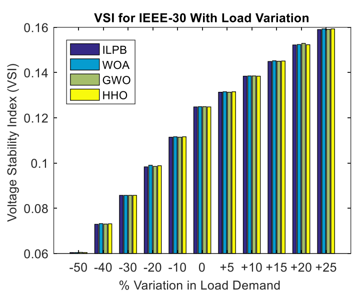

Fig.4: VSI with variable load for standard test system-1

The convergence characteristics of the objective function, total fuel cost (TFC) with two random loads are laid out in Fig.5. From Fig.5, for random load-1, ILPB and GWO are converged, whereas WOA and HHO are not converged. For random load-2, all the EAs are converged. The convergence characteristics of the objective function, total active power losses (TAPL) with two random loads, are set out in Fig.6. All the EAs are converged. The convergence characteristics of the objective function, total voltage deviation (TVD) with two random loads, are displayed in Fig.7. For two random loads, all the EAs are converged. The convergence characteristics of objective function, voltage stability index (VSI) with two random loads are posted in Fig.8. For two random loads, all the EAs are converged.

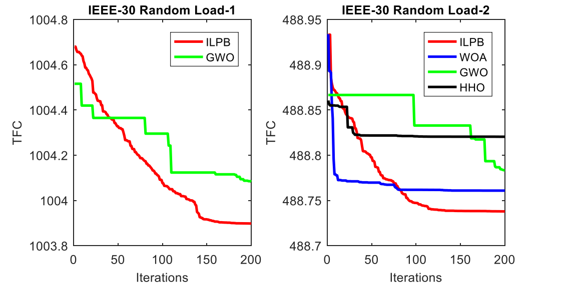

Fig.5: Convergence curve for TFC with random loads for standard test system-1.

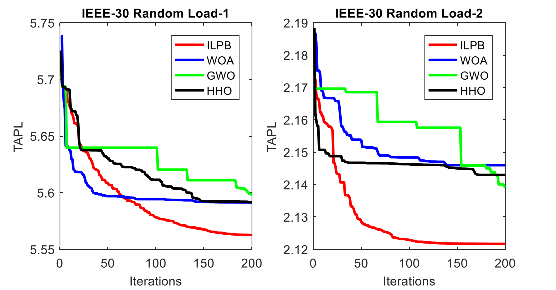

Fig.6: Convergence curve for TAPL with random loads for standard test system-1.

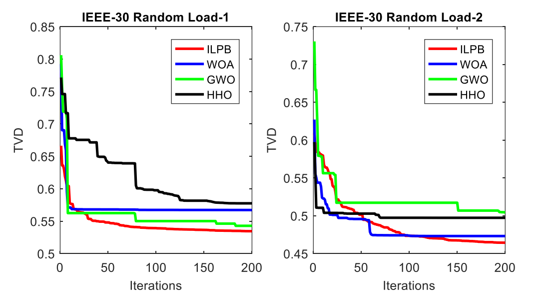

Fig.7: Convergence curve for TVD with random loads for standard test system-1.

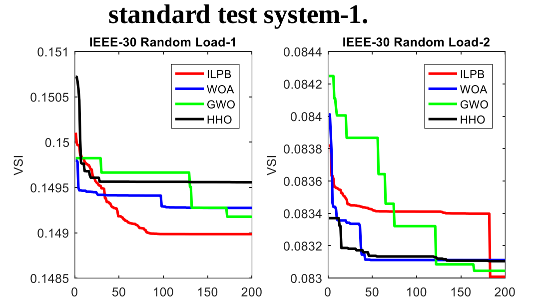

Fig.8: Convergence curve for VSI with random loads for standard test system-1.

The best optimum values for each objective function obtained by using different EAs under random loads 1 & 2 are given in Table II & Table II. The best optimum value is given by ILPB when compared with other EAs under random load conditions. For objective function TFC, with random load-1, WOA and HHO have not given the converged optimal value.

Table II: Comparison of the best value of each objective function for standard test system-1with two random load-1 using different EAs

EAs	TFC	TAPL	TVD	VSI
ILPB	1003.8981	5.5626	0.5346	0.1490
WOA	NC	5.5914	0.5672	0.1493
GWO	1004.0834	5.5984	0.5429	0.1492
HHO	NC	5.5915	0.5776	0.1496

Table III: Comparison of the best value of each objective function for standard test system-1with two random load-2 using different EAs

EAs	TFC	TAPL	TVD	VSI
ILPB	488.7379	2.1217	0.4644	0.0830
WOA	488.7609	2.1460	0.4732	0.0831
GWO	488.7834	2.1392	0.5045	0.0830
HHO	488.8204	2.1430	0.4973	0.0831

B. Standard Test System-2: IEEE-118 Bus System

The standard test system-2 contains 54 generators and 99 active load bus having 186 branches with 9 online tap changing transformers and 12 reactive power compensators. It observed that 129 decision variables with a total connected load of (4242+j 1438) MVA. The limit of voltage magnitude of generator bus is [0.96, 1.1] p.u. The limit of tap settings of online tap changing transformers is [0.9, 1.1] p.u. The limit of shunt capacitors is [0, 40] MVAR.

The comparison of the best value of each objective function for standard test system-2 with different EAs is given in Table-IV. The best value for all objective functions is obtained by using ILPB. ILPB is converged for the load raise of 100% and fall-off load of 99%. The first objective function (TFC) is not converged for fall-off load at 99% with GWO, and the fourth objective function (VSI) is not converged for raise of load at 100% with WOA, GWO, and HHO. Only ILPB is giving convergence solution for all objective functions at +100% raise load condition. The solutions for the OPF problem are obtained from EAs when the load is doubled (except ILPB) and at no-load condition is not converged.

The best values of the first objective function (TFC) with variable load condition for standard test system-2 using different EAs is shown in Fig.9. For -80% load change, the best value 18733.6251 $/hr is obtained by using ILPB, and the worst value 18828.1230 $/hr is obtained by using WOA. For +100% load change, the best value 308701.4151 $/hr is obtained from ILPB, and the worst value 308791.3128 $/hr is obtained from WOA.

The best values of the second objective function (TAPL) with variable load condition for standard test system-2 using different EAs is shown in Fig.10. For -99% load change, the best value 0.7701 MW is obtained by using ILPB, and the worst value 0.9612 MW is obtained by using GWO. For +100% load change, the best value 177.5186 MW is obtained from ILPB, and the worst value 180.1621 MW is obtained from WOA.

The best values of the third objective function (TVD) with variable load condition for standard test system-2 using different EAs is shown in Fig.11. For -99% load change, the best value 0.5530p.u is obtained by using ILPB, and the worst value 0.7010 is obtained by using HHO. For +100% load change, the best value 1.2103p.u is obtained from ILPB, and the worst value of 1.3485p.u is obtained from HHO.

The best values of forth objective function (VSI) with variable load condition for standard test system-2 using different EAs is shown in Fig.12. For -99%, -80%, -60%, -40%, -20%, 0%, +20% load change, the values0.0006 p.u, .00118 p.u, 0.0238 p.u, 0.0360 p.u, 0.0485 p.u, 0.0617 p.u, 0.0749 p.u is obtained by all EAs. For +40% load variation, the best value 0.0878 p.u is obtained from ILPB and worst value 0.0881 is obtained by using WOA and GWO. For +80% load change, the best value 0.1155 p.u is obtained from ILPB, WOA & HHO and the worst value 0.1186p.u is obtained from GWO. The objective function is not converged for increase load of 100% with WOA, GWO & HHO.

Table IV: Comparison of the best value of each objective function for standard test system-2 with load variation using different EAs

Load Variation	EAs	TFC	TAPL	TVD	VSI
-99 %	**ILPB**	**869.8129**	**0.7701**	**0.5530**	**0.0006**
	WOA	876.0480	0.7931	0.5808	0.0006
	GWO	*NC*	0.9612	0.5870	0.0006
	HHO	876.3674	0.7971	0.7010	0.0006
-80 %	**ILPB**	**18733.6251**	**5.4486**	**0.4568**	**0.0118**
	WOA	18828.1230	5.7733	0.5232	0.0118
	GWO	18733.9233	5.5055	0.4985	0.0118
	HHO	18738.6633	5.7863	0.5407	0.0118
-60 %	**ILPB**	**41003.7475**	**17.4745**	**0.5855**	**0.0238**
	WOA	41003.7537	17.5734	0.7843	0.0238
	GWO	41005.3680	17.8540	0.6789	0.0238
	HHO	41003.8726	17.7501	0.6558	0.0238
-40 %	**ILPB**	**66950.5178**	**38.6525**	**0.7058**	**0.0360**
	WOA	66954.8437	38.7506	0.8933	0.0360
	GWO	66953.8388	38.6625	0.7804	0.0360
	HHO	66954.4312	38.6528	1.0994	0.0360
-20 %	**ILPB**	**96689.9188**	**68.4047**	**0.9524**	**0.0485**
	WOA	96692.4737	68.6140	1.0244	0.0485

	GWO	96690.7137	68.5163	0.9656	0.0485
	HHO	96699.8482	68.6106	1.2586	0.0485
Normal load condition	**ILPB**	**129611.5389**	**76.5261**	**0.9702**	**0.0617**
	WOA	129625.8773	76.7294	1.1864	0.0617
	GWO	129619.7429	76.6517	0.9863	0.0617
	HHO	129631.5253	76.7381	1.3193	0.0619
+20 %	**ILPB**	**163663.9268**	**77.3984**	**0.9019**	**0.0749**
	WOA	163677.2465	77.7411	1.0427	0.0749
	GWO	163677.2790	77.6256	0.9019	0.0749
	HHO	163679.5190	77.8091	1.0670	0.0749
+40 %	**ILPB**	**198428.6687**	**85.0616**	**1.0814**	**0.0878**
	WOA	198449.3826	85.5621	1.0822	0.0881
	GWO	198440.7312	85.4477	1.2394	0.0881
	HHO	198454.0929	85.5854	1.1262	0.0879
+60 %	**ILPB**	**233955.4680**	**103.0500**	**1.1193**	**0.1015**
	WOA	233979.7052	103.5865	1.1772	0.1015
	GWO	233987.6681	103.3460	1.1903	0.1016
	HHO	233966.4871	103.7777	1.2302	0.1016
+80 %	**ILPB**	**270473.9980**	**135.3619**	**1.2053**	**0.1155**
	WOA	270537.9866	136.3003	1.2230	0.1155
	GWO	270484.1765	135.6727	1.2372	0.1186
	HHO	270477.9296	136.4068	1.3148	0.1155
+100 %	**ILPB**	**308701.4151**	**177.5186**	**1.2103**	**0.1281**
	WOA	308791.3128	180.1621	1.2603	*NC*
	GWO	308725.8751	178.7836	1.2181	*NC*
	HHO	308701.5428	179.4587	1.3485	*NC*

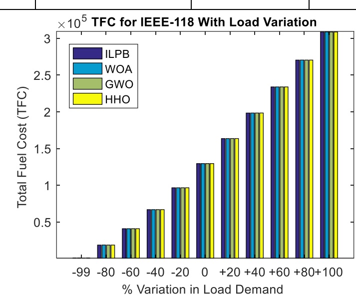

Fig.9: TFC with variable load for standard test system-2 using different EAs.

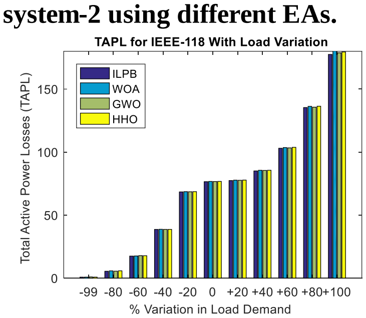

Fig.10: TAPL with variable load for standard test system-2 using different EAs.

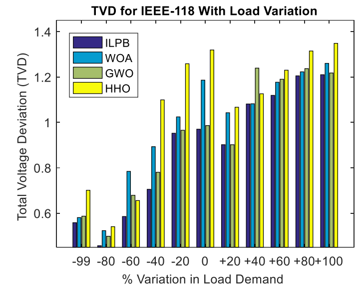

Fig.11: TVD with variable load for standard test system-2 using different EAs.

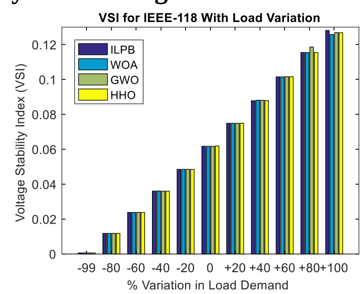

Fig.12: VSI with variable load for standard test system-2 using different EAs.

The characteristic convergence curves for objective functions with two random load conditions for standard test system-2 are shown in Fig.13-Fig.16. For the two random load conditions, the optimum values obtained are all converged values.

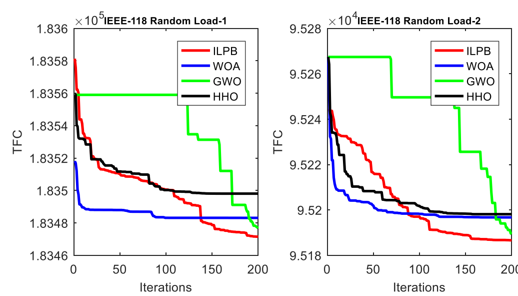

Fig.13: Convergence curve for TFC with random loads for standard test system-2.

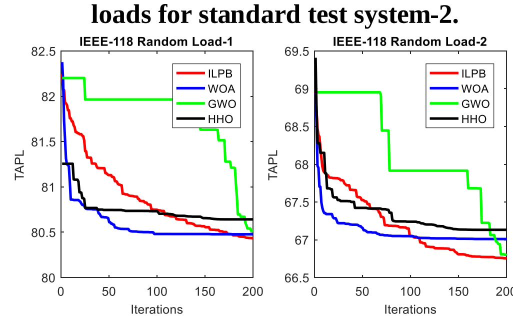

Fig.14: Convergence curve for TAPL with random loads for standard test system-2.

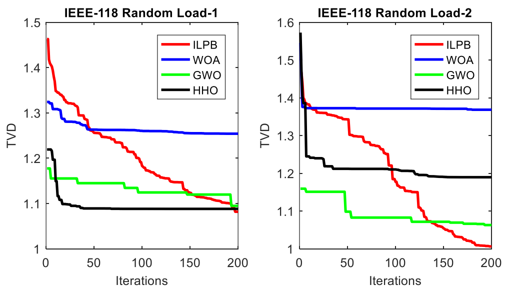

Fig.15: Convergence curve for TVD with random loads for standard test system-2.

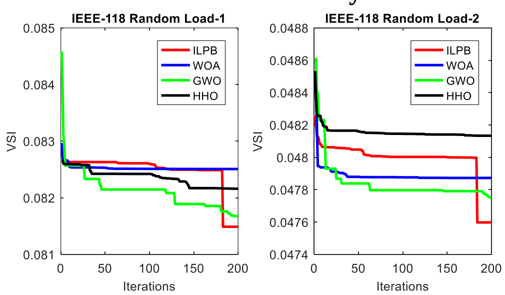

Fig.16: Convergence curve for VSI with random loads for standard test system-2.

A comparison of the best optimum value for standard test system-2 by using different EAs under random load conditions is given in Table V & VI. The best optimum value is given by ILPB when compared with other EAs under different load demands.

Table V: Comparison of the best value of each objective functions for standard test system-2 with random load-1 using different EAs

EAs	TFC	TAPL	TVD	VSI
ILPB	183471.4715	80.4343	1.0817	0.0815
WOA	183483.1070	80.4771	1.2541	0.0825
GWO	183476.8013	80.5149	1.0948	0.0817
HHO	183498.0743	80.6418	1.0882	0.0822

Table VI: Comparison of the best value of each objective functions for standard test system-2 with random load-2 using different EAs

EAs	TFC	TAPL	TVD	VSI
ILPB	95186.6492	66.7519	1.0063	0.0476
WOA	95196.7275	67.0099	1.3684	0.0479
GWO	95189.4459	66.7921	1.0930	0.0477
HHO	95198.1292	67.1320	1.1896	0.0481

C. Practical Test System: 62-bus Indian utility system

The practical test system consists of 19 generator buses and 44 active load buses, having 89 branches with 11 online tap changing transformers. The OPF model consists of 49 decision variables with a total connected load of (2908+j 1270) MVA. The limit of voltage magnitude of generator bus is [0.9, 1.1] p.u. The limit of tap settings of online tap changing transformers is [0.9, 1.1] p.u. The practical test system doesn't have any shunt capacitors.

The comparison of the best value of each objective function for a practical test system with different EAs is given in Table-VII. It is observed that the best value for all objective functions is obtained by using ILPB. ILPB is converged for the increasing load of 20% and a decreasing load of 20%. The second objective function (TAPL) is not converged for increasing and decreasing load other than static load condition with GWO. Above 20% and below -20% of static load, all EAs are not giving convergence solutions for the OPF problem.

The best values of the first objective function (TFC) with variable load condition for practical test system using different EAs is shown in Fig.17. For -20% load change, the best value 9529.4666 $/hr is obtained by using ILPB, and the worst value 9530.9329 $/hr is obtained by using WOA. For +20% load change, the best value 17738.5791 $/hr is obtained from ILPB, and the worst value 17747.8833 $/hr is obtained from HHO.

The best values of the second objective function (TAPL) with variable load condition for practical test system using different EAs is shown in Fig.18. For a no-load change, the best value of 73.8746 MW is obtained by using ILPB, and the worst value of 75.6726 MW is obtained by using GWO. For +20% and -20% load change, only ILPB is giving convergence solution for second objective function (TAPL) of OPF problem. GWO is not giving a converged solution other than static load condition. WOA is giving a convergence solution only for +5% changes in load. The convergence solution with HHO is not obtained for above +10% and below 10% change in load.

The best values of the third objective function (TVD) with variable load condition for practical test system using different EAs is shown in Fig.19. For -20% load change, the best value 0.5614p.u is obtained by using ILPB, and the worst value 0.6904 is obtained by using HHO. For +20% load change, the best value 0.9778p.u is obtained from ILPB, and the worst value 1.0181 p.u is obtained from WOA.

The best values of the fourth objective function (VSI) with variable load condition for practical test system using different EAs is shown in Fig.20. For -20% load change, the best value 0.0789p.u is obtained by using ILPB, GWO& HHO, and the worst value 0.0801 is obtained by using WOA. For +20% load change, the best value 0.1216p.u is obtained from ILPB & GWO and WOA gives worst value 0.1245p.u.

Table VII: Comparison of the best value of each objective function for practical test system with load variation using different EAs

Load Variation	EAs	TFC	TAPL	TVD	VSI
-20 %	**ILPB**	**9529.4666**	**59.8340**	**0.5614**	**0.0789**
	WOA	9530.9329	*NC*	0.6884	0.0801
	GWO	9530.3643	*NC*	0.6242	0.0789
	HHO	9529.5254	*NC*	0.6904	0.0789
-15 %	**ILPB**	**10414.7694**	**62.5738**	**0.6376**	**0.0838**
	WOA	10416.7006	*NC*	0.7777	0.0856
	GWO	10417.3007	*NC*	0.6503	0.0838
	HHO	10423.1835	*NC*	0.7394	0.0847
-10 %	**ILPB**	**11339.6623**	**65.8245**	**0.7188**	**0.0888**
	WOA	11343.0021	*NC*	0.7635	0.0907
	GWO	11343.4542	*NC*	0.7787	0.0888
	HHO	11343.4767	68.3816	0.7848	0.0894
-05 %	**ILPB**	**12302.9783**	**69.7499**	**0.9254**	**0.0937**
	WOA	1206.3554	*NC*	0.9739	0.0962
	GWO	12307.7957	*NC*	0.9617	0.0937
	HHO	12308.1212	70.0412	0.9285	0.0937
Normal load condition	**ILPB**	**13305.4267**	**73.8746**	**0.8049**	**0.0986**
	WOA	13309.6423	74.1200	0.8946	0.1004
	GWO	13309.4078	75.6726	0.8378	0.0986
	HHO	13309.3016	74.3201	0.8467	0.0994
+05 %	**ILPB**	**14350.4550**	**79.2281**	**0.6874**	**0.1038**
	WOA	14353.2951	79.8902	0.8592	0.1038
	GWO	14352.2559	*NC*	0.6896	0.1038
	HHO	14358.3237	80.4930	0.8599	0.1052
+10 %	**ILPB**	**15435.1115**	**85.9632**	**0.7269**	**0.1096**
	WOA	15442.0570	*NC*	0.9585	0.1119
	GWO	15442.3619	*NC*	0.7378	0.1096
	HHO	15442.4480	86.3737	1.0741	0.1096
+15 %	**ILPB**	**16565.6209**	**92.8508**	**0.8507**	**0.1155**
	WOA	16572.7578	*NC*	1.0206	0.1185
	GWO	16570.9340	*NC*	0.8776	0.1155
	HHO	16586.1248	93.4954	0.9859	0.1157
+20 %	**ILPB**	**17738.5791**	**100.6230**	**0.9778**	**0.1216**
	WOA	17745.5178	*NC*	1.0181	0.1245
	GWO	17746.4443	*NC*	0.9808	0.1216
	HHO	17747.8833	*NC*	1.0157	0.1223

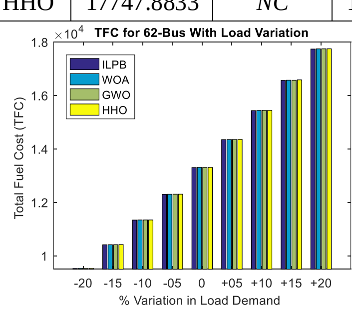

Fig.17: TFC with variable load for practical test system using EAs.

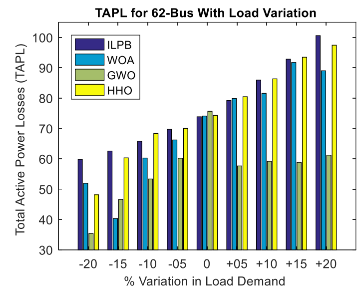

Fig.18: TAPL with variable load for practical test system using EAs.

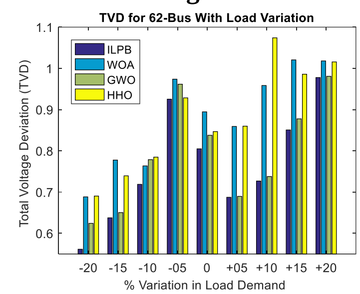

Fig.19: TVD with variable load for practical test system using EAs.

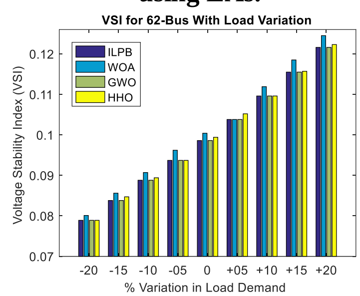

Fig.20: VSI with variable load for practical test system using EAs.

The convergence characteristic curve for objective functions with two random load conditions of the practical test system is shown in Fig.21 – Fig.24. With random load-1 conditions, for objective function TAPL, only ILPB has given the converged optimal value. With the random load-2 condition, for the objective function, TAPL, ILPB, and HHO have given the converged optimal value.

A comparison of the best optimum value by using different EAs under random load conditions for a practical test system is given in Table VIII & IX. The best optimum value is given by ILPB when compared with other EAs under random load demands. For objective function, TAPL, WOA, GWO, and HHO have not given the converged optimal value with random load-1. With random load-2, WOA and GWO have not given converged optimal value for objective function TAPL

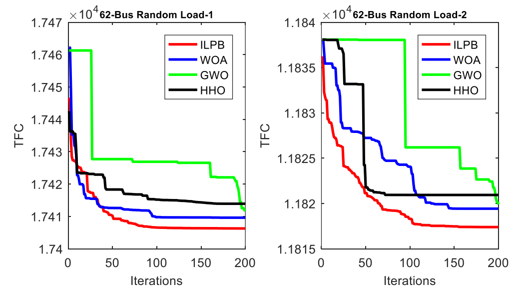

Fig.21: Convergence curve for TFC with random loads for the practical test system.

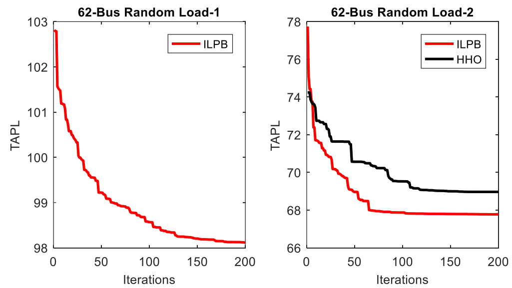

Fig.22: Convergence curve for TAPL with random loads for the practical test system.

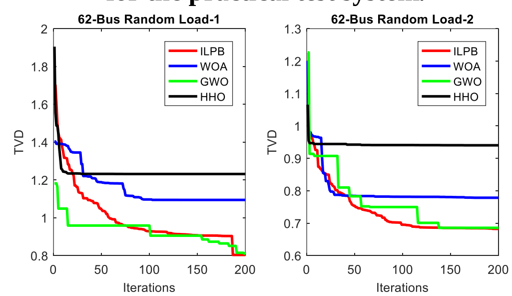

Fig.23: Convergence curve for TVD with random loads for the practical test system.

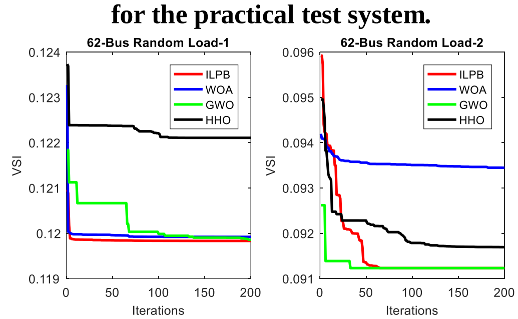

Fig.24: Convergence curve for VSI with random loads for the practical test system.

Table VIII: Comparison of the best value of each objective function for practical test system with random load-1 using different EAs

EAs	TFC	TAPL	TVD	VSI
ILPB	17406.2879	98.1169	0.8037	0.1198
WOA	17409.6244	NC	1.0945	0.1199
GWO	17411.8090	NC	0.8077	0.1199
HHO	17413.9365	NC	1.2316	0.1221

Table IX: Comparison of the best value of each objective functions for practical test system with random load-2 using different EAs

EAs	TFC	TAPL	TVD	VSI
ILPB	11817.3992	67.7747	0.6825	0.0912
WOA	11819.4308	NC	0.7785	0.0934
GWO	11819.9053	NC	0.6857	0.0912
HHO	11820.9436	68.9684	0.9403	0.0917

V. CONCLUSIONS

This paper successfully identifies the best optimal value and solution for each objective function of the optimal power flow problems using EAs viz., ILPB, WOA, GWO, and HHO with random load variation and definite raise and fall-off load conditions.WOA has poor convergence both in exploitation and exploration. WOA has less capability to avoid trapping from local minima in encircling. The imbalance between exploitation and exploration in GWO leads to an inaccurate global optimal value. Randomization technique of HHO has increased time computation time. The difficulties suffered by WOA, GWO, HHOare conquered by usingILPB to get a solution. The OPF problem is investigated for standard test systems 1 and 2 along with the Indian practical test system. The results have shown that the achievement of the inspired evolutionary approach, ILPB is better than the nature-inspired approaches WOA, GWO, HHO in terms of optimal value and convergence characteristics. ILPB has given converged optimal value for standard test system-1 with a raise of 25% load and a fall-off of 50% of the load. The standard test system-2 is converged for 100 % raise inrated load level and falls-off load up to 99% of its rated load level. Even though the load is doubled and reduced near to no-load conditions, ILPB has given converged optimal value for standard test system-2. The convergence and robust performance of ILPB can be assessed with a practical test system where the other EAs, viz., WOA, GWO, HHO are failed to give converged optimal value for TAPL objective function. ILPB has performed better than others, with an increase of 20% load and a decrease of 20% load for the 62-bus Indian utility system. The performance of ILPB can be increased by proper selection of crossover constant and mutation constant. In this paper, with the crossover probability of 0.88, crossover index of 18, ILPB has superior convergence characteristics than other techniques. The convergence solution obtained by using ILPB dominates the other algorithms. From the convergence characteristics of ILPB for a practical test system, the robustness of the algorithm is understood. The optimal value obtained by using ILPB method yields the best results for all the objective functions of the OPF problem with random load conditions and definite raise and fall-off load conditions. The solution of OPF can perform an important role in the efficient planning, maintenance, enhancement, and operation of electrical power systems.

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