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Optimal power flow using Modified Driving-Training Based Optimization algorithm

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ABSTRACT: The control and study of electric power system require solution of Optimal Power Flow (OPF) problem which is considered one of the most difficult optimization problems. The objective of OPF is finding the most secure operating point or the best control variables while considering equality and inequality constraints of the system, and optimizing certain objective functions. In this paper, five objective functions are considered: minimization of total generation fuel cost, voltage profile improvement, voltage stability enhancement, minimization of active power transmission losses and reactive power losses minimization. Modified Driving-Training Based Optimization (MDTBO) algorithm is used to solve the OPF problem. Driving-Training-Based Optimization (DTBO) is a human-based metaheuristic algorithm based on the simulation of driving training process. With MDTBO, a new method for choosing the number of driving learners and instructors is introduced. To evaluate the proposed method, the standard IEEE 30-bus network is used and results is compared to another metaheuristic algorithm such as Teaching-Learning Based Optimization (TLBO) and Particle Swarm Optimization (PSO) algorithm. The results show that the proposed approach is competitive with other algorithms.

KEYWORDS: Optimal Power Flow (OPF), generation cost, voltage stability, voltage profile, active power transmission losses, reactive power losses, Teaching-Learning Based Optimization (TLBO), Particle Swarm Optimization (PSO), Modified Driving-Training Based Optimization (MDTBO).

I. INTRODUCTION

OPF is firstly introduced by Carpentier in 1962 [1]. The goal of OPF is to optimize a selected objective functions such as generation fuel cost, voltage profile improvement, voltage stability enhancement, minimization of active power transmission losses, reactive power losses minimization, by adjusting the power system control variables which are the generator real powers, the generator bus voltages, the transformer tap settings, and the reactive power of switchable VAR sources. With considering power flow equations (equality constraints) and the limits on control variables (inequality constraints), OPF becomes a large-scale highly constrained nonlinear and nonconvex optimization problem. In the literature, Ebeed et al (2018) classify all methods of OPF solution in two main groups: conventional and recent optimization methods [2]. Conventional methods are deterministic and classic heuristic optimization techniques, such as linear, nonlinear and quadratic programming methods, Newton's method and interior point method, which are fully reviewed by Momoh et al. (1999) [3][4]. Recent optimization methods are metaheuristics and can be classified in swarm and bio-inspired, human inspired, evolutionary inspired, physics inspired and hybrid optimization techniques, Artificial neural networks (ANN) and fuzzy logic approaches. According to the state of the art about modern techniques by Emmanuel et al (2021) [5] and Risi et al. (2022)[6], Attia et al. (2012) proposed an adapted genetic algorithm with adjusting population size, applied in IEEE-30 bus system with fuel cost and voltage profile improvement as objective functions [7].The work of Adaryani et al. (2013) studies the application of Artificial bee colony algorithm for solving multi-objective OPF problem (fuel cost, quadratic cost with valve-point effect, piecewise quadratic cost, emission, voltage stability, active power transmission losses, voltage profile) on IEEE 9-bus,30-bus and 57-bus systems [8]. Kahourzade et al. (2015) proposed a comparative study of multi-objective OPF (fuel cost, emission minimization, voltage stability, active power transmission losses) based on particle swarm (PSO), evolutionary programming, and genetic algorithm, tested on IEEE-30 bus system [9]. Le Anh et al. (2015) study Cuckoo Optimization Algorithm for OPF with fuel cost, quadratic cost with valve-point effect, and piecewise quadratic cost as objective functions, tested on IEEE 30-bus, 57-bus and 118-bus system [10]. El-Fergany et al. (2015) are interested on grey wolf optimizer and differential evolution algorithms for minimizing generation fuel cost with valve-point effect, reactive power losses and active power transmission losses, on IEEE 30-bus and IEEE 118-bus [11]. The literature provides another human inspired algorithms applied on OPF problem, such as Teaching-Learning Based Optimization (TLBO) introduced by Bouchekara et al. (2014) where IEEE 30-bus and 118-bus is tested with quadratic fuel cost, piecewise quadratic cost, voltage stability, voltage profile and active power transmission losses as objective functions [12]. A modified version of TLBO for OPF is proposed by Shabanpour-Haghighi et al. (2014) where objective functions are quadratic fuel cost with valve-point effect and emission minimization, and test systems are IEEE 30-bus and 57-bus [13]. An improved teaching-learning based optimization algorithm using Levy mutation strategy for non-smooth optimal power flow is also proposed by Ghasemi et al. (2015), tested on IEEE 30-bus and 57-bus systems with voltage stability, emission minimization, generation cost, quadratic cost with valve-point effect and piecewise quadratic cost, as objective functions [14]. Duman (2016) develop Symbiotic organisms search algorithm for OPF based on valve-point effect and prohibited zones, tested on IEEE 30-bus [15]. Adaptive multiple teams perturbation-guiding Jaya is proposed by Warid (2020) for generation cost minimization, voltage stability enhancement and minimization of active power transmission losses on IEEE 30-bus and 118-bus [16]. Warid (2022) is also interested on Novel chaotic Rao-2 for OPF solution, with four objective functions (fuel cost, voltage profile and stability, active power transmission losses) tested on IEEE 30-bus and 118-bus [17]. New bio-inspired algorithms for OPF are also proposed since 2017 such as Moth swarm algorithm introduced by Mohamed et al. (2017) for optimizing fuel cost, quadratic cost with valve-point effect, piecewise quadratic cost, emission, voltage profile and stability, active power transmission losses, tested on IEEE 30-bus, 57-bus, 118-bus [18]; Modified coyote optimization algorithm by Li et al. (2019) for minimization of fuel cost and active power transmission losses on IEEE 30-bus [19]; Gorilla troops optimization technique by Shaheen et al. (2022) for fuel cost, emission, and active power transmission losses minimization, on IEEE 30-bus and Egypt Power System [20]. Improved stochastic fractal search algorithm is a physic inspired algorithm proposed by Nguyen et al. (2020) for fuel cost, emission, power losses minimizations, voltage profile and stability on IEEE 30-bus, IEEE 57-bus, IEEE 118-bus systems [21]. Yuan et al. (2017) work on improved strength Pareto evolutionary algorithm for generation cost and emission minimization on IEEE 30-bus and 57-bus [22]. Fuzzy logic approach for minimizing generation of fuel cost on IEEE 14-bus is introduced by Ramesh et al. (1997) [23] and Artificial neural network for voltage stability and minimization of generation fuel cost on IEEE 30-bus is developed by Venkatesh (2003) [24]. Yuhao et al. (2020) proposed Deep reinforcement learning for minimizing fuel cost on IEEE 14-bus and Illinois 200-bus system [25]. Singh et al. (2022) study Sensitivity-Informed Deep Neural Networks for minimizing fuel cost on IEEE 39-bus, IEEE 118-bus and Illinois 200-bus [26]. In 2023, Xiang Pan proposed a feasibility-optimized deep neural network for minimizing fuel cost on IEEE 30-bus, 118-bus, 300-bus and synthetic 2000-bus system [27]. After studying state of the art, no-one has studied MDTBO approach for solving OPF problem.

In this article, the main objective is to modify original DTBO by introducing a new equation for setting number of driving learners and instructors, and for optimizing five objective functions of OPF: minimization of total generation fuel cost (case 1), voltage profile improvement (case 2), voltage stability enhancement (case 3), minimization of active power transmission losses (case 4) and reactive power losses minimization (case 5).

II. MATERIALS AND METHODS

Used material for this article is IEEE 30-bus system which is composed of six power generators at buses 1, 2, 5, 8, 11 and 13; four transformers with off-nominal tap ratio at lines 6-9, 6-10, 4-12, and 28-27; and nine shunt VAR compensation buses at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 [11]. Buses are coded as 1 for slack bus, 2 for PV bus and 3 for PQ bus (Fig. 1).

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Bus data, generator data, line data and cost coefficients are giving in [28] [29]. The minimum and maximum limits for the control variables and for the line power transmissions are respectively tabulated in (Table 1) and (Table 2).

Data is manipulated in per unit with base equal to 100MVA. Precision's value is 0.001. Newton-Raphson method is used to determine load flow parameters in the IEEE 30-bus system.

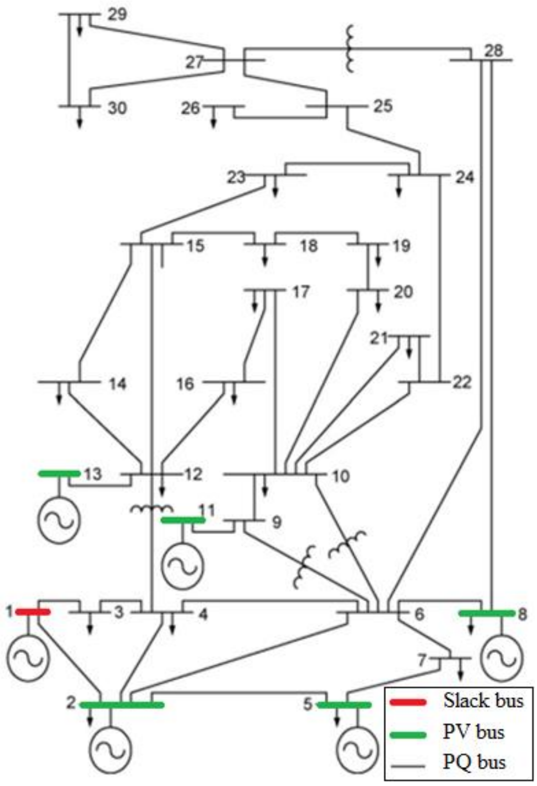

Fig.1: IEEE 30-bus system

Table 1: Limits for the control variables

Variables	Min	Max
P_1	50	200
P_2	20	80
P_5	15	50
P_8	10	35
P_{11}	10	30
P_{13}	12	40
V_1	0.95	1.1
V_2	0.95	1.1
V_5	0.95	1.1
V_8	0.95	1.1
V_{11}	0.95	1.1
V_{13}	0.95	1.1
T_{11}	0.9	1.1
T_{12}	0.9	1.1
T_{15}	0.9	1.1
T_{36}	0.9	1.1
Q_{10}	0.0	5.0
Q_{12}	0.0	5.0
Q_{15}	0.0	5.0

Q_{17}	0.0	5.0
Q_{20}	0.0	5.0
Q_{21}	0.0	5.0
Q_{23}	0.0	5.0
Q_{24}	0.0	5.0
Q_{29}	0.0	5.0

Table 2: Limit for the line power transmissions

Line No	From bus	To bus	S (p.u)
1	1	2	1.300
2	1	3	1.300
3	2	4	0.650
4	3	4	1.300
5	2	5	1.300
6	2	6	0.650
7	4	6	0.900
8	5	7	0.700
9	6	7	1.300
10	6	8	0.320
11	6	9	0.650
12	6	10	0.320
13	9	11	0.650
14	9	10	0.650
15	4	12	0.650
16	12	13	0.650
17	12	14	0.320
18	12	15	0.320
19	12	16	0.320
20	14	15	0.160
21	16	17	0.160
22	15	18	0.160
23	18	19	0.160
24	19	20	0.320
25	10	20	0.320
26	10	17	0.320
27	10	21	0.320
28	10	22	0.320
29	21	22	0.320
30	15	23	0.160
31	22	24	0.160
32	23	24	0.160
33	24	25	0.160
34	25	26	0.160
35	25	27	0.160
36	28	27	0.650
37	27	29	0.650
38	27	30	0.160
39	29	30	0.160
40	8	28	0.320
41	6	28	0.320

2.1. Optimal Power Flow formulation

OPF problem can be modelled by minimizing an objective function F composed of x, vector of dependent variables, and u, vector of control variables.

$$MinF(x,u) \tag{1}$$

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with

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

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

g_j and h_j represent equality and inequality constraints; m and p represent the number of each constraint.

x can be expressed as:

$$x = [P_{G1}, V_{L1} \dots V_{L,NPQ}, Q_{G1} \dots Q_{G,NG}, S_{TL,1} \dots S_{TL,NTL}] \quad (4)$$

where:

P_{G1} , active power output at slack bus; V_L , voltage magnitude at PQ buses ; Q_G , reactive power output of all generator units ; S_{TL} , transmission line loading; NPQ , number of load buses ; NG, number of generator units; NTL, number of transmission lines.

u can be expressed as:

$$u = [P_{G,2} \dots P_{G,NG}, V_{G,1} \dots V_{G,NG}, Q_{C,1} \dots Q_{C,NC}, T_1 \dots T_{NT}] \quad (5)$$

where:

P_G , active power generation at the PV buses except at the slack bus ; V_G, voltage magnitude at PV buses ; Q_C, shunt VAR compensation ; T , tap settings of transformer; NC, number of VAR compensators ; NT , number of regulating transformers.

2.2. Objectives functions

Case 1: Generation fuel cost

The objective function is the quadratic equation of total generation fuel cost, can be expressed as:

$$F_1 = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (6)$$

a_i, b_i, c_i are the cost coefficients of ith generator.

Case 2: Voltage profile improvement

Objective is minimizing the voltage deviations of load buses from a specified voltage.

$$F_3 = VD = \sum_{i=1}^{NPQ} |(V_i - 1)| \quad (7)$$

Case 3: Voltage stability enhancement

According to Kessel et al. [30], this objective function can be formulated by minimizing voltage stability index L_{max}:

$$F_4 = min(L_{max}) = min(max(L_n)) \quad n = 1,2,\dots,NPQ \quad (8)$$

$$L_n = \left|1 - \sum_{i=1}^{NPV} F_{ij} \frac{V_i}{V_j}\right| \quad (9)$$

Voltage stability index vary between 0 to 1 (no load case to voltage collapse case).

V_i and V_j are the voltage of ith generator bus and the voltage of jth load bus, respectively. F_{ij} can be expressed with submatrices of Y_{bus} matrix:

$$F_{ij} = [F_{LG}] - [Y_{LL}]^{-1}[Y_{LG}] \quad (10)$$

Case 4: Minimization of active power transmission losses

This can be formulated as follows:

$$P_{loss} = \sum_{i=1}^{NTL} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}) \quad (11)$$

G_{ij} conductance of a line, NTL number of transmission lines, and δ_{ij} phase difference of voltages.

Case 5: Reactive power losses minimization

This can be expressed by:

$$Q_{loss} = \sum_{i=1}^{NTL} B_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}) \quad (12)$$

B_{ij} susceptance of a line.

2.3. Constraints

The equality constraints represent the balance between generated and load powers:

$$P_{Gi} - P_{Di} = |V_i| \sum_{j=1}^{n} |V_j| (G_{ij} cos\delta_{ij} + B_{ij} sin\delta_{ij}) \quad (13)$$

$$Q_{Gi} - Q_{Di} = |V_i| \sum_{j=1}^{n} |V_j| (G_{ij} cos\delta_{ij} + B_{ij} sin\delta_{ij}) \quad (14)$$

The inequality constraints, also called security constraints, are directly associate with limits of system:

$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad i = 1,2,\dots,NG$ (15)

$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} \quad i = 1,2,\dots,NG$ (16)

$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad i = 1,2,\dots,NG$ (17)

$T_i^{min} \le T_i \le T_i^{max} \quad i = 1,2,\dots,NT$ (18)

$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max} \quad i = 1,2,\dots,NC$ (19)

$S_{Li} \le S_{Li}^{min} \quad i = 1,2,\dots,NTL$ (20)

$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max} \quad i = 1,2,\dots,NPQ$ (21)

2.4. DTBO

DTBO is human inspired metaheuristic algorithm developed by Mohammad Dehghani et al. (2022) in [31] where inspiration and main idea are explained as follow: “Driving training is an intelligent process in which a learner driver is trained and acquires driving skills. Learner driver can choose from several instructors when attending driving school. The instructor then teaches the learner driver the instructions and skills. The learner driver tries to learn driving skills from the instructor and drive following the instructor. In addition, personal practice can improve the driver's skills of the learner. These interactions and activities have extraordinary potential for designing an optimizer".

Population of DTBO is composed of driving learners and instructors where size N is selected manually. DTBO members are candidate solutions to the OPF problem modelled by the population matrix:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{Nm} \end{bmatrix}_{N\times m} \quad (22)$$

m is the number of problem variables, X_i is the ith candidate solution, x_{ij} is the value of the jth variable determined by the ith candidate solution and is randomly initialized using following equation:

$$x_{ij} = lb_j + r \cdot (ub_j - lb_j), \quad i = 1,2,\dots,N, \quad j = 1,2,\dots,m \quad (23)$$

lb_j and ub_j are respectively the lower and upper bounds of the jth variable; r is a random number from [0,1].

Each candidate is placed in the objective function, and the member that has the best value is known as the best member of the population (X_{best}).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (24)$$

DTBO is modelled in three different phases:

Phase 1: Training by the driving instructor (exploration)

The first phase consists on the choice of the driving instructor by the learner driver and then the training of the driving by the selected instructor to the learner driver. It can be expressed as:

$$DI = \begin{bmatrix} DI_{11} & \cdots & DI_{1j} & \cdots & DI_{1m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ DI_{i1} & \cdots & DI_{ij} & \cdots & DI_{im} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ DI_{N_{DI}1} & \cdots & DI_{N_{DI}j} & \cdots & DI_{N_{DI}m} \end{bmatrix}_{N_{DI}\times m} \quad (25)$$

In each iteration t, the best members are considered as driving instructors and the rest as learner drivers. The number of driving instructors N_{DI} decrements for each iteration by using the following equation:

$$N_{DI} = 0.1 \cdot N \cdot (1 - t/T) \quad (26)$$

T is the maximum number of iterations.

The new position for each member is calculated using next equation:

$$x_{i,j}^{P1} = \begin{cases} x_{i,j} + r \cdot \left(DI_{k_{i,j}} - I \cdot x_{i,j}\right), & F_{DI_{k_i}} < F_i \\ x_{i,j} + r \cdot \left(x_{i,j} - DI_{k_{i,j}}\right), & otherwise. \end{cases} \quad (27)$$

I is a number randomly selected from the set [1,2], r is a random number in the interval [0,1].

This new position replaces the previous one if it improves the value of the objective function.

$$X_i = \begin{cases} X_i^{P1}, & si F_i^{P1} < F_i \\ X_i, & otherwise \end{cases} \quad (28)$$

Phase 2: Patterning of the instructor skills of the student driver (exploration)

The second phase is based on the learner driver imitating the instructor. This process moves population to different positions in the search space, thus increasing the DTBO's exploration power.

$$x_{i,j}^{P2} = P \cdot x_{i,j} + (1 - P) \cdot DI_{k_{i,j}} \quad (29)$$

$$X_i = \begin{cases} X_i^{P2}, & si\ F_i^{P2} < F_i \\ X_i, & otherwise \end{cases} \quad (30)$$

P is the patterning index given by

$$P = 0.001 + 0.9(1 - t/T) \quad (31)$$

Phase 3: Personal practice (exploitation)

This third phase is based on the personal practice of each learner driver to improve and enhance driving skills.

$$x_{i,j}^{P3} = x_{i,j} + (1 - 2r) \cdot R \cdot (1 - t/T) \cdot x_{i,j} \quad (32)$$

$$X_i = \begin{cases} X_i^{P3}, & si\ F_i^{P3} < F_i \\ X_i, & otherwise \end{cases} \quad (33)$$

r is a random real number of the interval [0,1], R is the constant set to 0.05.

2.5. MDTBO

MDTBO introduce two modifications of original DTBO method. Firstly, size of population is fixed at the same value of problem's dimension.

$$N = m \quad (34)$$

Secondly, the number of driving instructors in first phase is updated to the following equation:

$$N_{DI} = 1 + 0.2 \cdot N \cdot (1 - t/T) \quad (35)$$

Member of driving instructors decrement slowly for each iteration, but it not gets zero value until the end of iteration. Phase of exploration is improved. Fig. 2 shows variation of N_{DI} for $N = 24$ and $T = 500$ width DTBO and MDTBO.

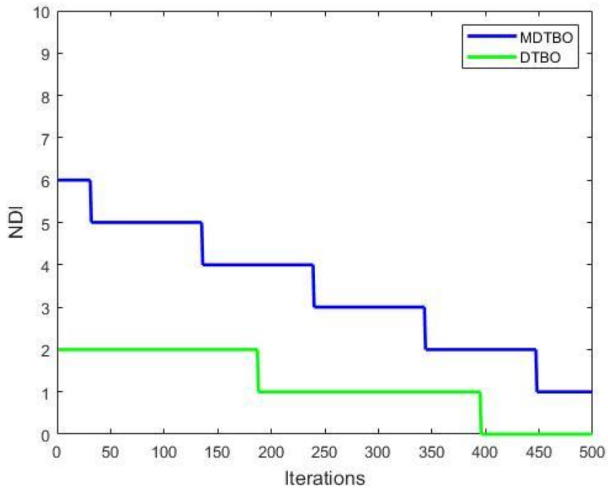

Fig.2: Variations of the number of driving instructors with MDTBO and DTBO

Flowchart of MDTBO is presented in the following figure.

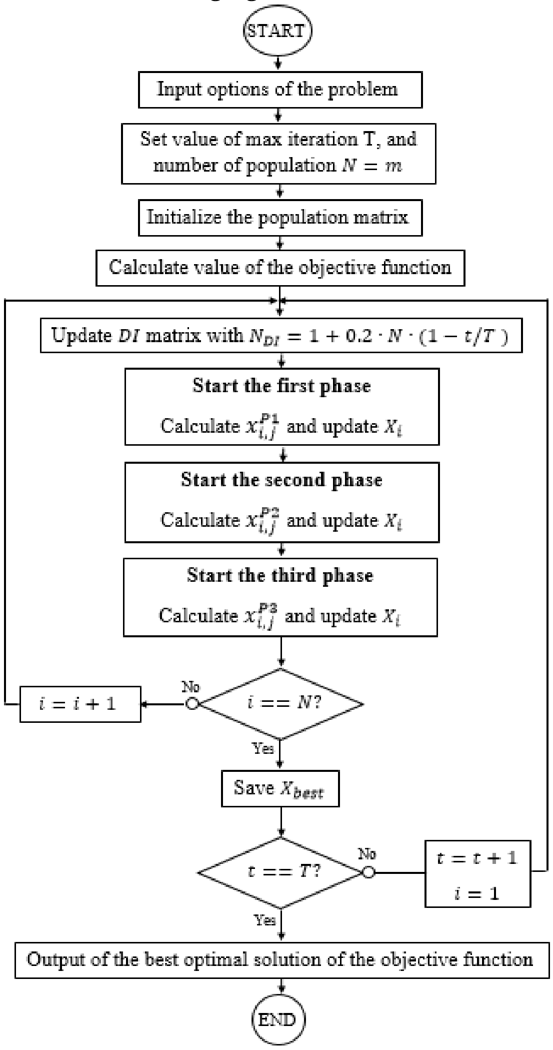

Fig.3: Flowchart of MDTBO

III. RESULTS

For solving OPF problem, MDTBO algorithm has been tested on the standard IEEE 30-bus system using Matlab software for coding and simulation, with Intel Core i5-3230M CPU @ 2.60GHz processor and 8GO RAM.

The variation of fuel cost is shown in Fig.4 for case 1 (minimization of fuel cost), with MDTBO, TLBO and PSO algorithms.

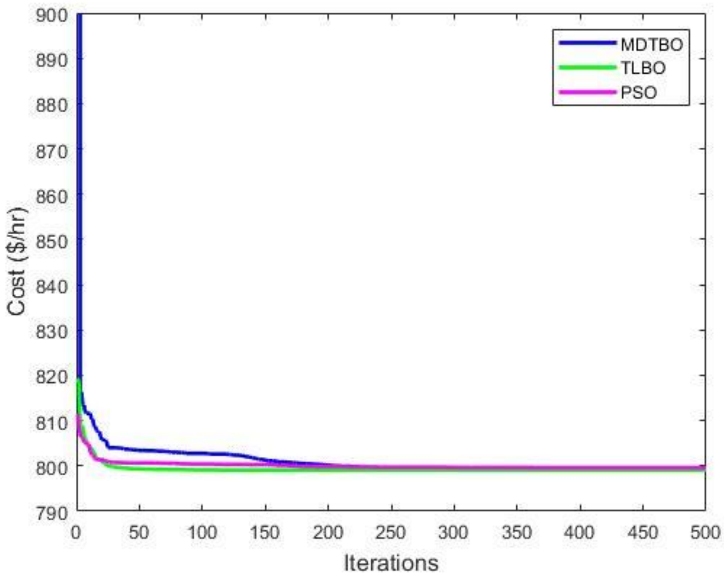

Fig.4: Fuel cost variation for case 1 with MDTBO, TLBO and PSO

For case 2, voltage profile improvement, variations of fuel cost and voltage deviations (VD) with MDTBO approach is presented in Fig. 5.

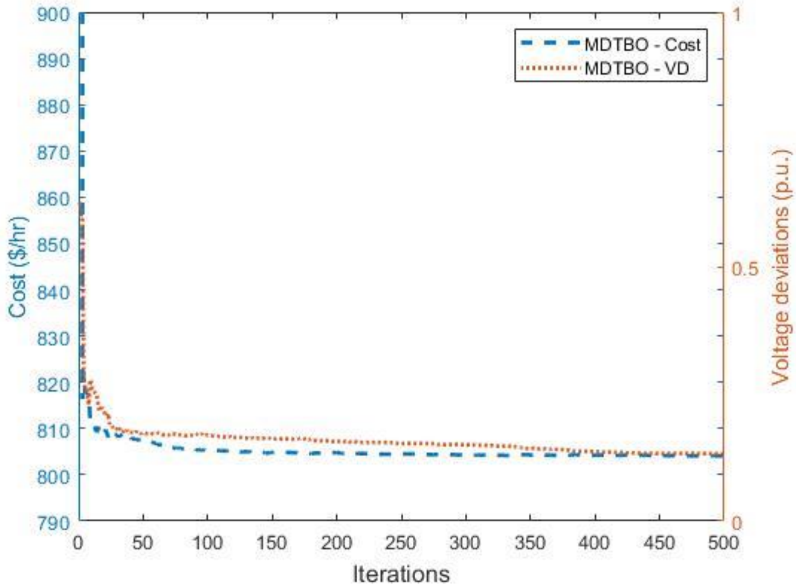

Fig.5: Variations of fuel cost and voltage deviations for case 2 with MDTBO

Result of voltage stability enhancement (case 3), is shown in Fig. 6, where MDTBO is used for fuel cost and voltage stability index L_{max} variations.

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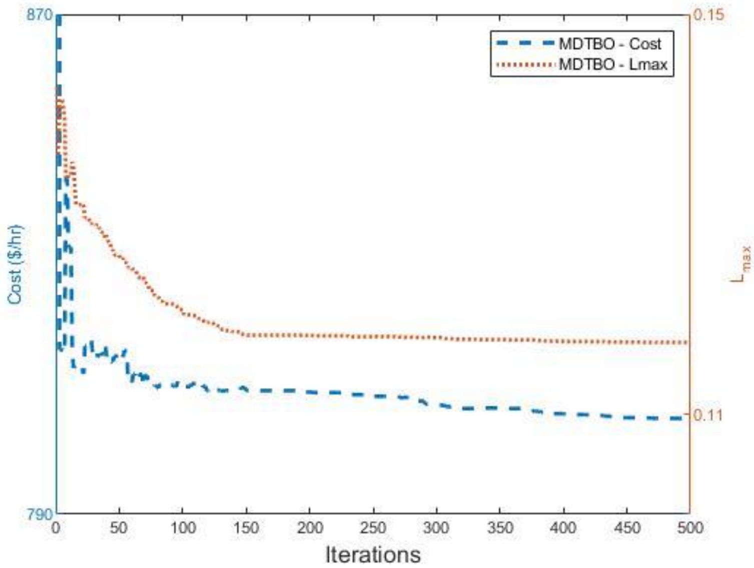

Fig.6: Variations of fuel cost and voltage stability index for case 3 with MDTBO

Fig. 7 and Fig. 8 represent, respectively, the variations of active power transmission losses P_{loss} for case 4, and reactive power losses Q_{loss} for case 5. Results of MDTBO is compared to TLBO and PSO.

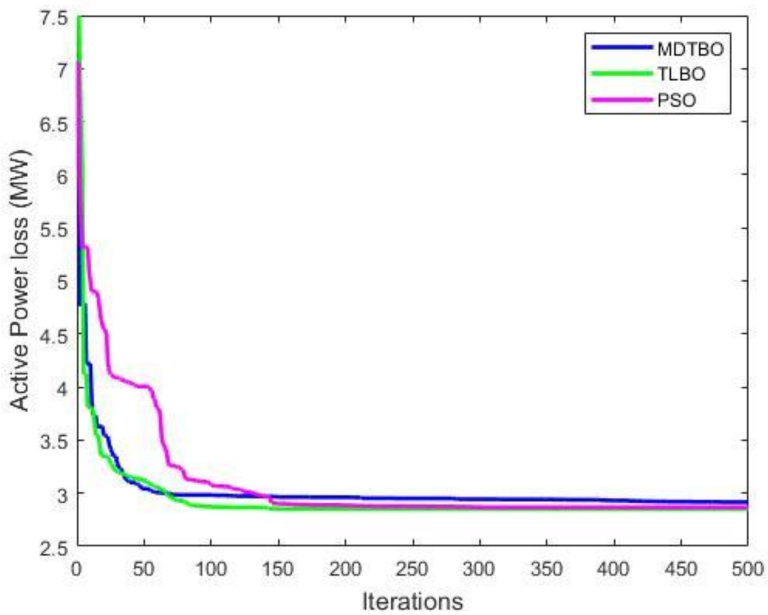

Fig.7: Variations of active power transmission losses for case 4 with MDTBO, TLBO and PSO

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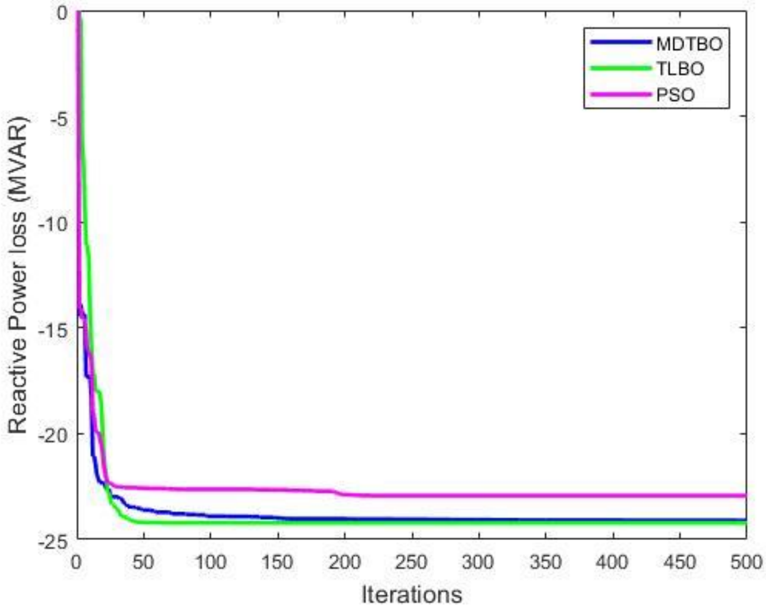

Fig.8: Variations of reactive power losses for case 5 with MDTBO, TLBO and PSO

With MDTBO approach, voltage magnitude of 30-bus system for case 1 is compared to case 2 in Fig.9.

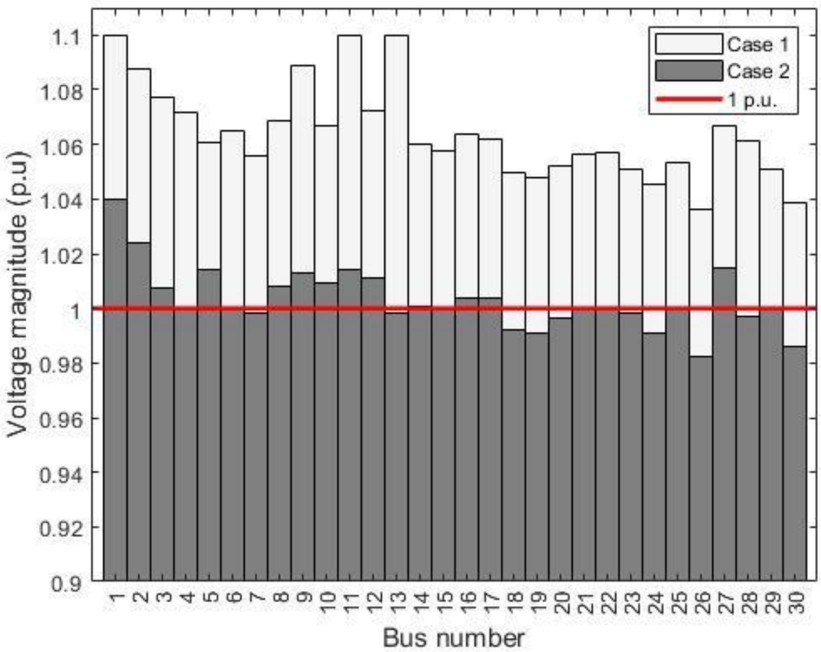

Fig.9: System voltage profiles for case 1 and case 2 with MDTBO

Active power transmission losses for case 4 is compared to case 1 and illustrate in Fig. 10.

Reactive power losses for case 5 is also compared to case 1 and illustrate in Fig. 11.

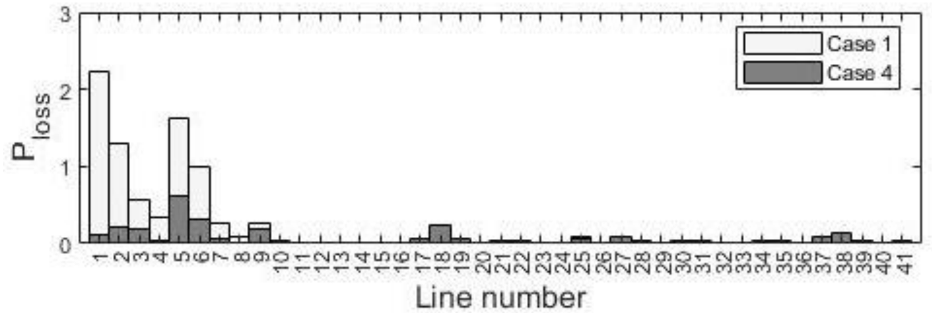

Fig.10: Active power transmission losses for case 1 and case with MDTBO

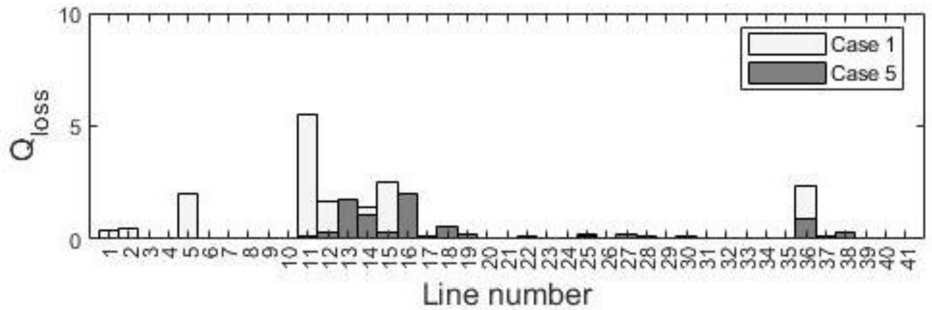

Fig.11: Reactive power losses for case 1 and case 5 with MDTBO

Optimal settings of control variables and elapsed times for case 0 (initial case), case 1, case 2, case 3, case 4 and case 5, with MDTBO, TLBO and PSO, are given in Table 3 and Table 4.

IV. DISCUSSION

Initially, the total fuel cost was $901.9501. The total cost obtained by MDTBO in case 1 is $799.5753, while with PSO it is $799.5823. Fuel cost is greatly reduced (11.35% reduction) and MDTBO is more accurate than PSO. With TLBO, fuel cost in case 1 has a best value $799.0680, but elapsed time (305.0494s) is not interesting compared to MDTBO (177.6250s). In initial case, there are some voltage violations at bus 19 through bus 30, but there are no longer violations in the results obtained using MDTBO (Fig. 9). In Fig. 4, it appears that the convergence of the proposed method is competitive with TLBO and PSO.

In case 2, width MDTBO, the total generation fuel cost and voltage deviations are $804.1092 and 0.1322 p.u. compared to $799.5753 and 1.4079 p.u. for case 1. So the cost has been increased by 0.57%, and the voltage profile has been improved by 90.61% with MDTBO (Fig. 5). Voltage profile improvement is interesting with TLBO but execution time of one iteration is not.

Table 3: Optimal settings of control variables for case 1 and case 2, with PSO, TLBO and MDTBO

Variables	Min	Max	Case 0	Case 1 PSO	Case 1 TLBO	Case 1 MDTBO	Case 2 PSO	Case 2 TLBO	Case 2 MDTBO
P_1	50	200	99.2225	177.301	177.057	176.934	181.368	176.361	174.367
P_2	20	80	80	48.7654	48.6972	48.6810	45.7325	48.8767	48.5661
P_5	15	50	50	21.3155	21.3043	21.2255	22.1605	21.6590	21.1154
P_8	10	35	20	20.8126	21.0814	20.9396	19.2589	22.1195	21.2827
P_{11}	10	30	20	11.8358	11.8842	11.7209	12.5495	12.1699	13.5531
P_{13}	12	40	20	12.1574	12.000	12.6520	12.5255	12.0001	14.2735
V_1	0.95	1.1	1.0500	1.1000	1.1000	1.1000	1.0370	1.0401	1.0397
V_2	0.95	1.1	1.0400	1.0873	1.0879	1.0876	1.0199	1.0237	1.0237
V_5	0.95	1.1	1.0100	1.0613	1.0617	1.0608	1.0190	1.0140	1.0143

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V_8	0.95	1.1	1.0100	1.0695	1.0694	1.0689	1.0016	1.0046	1.0083
V_{11}	0.95	1.1	1.0500	1.0999	1.1000	1.1000	1.0528	1.0606	1.0141
V_{13}	0.95	1.1	1.0500	1.0999	1.1000	1.1000	0.9997	0.9876	0.9984
T_{11}	0.9	1.1	1.0780	0.9902	1.0447	0.9497	1.0051	1.0833	0.9793
T_{12}	0.9	1.1	1.0690	1.0436	0.9000	1.0125	0.9311	0.9012	0.9272
T_{15}	0.9	1.1	1.0320	1.0999	0.9863	1.0177	0.9653	0.9379	0.9506
T_{36}	0.9	1.1	1.0680	1.0123	0.9657	0.9717	0.9736	0.9707	0.9582
Q_{10}	0.0	5.0	0	0.0018	5.000	2.2939	1.7482	4.8524	2.4286
Q_{12}	0.0	5.0	0	4.8882	5.000	1.5445	4.8098	0	2.7292
Q_{15}	0.0	5.0	0	1.4461	5.000	2.1016	4.2538	4.9999	3.3897
Q_{17}	0.0	5.0	0	4.9987	5.000	2.4704	0.0887	0	2.5774
Q_{20}	0.0	5.0	0	1.8570	5.000	0.8641	4.8249	5	2.3691
Q_{21}	0.0	5.0	0	0.0004	5.000	3.6410	2.6886	4.9998	4.5337
Q_{23}	0.0	5.0	0	4.9983	3.8490	1.7289	4.3941	5	5
Q_{24}	0.0	5.0	0	3.1354	5.000	0.77854	3.9468	5	1.3463
Q_{29}	0.0	5.0	0	4.9907	2.7434	1.0707	4.7485	2.6146	1.7527
Cost ($/h)			901.950	799.582	799.068	799.575	804.346	803.460	804.109
P_{loss} (MW)			5.8225	8.7880	8.6245	8.7532	10.2958	9.8872	9.8513
Q_{loss} (MVAR)			-4.6063	3.2444	4.1827	5.0820	14.1149	12.3560	11.4872
V_D			1.1496	1.0757	1.8583	1.4079	0.11969	0.0945	0.1322
Lmax			0.1723	0.1270	0.1164	0.1268	0.13649	0.1369	0.1390
Elapsed time				107.916	305.049	177.625	110.503	293.685	177.895

We can notice from Fig. 9 that the voltage profile has been greatly improved with MDTBO.

In case 3, voltage stability index is significantly reduced compared to case 1 and case 2. Fig. 6 shows that voltage stability is greatly improved while optimizing generation of fuel cost.

Active power transmission losses are greatly reduced in case 4 with MDTBO (Total of 8.7532MWfor case 1 to 2.9162MW for case 4), and it is illustrated in Fig.10. Fig.7 shows that convergence of the proposed method is interesting compared to TLBO and PSO.

Fig.11 demonstrates that Reactive power losses are also reduced in case 5 compared to case 1. Finally, with Fig. 8 we can say that MDTBO is more interesting than PSO, and very competitive with TLBO.

V. CONCLUSION

In this paper, we have introduced and presented a novel technique to solve the OPF problem in electric power systems that is MDTBO. Original DTBO is a human-inspired metaheuristic algorithm, based on imitating human actions when learning to drive. It has three update phases: training by the driving instructor, patterning of the instructor skills of the student driver, and personal practice. The MDTBO is a modified version of original DTBO, where population is set to the dimension of the problem and number of driving instructor in first phase is updating to avoid convergence to none instructor. Five objective functions have been considered to minimize the fuel cost, to improve the voltage profile, to enhance voltage stability, and to minimize active power transmission losses and reactive power losses. The proposed method has been tested on IEEE 30-bus system. Compared to TLBO and PSO, the results width MDTBO confirm the potential of proposed approach and show his robustness and effectiveness to solve OPF problem.

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Table 4: Optimal settings of control variables for case 3, case 4 and case 5, with PSO, TLBO and MDTBO

Variables	Case 3 PSO	Case 3 TLBO	Case 3 MDTBO	Case 4 PSO	Case 4 TLBO	Case 4 MDTBO	Case 5 PSO	Case 5 TLBO	Case 5 MDTBO
P_1	182.767	174.660	155.972	51.2654	51.2493	51.3149	51.8113	51.4494	52.1202
P_2	50.9850	49.8639	47.6195	80	80	80	80	80	80
P_5	21.6500	21.5708	25.3178	50	50	50	50	50	50
P_8	12.5835	20.9978	26.5968	35	35	35	35	35	35
P_{11}	11.3407	12.7767	17.0993	30	30	30	30	30	29.3955
P_{13}	13.7921	12.1572	18.1837	40	40	40	40	40	39.9990
V_1	1.0934	1.1	1.1	1.1000	1.1	1.1	1.1	1.1	1.1
V_2	1.0696	1.0882	1.0896	1.1000	1.0976	1.0987	1.1	1.1	1.1
V_5	1.0678	1.0758	1.0876	1.0827	1.0799	1.0813	1.1	1.0928	1.0928
V_8	1.0582	1.0870	1.0878	1.0898	1.0869	1.0887	1.1	1.1	1.1
V_{11}	1.0678	1.0995	1.0903	1.1000	1.1	1.0947	1.0454	1.0371	1.0378
V_{13}	1.0762	1.0999	1.0996	1.1000	1.1	1.0919	1.1	1.0644	1.0651
T_{11}	0.9267	0.9826	0.9433	1.1000	1.0545	0.9955	1.0452	1.0788	1.0754
T_{12}	0.9984	0.9211	1.0084	0.9000	0.9	1.0097	1.1	1.0245	1.0187
T_{15}	0.9865	0.9789	1.0096	0.9920	0.9842	1.0188	1.0091	1.0264	1.0228
T_{36}	0.9352	0.9749	0.9553	0.9804	0.9726	0.9957	1.0456	1.0490	1.0530
Q_{10}	4.0461	0.0033	4.9988	5	5	3.3467	0	5	4.6580
Q_{12}	2.2936	4.9985	1.4813	4.9997	5	3.7073	5	5	4.8339
Q_{15}	4.2379	4.9825	1.9031	4.9875	4.9999	4.8351	5	5	4.9675
Q_{17}	4.4928	4.9669	3.3039	5	5	3.4718	5	5	2.5841
Q_{20}	3.8630	5	1.1050	5	4.8436	4.4972	0	5	4.6726
Q_{21}	4.4736	4.9984	4.9856	5	5	4.0682	0	5	4.9976
Q_{23}	1.7748	4.9840	3.4176	3.6861	3.6553	4.5559	0	5	4.8840
Q_{24}	4.0680	4.9994	0.2098	5	5	2.3341	5	5	1.8897
Q_{29}	4.8952	4.9993	3.0800	2.3548	2.5142	4.1913	5	.1496	4.5322
Cost ($/h)	802.042	799.64	805.332	967.103	999.971	967.221	968.406	967.542	966.428
P_{loss} (MW)	9.7183	8.6280	7.3901	2.8669	2.8506	2.9162	3.4133	3.0513	3.1164
Q_{loss} (MVAR)	12.2530	4.6505	-0.8028	-20.131	-18.567	-20.281	-22.924	-24.213	-24.098
V_D	1.6006	2.1242	1.8505	1.9314	2.0502	1.6784	1.0637	1.0679	1.0211
Lmax	0.1161	0.1139	0.1172	0.1163	0.1150	0.1196	0.1291	0.1273	0.1285
Elapsed time	113.255	309.208	177.121	114.205	304.039	183.019	112.637	305.913	173.800

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