Minimization of Active and Reactive Power Losses Using Improved Driving Training Based Optimization

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Abstract: Efficient power grid operation requires minimizing technical losses to ensure economic viability and system stability. This paper presents an Improved Driving Training Based Optimization (IDTBO) algorithm to minimize active and reactive power losses in electrical transmission systems. The problem is formulated as a highly non-linear, multi-variable, and heavily constrained Optimal Reactive Power Dispatch (ORPD) problem. The proposed method enhances the standard Driving Training Based Optimization (DTBO) algorithm by integrating advanced mathematical mechanisms, such as Levy Flight distribution and Crowding Distance techniques. These improvements prevent premature convergence and balance global exploration with local exploitation. The algorithm fine-tunes critical network control variables, including generator voltage magnitudes, transformer tap settings, and switchable reactive power compensators, while strictly respecting system operating and security limits. The effectiveness and robustness of the IDTBO approach are validated on standard IEEE 30-bus system. Simulation results demonstrate that the proposed method achieves a higher percentage of power loss reduction and superior convergence speed compared to the Modified Driving Training Based Optimization (MDTBO) algorithm. Consequently, the IDTBO emerges as a highly competitive and efficient tool for modern power system optimization.

Keywords: *Active power loss, Reactive power loss, Optimal Reactive Power Dispatch, Improved Driving Training Based Optimization, Levy Flight, Crowding Distance.*

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I. INTRODUCTION

In modern electrical systems, efficient energy management and the optimization of transmission networks are major challenges for network operators. Faced with continuously increasing electricity demand and the growing integration of intermittent renewable energy sources, reducing technical losses has become an economic and environmental priority. Active power losses directly affect generation costs and overall network efficiency, while reactive power losses degrade the voltage profile and reduce the transmission capacity of lines. Therefore, the minimization of these losses is essential to ensure safe, stable and economically viable operation of the electrical system.

In the literature, Hardik M. and al. used Particle Swarm Optimization (PSO) to minimize active power loss for optimum reactive power dispatch (ORPD) [1]. Bouchekara H. and al. proposed in their study a Teaching Learning Based Optimization (TLBO) technique to minimize active and reactive power losses in IEEE 30-bus and 118-bus power systems [2]. Recently, a new metaheuristic algorithm inspired from driving training process (Driving Training Based Optimization / DTBO) is developed by Mohammad D. and al. (2022) [3], and O. M. Ranarison (2025) proposed a modified version of this algorithm (MDTBO) to solve optimal power flow problem where minimization of active and reactive power losses are the objective functions [4].

In this paper, an Improved version of the DTBO called IDTBO developed by Daniel K. and al. (2024) is used to optimize active and reactive power losses in IEEE 30-bus system. IDTBO implements Levy Flight and Crowding Distance techniques to enhance the original DTBO [5]. This approach was introduced in [6] to address the optimal power flow problem, where the primary objective is minimizing costs.

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II. MATERIALS AND METHODS

IEEE 30-bus system is composed of 9 shunt VAR compensators and 4 tap transformer settings. Bus 1 is the slack bus, bus 2, 5, 8, 11, 13 are the PV bus, and others are PQ bus (Fig 1). Bus data and line data in [2] and [4] are used in this study and results are compared with MDTBO to evaluate performance of the proposed method.

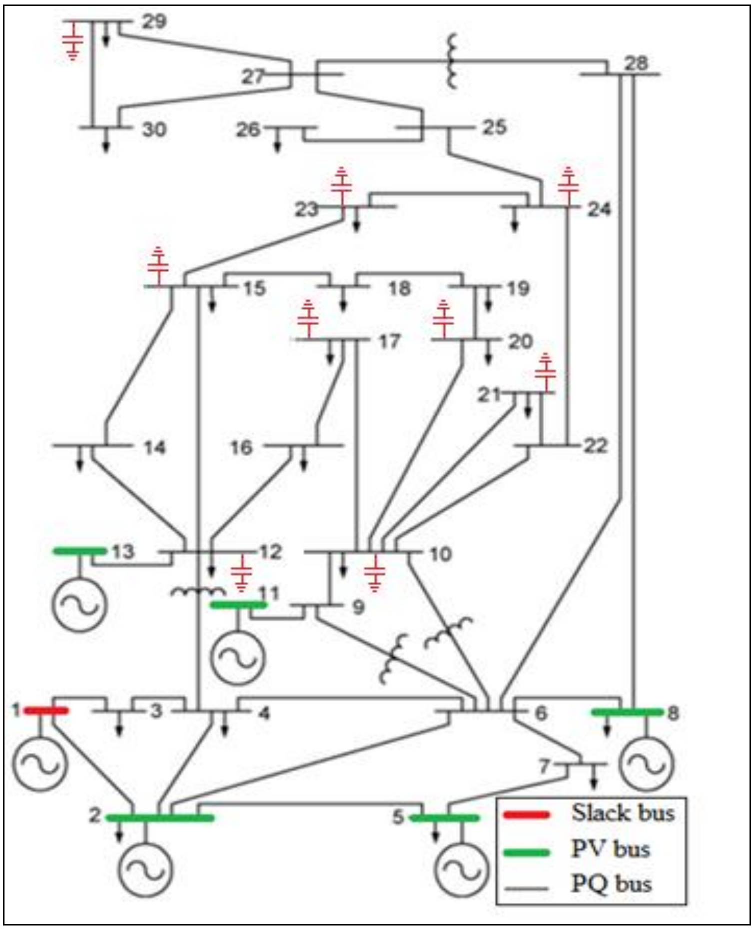

Fig 1 IEEE 30-Bus System with Shunt VAR Compensators and Tap Transformer Setting.

➢ *Optimal reactive power dispatch*

The ORPD problem is mathematically modeled as a non-linear, global optimization problem subject to both equality and inequality constraints. The optimization problem is formulated to minimize a core objective function alongside penalty functions used to handle any violations of the dependent variable constraints:

$$Min\ F(x,u) = f(x,u) + Penalties \tag{1}$$

Where:

u is the vector of control variables (independent parameters), directly manipulated by the optimization algorithm.

$$u = [V_{G_1}, \dots, V_{G_{NG}}, T_1, \dots, T_{N_T}, Q_{C_1}, \dots, Q_{C_{NC}}]^T \tag{2}$$

V_G: voltage magnitudes at generator buses (N_G: number of generators).

T: tap ratios of regulating transformers (N_T: number of tap-changing transformers).

Q_C: reactive power injections of switchable VAR compensators (N_C: number of shunt capacitor/reactor banks).

x is the vector of state variables (dependent parameters), that result from executing the power flow (load flow) calculation.

$$x = [V_{L_1}, \dots, V_{L_{NL}}, Q_{G1}, \dots, Q_{G_{NG}}, S_{l1}, \dots, S_{l_{Nl}}]^T \tag{3}$$

V_L: voltage magnitudes at load (PQ) buses (N_L: number of load buses).

Q_G: Reactive power outputs of the generation units.

S_l: apparent power flows through the transmission lines (N_l: number of transmission lines).

To force the optimization algorithm to reject candidate solutions that violate state variable thresholds, quadratic penalty factors λ_V, λ_Q, λ_S are introduced:

$$Penalties = \lambda_V \sum_{i=1}^{N_L} (\Delta V_{Li})^2 + \lambda_Q \sum_{i=1}^{N_G} (\Delta Q_{Gi})^2 + \lambda_S \sum_{k=1}^{N_l} (\Delta S_{lk})^2 \tag{4}$$

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Where the violation function ΔX for a given variable X is defined as:

$$\Delta X = \begin{cases} X - X^{max} & if\ X > X^{max} \\ X^{min} - X & if\ X < X^{min} \\ 0 & if\ X^{min} \le X \le X^{max} \end{cases} \quad (5)$$

The equality constraints represent the fundamental physical laws governing the balance of active and reactive power at each bus i (power flow equations):

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_{bus}} V_j \left[G_{ij}cos\left(\theta_{ij}\right) + B_{ij}sin(\theta_{ij})\right] = 0 \quad (6)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_{bus}} V_j \left[G_{ij}sin\left(\theta_{ij}\right) - B_{ij}cos(\theta_{ij})\right] = 0 \quad (7)$$

Where P_{Di} and Q_{Di} represent the active and reactive power demands at bus i, and $Y_{ij} = G_{ij} + jB_{ij}$ represents the elements of the network bus admittance matrix Y_{bus}.

Inequality constraints (security limits) are:

Control variable limits (hard bounds of the search space):

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i = 1, \ldots, N_G \quad (8)$$

$$T_k^{min} \le T_k \le T_k^{max}, k = 1, \ldots, N_T \quad (9)$$

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i = 1, \ldots, N_C \quad (10)$$

And state variable limits (enforced via penalty functions):

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i = 1, \ldots, N_L \quad (11)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i = 1, \ldots, N_G \quad (12)$$

$$S_{lk} \le S_{lk}^{max}, k = 1, \ldots, N_l \quad (13)$$

➢ *Minimization of active power losses*

This function aims to reduce energy dissipation caused by Joule effect in the transmission lines:

$$P_{loss} = \sum_{k=1}^{N_l} G_k \left[V_i^2 + V_j^2 - 2V_iV_j cos\left(\theta_i - \theta_j\right)\right] \quad (14)$$

Where G_k is the conductance of line k connecting bus i to bus j, V_i, V_j are the bus voltage magnitudes, and θ_i, θ_j are the voltage phase angles.

➢ *Minimization of reactive power losses*

Objective is to minimize the total reactive power consumed by line reactances. This can be expressed by:

$$Q_{loss} = \sum_{k=1}^{N_l} B_k[V_i^2 + V_j^2 - 2V_iV_j cos(\theta_i - \theta_j)] - \sum_{i=1}^{N} V_i^2 B_{sh,i} \quad (15)$$

Where B_k is the susceptance of a line k and $B_{sh,i}$ the shunt charging susceptance at bus i.

➢ *Improved Driving Training Based Optimization*

DTBO is a metaheuristic algorithm inspired by driving training process. IDTBO is an improved version of DTBO incorporating Levy Flight and Crowding distance technique. Implementation of IDTBO algorithm is detailed in [5]. Mapping of IDTBO concepts to the ORPD problem is presented in table 1.

Table 1 Mapping of IDTBO Concepts to the ORPD Problem

IDTBO Concept	**ORPD problem equivalent**
Learner / Driver	A candidate power grid configuration (vector of control variables)
Driving Instructor	The current best solutions in the search space
Driving Training	The optimization process where grid variables are adjusted to minimize active / reactive power losses
Fitness Function	The objective function with penalty functions for any constraint violations (power flow with Newton Raphson is used to calculate the state variables)
Crowding Distance	A diversity maintenance mechanism used to select instructors widely spread across the search space, preventing premature convergence
Levy Flight	Long-step random perturbations applied to control variables to escape local optima
Traffic Rules / Regulations	The physical and operational constraints of the power system (equality and inequality constraints)

III. RESULTS AND DISCUSSION

Optimal result of ORPD problem obtained with IDTBO is compared with MDTBO for the two objective functions and presented in table 2. For 500 iterations, optimal values for the control variables with IDTBO are getting in 176 seconds and 160 seconds respectively for active and reactive power losses minimization, which is 7 seconds and 14 seconds faster compared to the MDTBO algorithm.

Active and reactive power losses variations are presented respectively in Figure 1 and Figure 2. For min(Ploss), IDTBO has the best value with 2.8883 MW, this represents a 50.49% reduction compared to value before

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optimization. For min(Qloss), the difference between the two methods is very small (0.1145MVAR). In Figure 3, active power losses through transmission lines are very improved compared to the case where cost minimization is the objective function. In Figure 4, reactive power losses through transmission lines are also improved compared to the cost minimization.

IDTBO and MDTBO are very competitive in the two case as shown in the active power flow through transmission lines in figure 5. The reactive power flow through transmission lines are very reduced in the case where objective function is Qloss minimization (figure 6). Apparent power flow through transmission lines are presented in figure 7. There is still a large margin of apparent power before the limits are reached.

The figure 8 shows that the profile voltage with IDTBO respects the inequality constraints. In the case of Qloss minimization, voltage magnitudes are near the best (1 p.u) with IDTBO (Voltage Deviation is 0.9625).

Table 2 Optimal Result of ORPD Problem

Variables	**Min**	**Max**	**Initial case**	**MDTBO min(Ploss)**	**IDTBO min(Ploss)**	**MDTBO min(Qloss)**	**IDTBO min(Qloss)**
P_1	50	200	99.2225	51.3149	51.3817	52.1202	51.5866
P_2	20	80	80	80	79.9054	80	80
P_5	15	50	50	50	50	50	50
P_8	10	35	20	35	35	35	35
P_{11}	10	30	20	30	30	29.3955	29.9068
P_{13}	12	40	20	40	40	39.9990	40
V_1	0.95	1.1	1.0500	1.1	1.1	1.1	1.1
V_2	0.95	1.1	1.0400	1.0987	1.0976	1.1	1.1
V_5	0.95	1.1	1.0100	1.0813	1.0808	1.0928	1.0926
V_8	0.95	1.1	1.0100	1.0887	1.0874	1.1	1.1
V_{11}	0.95	1.1	1.0500	1.0947	1.0993	1.0378	1.0344
V_{13}	0.95	1.1	1.0500	1.0919	1.0999	1.0651	1.0643
T_{11}	0.9	1.1	1.0780	0.9955	1.0016	1.0754	1.0833
T_{12}	0.9	1.1	1.0690	1.0097	0.9572	1.0187	0.9845
T_{15}	0.9	1.1	1.0320	1.0188	0.9993	1.0228	1.0178
T_{36}	0.9	1.1	1.0680	0.9957	0.9819	1.0530	1.0398
Q_{10}	0.0	5.0	0	3.3467	2.9134	4.6580	2.2854
Q_{12}	0.0	5.0	0	3.7073	1.5947	4.8339	1.6692
Q_{15}	0.0	5.0	0	4.8351	3.3445	4.9675	1.6832
Q_{17}	0.0	5.0	0	3.4718	3.4022	2.5841	5.0
Q_{20}	0.0	5.0	0	4.4972	3.1129	4.6726	4.8508
Q_{21}	0.0	5.0	0	4.0682	4.9996	4.9976	4.9252
Q_{23}	0.0	5.0	0	4.5559	2.2325	4.8840	3.4337
Q_{24}	0.0	5.0	0	2.3341	4.2014	1.8897	1.6164
Q_{29}	0.0	5.0	0	4.1913	2.4292	4.5322	1.784
Cost ($/h)			901.9501	967.2208	966.9500	966.4273	967.4501
P_{loss}(MW)			5.8225	2.9162	2.8883	3.1164	3.0951
Q_{loss}(MVAR)			-4.6063	-20.2812	-19.0521	-24.0982	-23.9837
V_D			1.1496	1.6784	1.8278	1.0211	0.9625
Lmax			0.1723	0.1196	0.1194	0.1285	0.1319
Elapsed time (s)				183.0187	176.1475	173.7996	159.9142

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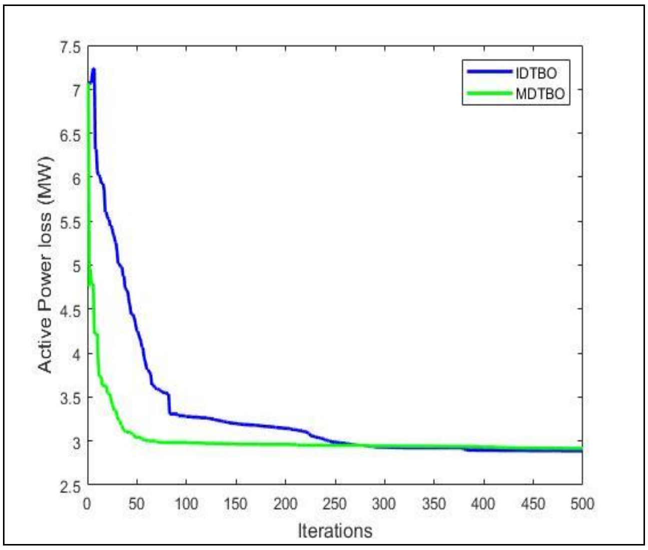

Fig 1 Active Power Loss Variation with MDTBO and IDTBO where Objective is Min(Ploss).

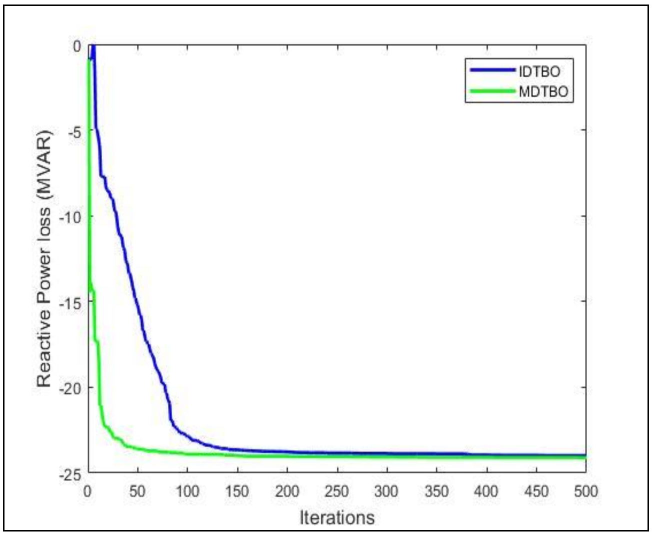

Fig 2 Reactive Power Loss Variation with MDTBO and IDTBO where Objective is Min(Qloss).

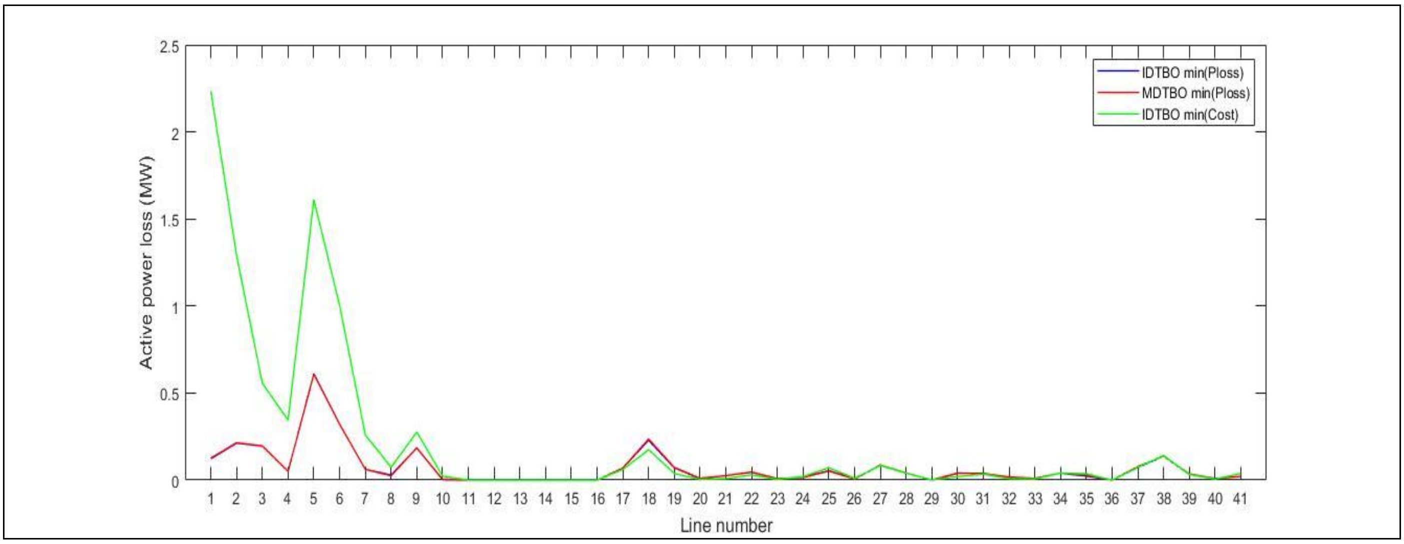

Fig 3 Active Power Losses Through Transmission Lines with MDTBO and IDTBO.

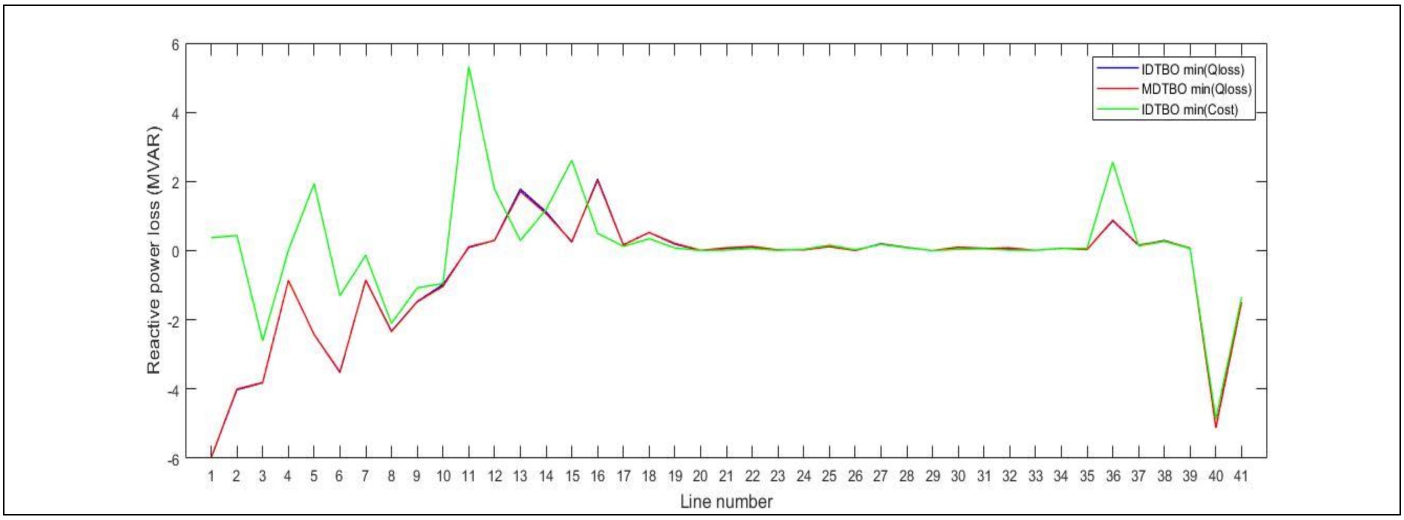

Fig 4 Reactive Power Losses Through Transmission Lines with MDTBO and IDTBO.

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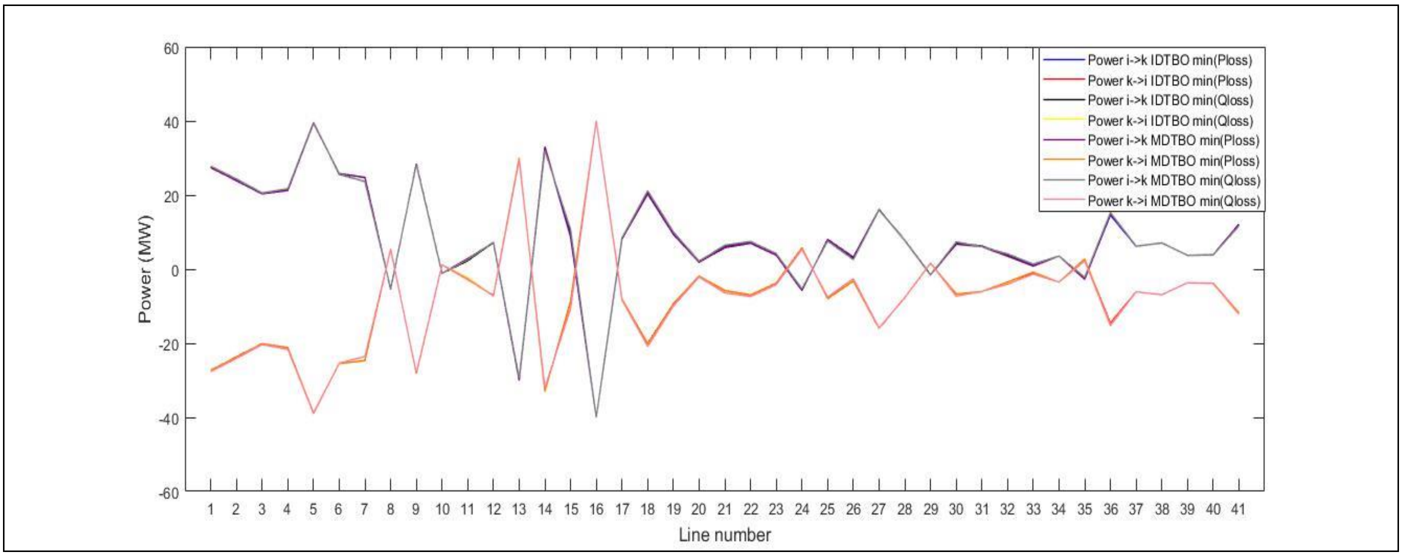

Fig 5 Active Power Flow Through Transmission Lines with MDTBO and IDTBO.

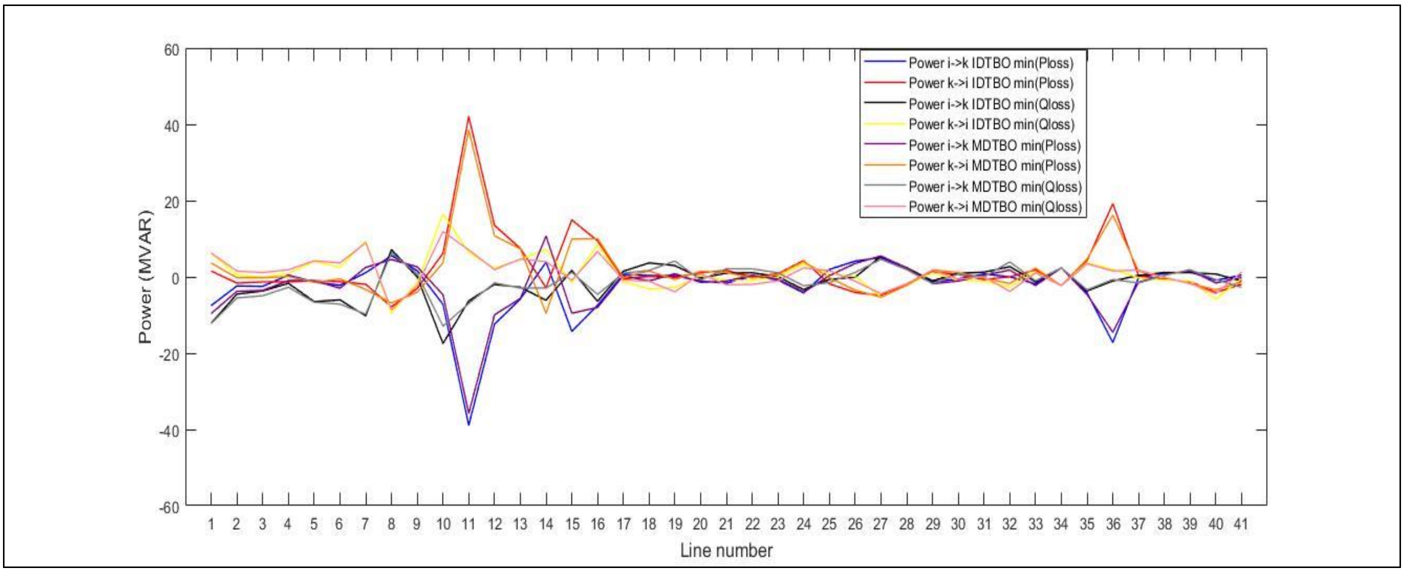

Fig 6 Reactive Power Flow Through Transmission Lines with MDTBO and IDTBO.

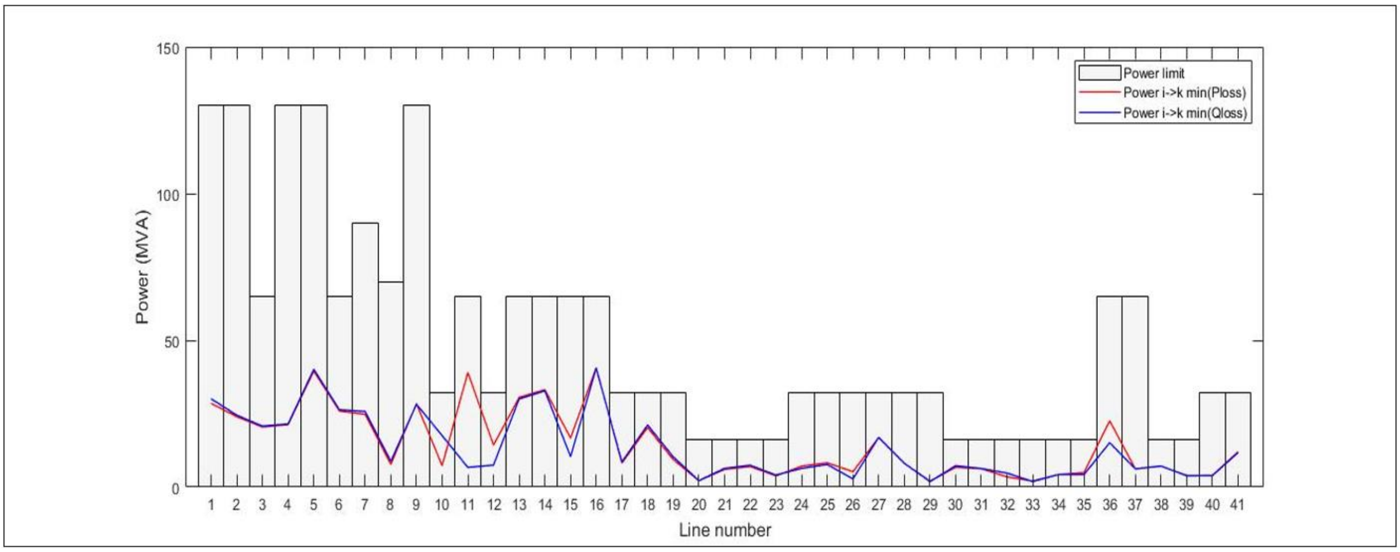

Fig 7 Apparent Power Flow Through Transmission Lines with IDTBO.

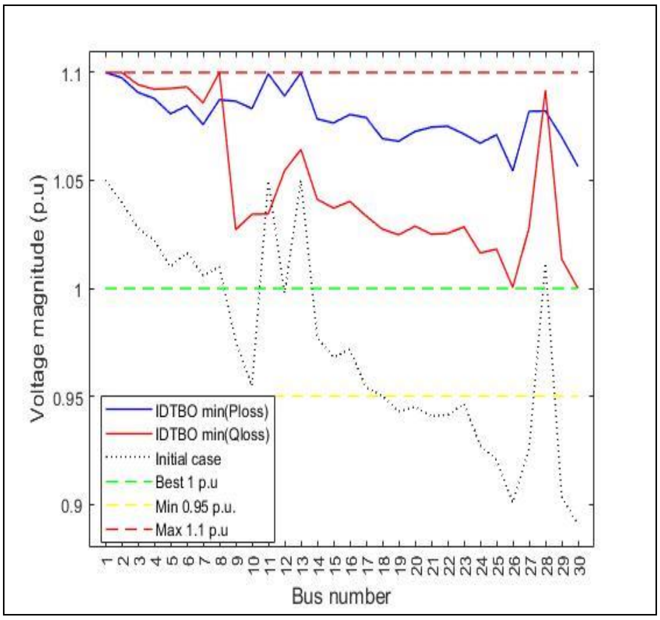

Fig 8 System Voltage Profiles with IDTBO for Objective Min(Ploss) and Min(Qloss).

IV. CONCLUSION

This paper suggests the solution to ORPD problem using IDTBO algorithm for two mono-objective functions: minimization of active and reactive power losses. The results of the test with the IEEE 30-bus system are promising and show the effectiveness and robustness of the proposed method. IDTBO and MDTBO are very competitive, but the IDTBO is the best in convergence speed, which is a very important point, especially for large-scale networks.

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