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# Reducing Real Power Loss of AC/DC Hybrid Systems by using Teaching Learning based Algorithm

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***ABSTRACT*** *– This Paper Presents a Teaching Learning based Optimization (TLBO) for the Solution of the Optimal Power Flow (OPF) for AC/DC Systems, aiming to reduce the Real Power loss(RPL). Optimal Power Flow (OPF) is an important operational and planning problem in minimizing the chosen objectives of the power system. The recent developments in power electronics allow replacing the existing transmission lines by DC links with a view of making the operation more flexible, secure and economical. This paper formulates a new DC link placement problem through extending the standard OPF to embrace DC link equations and presents a heuristic optimization technique, inspired from the teaching-learning process in class rooms, for solving the problem. The solution process involves sequential NR based AC/DC power flowThe proposed algorithm (PA) is applied to the standard three IEEE test systems and the results are presented to demonstrate its effectiveness.*

***Keywords: real power loss, AC/DC power flow, teaching-learning based optimization ,valve point effect.***

## 1. INTRODUCTION

The optimal power flow (OPF) has been widely used in power system operation and planning since its introduction by Carpenter in 1962 [1]. The OPF determines optimal settings for certain power system control variables by optimizing a few selected objective functions while satisfying a set of equality and inequality constraints for given settings of loads and system parameters. The control variables include generator active powers, generator bus voltages, transformer tap ratios and the reactive power generation of shunt compensators. In general, the total fuel cost (FC) is commonly used as the main objective for OPF problems. However, the other objectives, such as reduction of real power loss (RPL), improvement of the voltage profile (VP) and enhancement of the voltage stability (VS) can also be included, as it has progressively become easy to formulate and solve large-scaled complex problems with the advancement in computing technologies. The equality constraints are the power flow balance equations, while the inequality constraints are the limits on the control variables and the operating limits of the power system dependent variables.

The recent developments in power electronics have introduced DC transmission links in the existing AC transmission systems with a view of achieving the benefits of reduced network loss, lower number of power conductors, increased stability, enhanced security, etc. They are often considered for transmission of bulk power via long distances. The attributes of DC transmission links include low capacitance, low average transmission cost in long distances, ability to prevent cascaded outages in AC systems, rapid adjustments for direct power flow controls, ability to improve the stability of AC systems, mitigation of transmission congestion, enhancement of transmission capacity, rapid frequency control following a loss of generation, ability to damp out regional power oscillations following major contingencies and offering major economic incentives for supplying loads. Flexible and fast DC controls provide efficient and desirable performance for a wide range of AC systems.

While most of the existing DC links are designed for point to point transmissions, the multi-terminal DC system operation has become a reality and its usage is expected to increase in future with a view of making the operation more flexible, secure and economical. The realization of multi-terminal DC systems cannot be done at once but can be executed through replacing the existing AC transmission lines by DC links over a period of time.

It is to be noted that such modernization through heuristic replacement of AC lines by DC links in the system may not be optimal and may not ensure enhanced system performance. The decision as to which of the transmission lines is to be replaced by DC links and their parameters, besides determining the optimal settings for control parameters, is of great significance in achieving the desired performances. The problem of replacing the transmission lines by DC links may be represented as "DC link placement problem". There is thus a need for extending the OPF problem to embrace the problem of placing the DC links in the existing power systems. The resulting optimization problem, designated as OPF with DC link placement problem (OPFDC), is a large scale, non-linear non-convex and multimodal optimization problem with continuous and discrete control variables. The existence of nonlinear power flow constraints and the DC link equations make the problem non-convex even in the absence of discrete control variables [2-6].

In the recent decades, numerous mathematical programming techniques such as gradient method [1], linear programming [7,8], nonlinear programming [9,10], interior point method [11-13] and quadratic programming [14] with various degrees of near-optimality, efficiency, ability to handle difficult constraints and heuristics, have been widely applied in solving the OPF problems. Although many of these techniques have excellent convergence characteristics, they have severe limitations in handling non-linear and discontinuous objectives and constraints. The gradient method suffers from the difficulty in handling inequality constraints, and the linear programming requires the objective and constraint functions to be linearized during optimization, which may lead to the loss of accuracy. Besides they may converge to local solution instead of global ones, when the initial guess is in the neighborhood of a local solution. Thus there is always a need for simple and efficient solution methods for obtaining global optimal solution for the OPF problems.

Apart from the above methods, another class of numerical techniques called evolutionary search algorithms such as genetic algorithm [15-18], evolutionary programming [19-21], particle swarm optimization (PSO) [22-24], differential evolution [25-28], frog leaping [29], harmony search optimization (HSO) [30], gravitational search [31], clonal search [32], artificial bee colony [33] and teaching-learning [34] have been widely applied in solving the OPF problems. Having in common processes of natural evolution, these algorithms share many similarities; each maintains a population of solutions that are evolved through random alterations and selection. The differences between these procedures lie in the techniques they utilize to encode candidates, the type of alterations they use to create new solutions, and the mechanism they employ for selecting the new parents. These algorithms have yielded satisfactory results across a great variety of power system problems. The main difficulty is their sensitivity to the choice of the parameters, such as temperature in SA, the crossover and mutation probabilities in GA and the inertia weight, acceleration coefficients and velocity limits in PSO.

Recently, teaching learning based optimization (TLO) has been suggested for solving optimization problems [35,36]. It is inspired from teaching-learning process in class rooms. It mimics the behavior of the students in improving their performance through gaining the knowledge from the teacher and interacting with other students. It has been applied to a variety of power system problems [37-39] and found to yield satisfactory results.

This paper formulates the problem of OPFDC, suggests a solution methodology involving TLO with a view of obtaining the global best solution and demonstrates its performance through simulation results on IEEE 14,30 and 57 bus systems.

## 2. TEACHING LEARNING BASED OPTIMIZATION

TLO, inspired from teaching–learning process in class rooms, is suggested for solving multimodal optimization problems.

**Teaching Phase:** The teaching phase represents the global search property of the TLBO algorithm. During this phase, the teacher, who is the most experienced and knowledgeable person in the class, imparts knowledge to all the students with a view of improving the performance of the whole class from initial level to his own level. In the light of the fact that the students will gain knowledge according to the quality of the teaching delivered by a teacher and the quality of the students present in the class, the mean grade point of the subject increases and the difference between the grade point of the teacher and the mean grade point of the subject is expressed as

$$\Delta S^{j\,k} = rand(0,1) \times \left( S^{j\,k}_{teacher} - t_f \; S^{j\,k\,ave} \right) \tag{1}$$

Where

$S^{j\,k\,ave}$ is the mean grade of the j-th subject at k-th iteration and computed by

$$S^{j\,k\,ave} = \frac{1}{nS} \sum_{i=1}^{nS} S_i^{j\,k} \tag{2}$$

$S^{j\,k}_{teacher}$ is the grade point of the j-th subject of the teacher at k-th iteration

$t_f$ is the teaching factor, which decides the value of mean to be changed and can be either 1 or 2, evaluated by

$$t_f = round([1 + rand\ (0,1)\{2-1\}] \tag{3}$$

The new grade point of the j-th subject of the i-th student, as a result of teaching, is mathematically modeled by

$$S_i^{j\,k+1} = S_i^{j\,k} + \Delta S^{j} \tag{4}$$

The grade points of all the students at the teachers phase are further improved by the learner phase.

**Learning Phase:** The learner phase stands for the local search process of the TLBO algorithm. In this phase, the students enrich their knowledge by interaction among themselves, which helps in improving their performances. In this phase, a student randomly chooses another student for interaction and enriches the knowledge through learning if the other student has more knowledge than him or her. The influence on the grade points due to the interaction of $p$-th student with $q$-th student may be mathematically expressed as follows:

$$S_p^{j\,k+1} = \begin{cases} S_p^{j\,k} + rand \times \left( S_p^{j\,k} - S_q^{j\,k} \right) & if\ F_p > F_q \\ S_p^{j\,k} + rand \times \left( S_q^{j\,k} - S_p^{j\,k} \right) & otherwise \end{cases} \tag{5}$$

$F_p$ and $F_q$ are the performance, indicating the fitness, of the p-th and q-th student respectively.

## 3.PROBLEM FORMULATION

The OPFDC problem is formulated as a constrained nonlinear optimization problem through combining the standard OPF problem and the DC set of equations as

Minimize $\Phi(x,u)$

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(6)

Subject to

$$b(x,u) = 0 \qquad (7)$$

$$g(x,u) \le 0$$

(8)

Where

$x = [V_i^L, Q_j^G, P_s^G]$ ,the vector of dependant variables (9)

$u = [P_k^G, V_j^G, T_v, Q_q^C, L_p^{dc}, I_p^{dc}]$, the vector of control or independent variables (10)

$$b(x,u) = \begin{Bmatrix} P_m^G - P_m^D - V_m \sum_{n\in\{\Omega,\Pi\}}^{nb} V_n (G_{mn} \cos ¢_{mn} + B_{mn} \sin ¢_{mn}) = 0 \\ Q_m^G - Q_m^D - V_m \sum_{n\in\{\Omega,\Pi\}}^{nb} V_n (G_{mn} \sin ¢_{mn} - B_{mn} \cos ¢_{mn}) = 0 \\ h(x,u) = 0 \end{Bmatrix}$$ ,(11) the equality constraints

$$g(x,u) = \begin{Bmatrix} P_k^{G(\min)} \le P_k^G \le P_k^{G(\max)} \\ Q_j^{G(\min)} \le Q_j^G \le Q_j^{G(\max)} \\ Q_q^{C(\min)} \le Q_q^C \le Q_q^{C(\max)} \\ T_v^{\min} \le T_v \le T_v^{\max} \\ V_j^{G(\min)} \le V_j^G \le V_j^{G(\max)} \\ V_i^{L(\min)} \le V_i^L \le V_i^{L(\max)} \\ I_p^{dc(\min)} \le I_p^{dc} \le I_p^{dc(\max)} \\ |S_{Li}| \le S_{Li}^{\max} \end{Bmatrix},$$

the inequality constraints (12)

$$h(x,u) = \begin{Bmatrix} V_m^{dc} - s_m c_2\, h_m\, V_w^{ac}\, \cos\theta_m + s_m\, c_3\, X_m^c\, I_m^{dc} = 0 \\ V_m^{dc} - 0.995 s_m c_2\, h_m\, V_w^{ac}\, \cos\varphi_m = 0 \\ Q_w^{ac} - V_w^{ac}\, c_2\, h_m\, I_m^{dc}\, \sin\varphi_m = 0 \\ P_w^{ac} - V_w^{ac}\, c_2\, h_m\, I_m^{dc}\, \cos\varphi_m = 0 \\ P_m^{dc} - V_m^{dc}\, I_m^{dc} = 0 \\ I_m^{dc} - \left(V_m^{dc} - V_n^{dc}\right) / R_{mn}^{dc} = 0 \\ V_m^{dc} - V_n^{dc} - I_m^{dc}\, R_{mn}^{dc} = 0 \end{Bmatrix}$$

, the DC link equations (13)

$s_m$ = 1 for rectifier and -1 for inverter

$c_2 = 3\sqrt{2}/®$

$c_3 = 3/®$

$i \in \Omega$ , a set of load buses

$j \in \Pi$ , a set of generator buses

$k \in \Psi$ , a set of PV buses

$v \in \Re$ , a set of tap changing transformers

$p \in \Im$ , a set of DC links

$q \in \aleph$ , a set of shunt compensators

The objective function $\Phi(x,u)$ can take different forms. The different cases involving FC, RPL, VP and VS, which are calculated from the power flow solution, are considered in tailoring the objectives in this paper.

**Minimization of Fuel Cost**

Minimize $\Phi_1(x,u) = \sum_{j\in\Pi} a_j P_j^{G^2} + b_j P_j^G + c_j + \left| d_j \sin(e_j (P_j^G(\min) - P_j^G)) \right|$ (14)

**Minimization of Real Power Loss**

Minimize $\Phi_2(x,u) = \sum_{w=1}^{nl} g_{mn} \left( |V_m|^2 + |V_n|^2 - 2\,|V_m|\,|V_n| \cos ¢_{mn} \right)$ (15)

**Enhancement of Voltage Stability**

The VS can be enhanced by minimizing the largest value of VS index (VSI) of load buses [40] as

Minimize

$$\Phi_3(x,u) = \max\{L_i ; i \in \Omega\} \quad (16)$$

Where $L_i = \left| 1 - \sum_{j=\Pi} F_{ji} \frac{V_j}{V_i} \right|$ (17)

The values of $F_{ji}$ are obtained from the bus admittance matrix.

The multi-objective OPFDC problem is tailored by combining several objectives through weight factors so as to optimize all the objectives simultaneously.

Minimize $\Phi(x,u) = \sum_{i=1}^{nobj} w_i \, \Phi_i$ (18)

## 4 . PROPOSED ALGORITHM

The proposed TLO based method involves representation of problem variables and the formation of a performance function.

### 4.1 Representation of decision variables

The decision variables in the PM thus comprises real power generation at PV buses, voltage magnitudes at generator buses, transformer tap settings, transmission line to be replaced by DC links and DC link currents. $S$ denotes the grade points of each student in the PM and represents the control variables in vector form as:

$$S = [P_k^G, V_j^G, T_v, I_p^{dc}]; \quad j \in \Pi \quad k \in \Psi \quad v \in \Re \quad p \in \Im \qquad (19)$$

### 4.2 Performance Function

The TLO searches for optimal solution by maximizing a fitness function, denoted by $F$, which is formulated from the objective function of Eq. (10) and the penalty terms representing the limit violation of the dependant variables such as reactive power generation at generator buses, voltage magnitude at load buses and real power generation at slack bus. $F$ can be built as

$$Max \quad F = \frac{1}{1+\Phi^A} \qquad (20)$$

Where

$$\Phi^A = \Phi(x,u) + a_V \sum_{i\in\Omega} \left(V_i^L - V_i^{\text{limit}}\right)^2 + a_Q \sum_{i\in\Pi} \left(Q_i^G - Q_i^{\text{limit}}\right)^2 + a_P \left(P_s^G - P_s^{\text{limit}}\right)^2 + a_S \sum_{i\in M} \left(S_{Li} - S_{Li}^{max}\right)^2$$

(21)

$$V_i^{\text{limit}} = \begin{cases} V_i^{L(\min)} & if\ V_i^L < V_i^{L(\min)} \\ V_i^{L(\max)} & if\ V_i^L > V_i^{L(\max)} \\ V_i^L & else \end{cases} \qquad (22)$$

$$Q_i^{\text{limit}} = \begin{cases} Q_i^{G(\min)} & if\ Q_i^G < Q_i^{G(\min)} \\ Q_i^{G(\max)} & if\ Q_i^G > Q_i^{G(\max)} \\ Q_i^G & else \end{cases} \qquad (23)$$

$$P_s^{\text{limit}} = \begin{cases} P_s^{G(\min)} & if\ P_s^G < P_s^{G(\min)} \\ P_s^{G(\max)} & if\ P_s^G > P_s^{G(\max)} \\ P_s^G & else \end{cases} \qquad (24)$$

### 4.3 Solution Process

An initial population of students is obtained by generating random values within their respective limits to every individual in the population. The fitness $F$ is calculated by considering $gp_S$ of each student; and the teaching and learning phases are performed for all the students in the population with a view of maximizing their performances. The iterative process is continued till convergence. The pseudo code of the PM is presented below

***Read*** *the Power System Data*

***Choose*** *the number of students in the population,* $ns$ *and* $Iter^{\max}$ *for convergence check.*

***Generate*** *the initial population of students*

***Set*** *the iteration counter* $t = 0$

***while*** *(termination requirements are not met) do*

***for*** $i = 1 : ns$

- *Repair the* $i$*-th student*
- *Replace the transmission lines by DC links and set the control parameters according to* $i$*-th student values*
- *Run AC/DC power flow*
- *Evaluate the augmented objective function* $\Phi^A$ *and performance function* $F_i$ *using Eqs. 21 and 20 respectively*

***end***-($i$)

***Choose*** *the best student possessing the largest* $F_i$ *in the population as the teacher*

***Evaluate*** *the mean grade point for each subject by Eq. (2)*

***Perform*** *the Teaching phase to modify the grade points of each student by Eq. (4)*

***Perform*** *the Learning phase to update the grade points of each student by Eq. (5)*

***end***-*(while)*

***Choose*** *the best student with highest* $F_i$ *in the population as the optimal solution*

## 5. SIMULATIONS

The PM is tested on IEEE 14,30 and 57 bus test systems, whose data have been taken from Ref. [41]. The fuel cost coefficients, lower and upper generation limits for these two test systems are taken from Ref. [42-44].The sequential AC/DC power flow involving NR technique is used during the optimization process [4-6]. Programs are developed in Matlab 7.5 and executed on a 2.3 GHz Pentium-IV personal computer. The OPFDC problem is also solved using the PSO and HSO with a view of demonstrating the efficacy of the PM.

The performances in terms of FC, RPL, LVSI and lower and upper VM at load buses of PM are compared with those of the PSO and HSO based algorithms for test cases Tables 1-3 for all the test systems under study. The table 3 also contain the base-case results, representing the performances before optimization. The transmission lines that are chosen for replacement by DC links in Table 2 for 14, 30 and 57 bus systems . The parameters chosen for the PA are given in Table 1.

**Table 1 TLBO Parameter**

| Parameter | Value |
|---|---|
| $ns$ | 30 |
| $Iter^{\max}$ | 300 |

**Table 2 Transmission lines replaced by DC links**

| System | Line No |
|---|---|
| 14 bus | 9 |

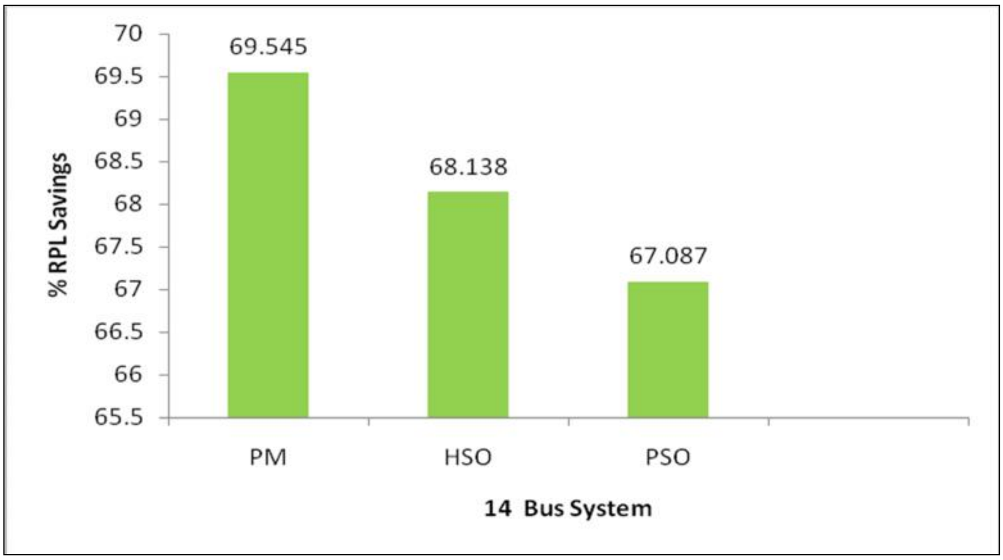
| | |
|---|---|
| 30 bus | 31 and 11 |
| 57 bus | 3, 40 and 70 |

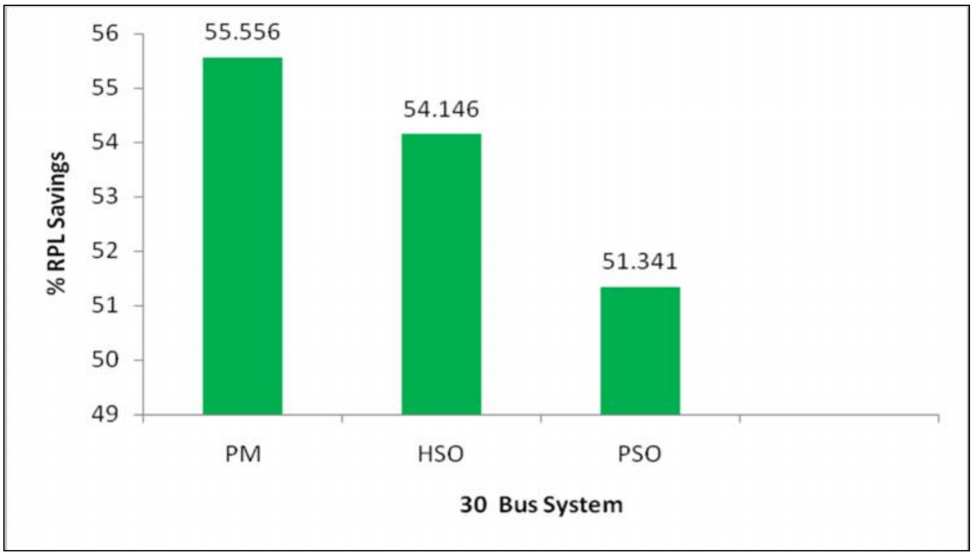
**Table 3 Comparison of Performances for RPL**

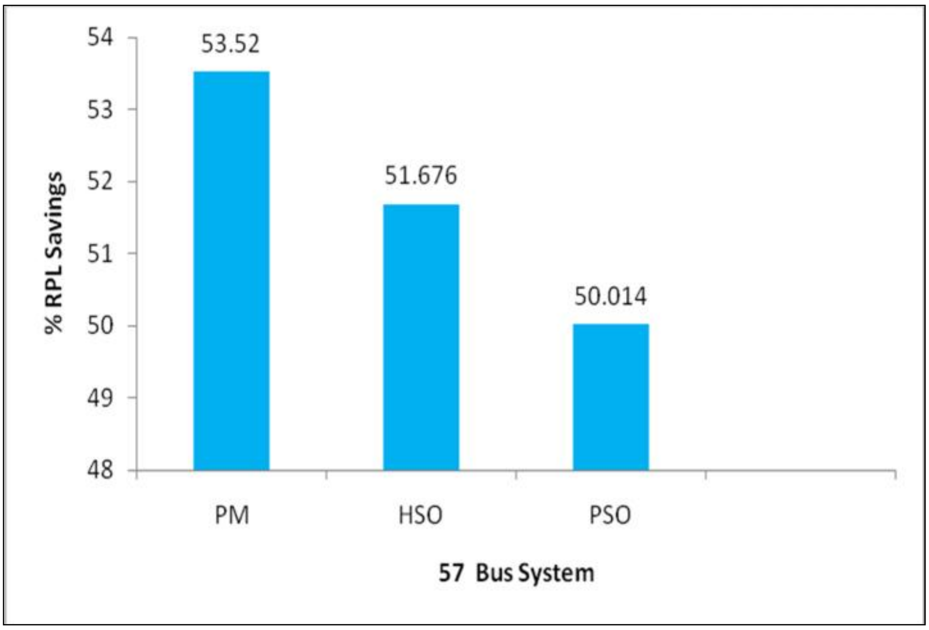
| | | Before Placement | RPL | | |
|---|---|---|---|---|---|
| | | | **PM** | **PSO** | **HSO** |
| 14 | FC | 834.6716 | 1022.3772 | 1020.8308 | 1021.6420 |
| | RPL | 8.9737 | 2.7329 | 2.9535 | 2.8592 |
| | NVSI | 0.3724 | 0.3590 | 0.3705 | 0.3921 |
| | LVSI | 0.0750 | 0.0724 | 0.0739 | 0.0805 |
| 30 | FC | 813.6941 | 966.0839 | 959.8069 | 961.2365 |
| | RPL | 7.0990 | 3.1551 | 3.4543 | 3.2552 |
| | NVSI | 1.6705 | 1.6423 | 1.6469 | 1.6821 |
| | LVSI | 0.1336 | 0.1249 | 0.1233 | 0.1281 |
| 57 | FC | 4556.5930 | 5729.4972 | 5970.4908 | 5906.7104 |
| | RPL | 28.8037 | 13.3881 | 14.3978 | 13.9190 |
| | NVSI | 5.7914 | 6.0793 | 5.8879 | 6.4445 |
| | LVSI | 0.2887 | 0.3003 | 0.2813 | 0.3294 |

The minimization of the RPL is considered as the objective in this case. It is observed from Table 3 that the initial RPL of 8.9737 MW is reduced to 2.7329, 2.9535 and 2.8592 MW by the PM, PSO and HSO respectively for 14 bus system. In case 30 bus system that the initial RPL of 7.0990 MW is reduced to 3.1551, 3.4543 and 3.2552 MW by the PM, PSO and HSO respectively. Similarly, PM, PSO and HSO reduce the initial RPL of 28.8037 MW to 13.3881, 14.3978 and 13.9190 MW respectively for 57 bus system. It is very clear from the results that the offers best possible control settings with optimal DC link parameters, which minimize the RPL to the lowest possible value, when compared with those of PSO and HSO. As minimization of FC and LVSI are not considered as objectives in this case, the FC and LVSI are away from the respective best values for all the test systems, while reducing the RPL. The % RPL savings of PM is graphically compared with those of PSO and HSO in Figure 1 for all the test systems. It is seen from the figures that the %RPL savings of PM is greater than those of PSO and HSO.

**Figure 1 Comparison of % RPL Savings**


70
69.5
69
68.5
68
67.5
67
66.5
66
65.5
% RPL Savings
69.545
68.138
67.087
PM
HSO
PSO
14 Bus System


56
55
54
53
52
51
50
49
% RPL Savings
55.556
54.146
51.341
PM
HSO
PSO
30 Bus System




6. **CONCLUSION**

The study of OPF is an important analysis in power system operational planning. A multi-objective OPF with DC link placement problem is formulated and a TLO based solution strategy for the developed problem is suggested with a view to obtain the global best solution. TLO is a population-based stochastic optimization technique through mimicking the behavior of the students in improving their performance by gaining the knowledge from the teacher and interacting with other students. The solutions are treated as grade points of students and the best student in the population is considered as the teacher. The grade points are adjusted towards the best solution point based on the teaching and learning process.. The algorithm uses sequential AC/DC load flow involving NR technique for computing the objective function during search and is able to offer the global best solution. The objective in this case is the minimization of the RPL and tested on three IEEE bus test systems.

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