

A novel multi-objective optimizer for handling reactive power

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Abstract—A novel population-based optimization algorithm for solving a reactive power handling problem is proposed. The algorithm mimics the interaction between the teacher and students. The searching process is broken down in two parts: the Teacher Phase and the Learner Phase. This paper proposes a multi-objective teaching learning algorithm based on decomposition (MOTLA/D). The proposed method is validated on a 190-buses test system, and it is compared with respect to a decomposition-based multi-objective evolutionary algorithm (MOEA/D), which represents a state-of-the-art algorithm.

Index Terms— Optimization, Reactive power, Power system planning.

I. INTRODUCTION

The optimal reactive power problem (ORP) is a nonlinear, non-convex, over-determined system, a large-scale optimization problem with both continuous and discrete variables; additionally, its high dimensionality becomes a major difficulty. This problem is quite important for power system security. In this paper, the basic objective is to estimate proper adjustments on the control variables, such as generator voltages and transformer taps that help to maintain an acceptable voltage profile and minimize the reactive power losses. Thus, an optimal formulation that contributes to attain these purposes becomes appropriate. In general, it may include several objective functions, possibly in conflict among them.

Such kind of optimization problem has a set of optimal solutions (named Pareto optimal set), which represent a tradeoff among the objectives [1]. Several optimization techniques have been presented to solve such reactive optimization problem. Two major approaches may be identified [2]:

The first approach is based on the use of evolutionary algorithms such as the Differential Evolution (DE) [3], the Nondominated Sorting Genetic Algorithm II (NSGA-II) [4], the Particle Swarm Optimization (PSO) [5], an Improved Hybrid Evolutionary Programming Technique [6], and the Artificial Bee Colony Algorithm (ABC) [7].

The second approach is based on conventional methods. They include the Non-Linear Programming (NLP), Quadratic Programming (QP), Linear Programming (LP) and Interior Point Methods [8-12], the Weighting Method [13], and the ϵ -Constraints Method [14]. Due to difficulties of differentiability, non-linearity, and non-convexity, these methods do not guarantee to reach the global optimum [15].

In this paper, a multi-objective teaching learning algorithm based on decomposition (MOTLA/D) for reactive power handling is proposed. In order to minimize the reactive power losses and a voltage stability index [19], the proposed algorithm estimates the following optimal values: (i) generator voltage magnitudes; (ii) transformer tap settings. The effectiveness of the proposed approach is demonstrated and compared with respect to a multi-objective evolutionary algorithm based on decomposition (MOEA/D) [16], which is representative of the state-of-the-art on the subject; both methods are tested on a 190-buses power system, which represents an equivalent of the Mexican electrical grid [20-21].

II. MULTI-OBJECTIVE OPTIMIZATION

A multi-objective optimization problem (MOP) may be formulated as follows:

$$\begin{aligned} \min F(x) &= \{f_1(x), \dots, f_k(x)\} \\ \text{subject to } \mathbf{h}(\mathbf{x}) &= \mathbf{0} \\ \mathbf{g}(\mathbf{x}) &\leq \mathbf{0} \\ x &\in \Omega \end{aligned} \quad (1)$$

where x is the vector of decision variables, $\mathbf{h}(\mathbf{x})$ and $\mathbf{g}(\mathbf{x})$ represent equality and inequality constraints, respectively, while Ω is the feasible region within the decision space. $F: \Omega \rightarrow \mathfrak{R}^k$ is defined as the mapping of k objective functions.

The original teaching learning based optimization (TLBO) algorithm was proposed by Rao et al. [17] to obtain global solutions for continuous non-linear functions. In optimization algorithms, the population consists of different design

variables. In TLBO, the design variables are analogous to different subjects offered to learners. The learners' grade is analogous to the 'fitness' as in any other evolutionary algorithm, and the teacher is considered to be the best solution obtained so far [17]. Hence, the performance of TLBO is based on two main steps: the teacher phase, which involves learning from the teacher, and the learner phase, which involves learning through the interaction among learners.

III. MULTI-OBJECTIVE TEACHING LEARNING BASED ON DECOMPOSITION

The proposed Multi-Objective Teaching Learning Algorithm based on Decomposition (MOTLA/D) utilizes the *Tchebycheff* approach to decompose the MOP into N scalar optimization sub-problems. In this approach, the scalar optimization problem can be stated as [18]:

$$\begin{aligned} & \text{Minimize } g(x|w, z^*) = \max_{i \in \{1, \dots, k\}} \{w_i | f_i(x) - z_i^*\} \\ & \text{Subject to } x \in \Omega \end{aligned} \quad (2)$$

where $w = (w_1, \dots, w_k)$ is a weighting vector and $w_i \geq 0$ for all $i = 1, \dots, k$, $\sum_{i=1}^k w_i = 1$; $z^* = (z_1^*, \dots, z_k^*)$ represents the reference point, i.e., $z_i^* = \min\{f_i(x) | x \in \Omega\}$, for $i = 1, \dots, k$.

For each Pareto optimal solution x^* there exists a weighting vector w such that x^* is the optimal solution of (2), and each optimal solution is a Pareto optimal solution for (1). Therefore, it is possible to obtain different Pareto optimal solutions using different weighting vectors w [16].

Let w^1, \dots, w^N be a set of even spread weighting vectors and z^* be the reference point. Hence, using eq. (2) the objective function of the j -th sub-problem becomes $g(x|w^j, z^*) = \max_{i \in \{1, \dots, k\}} \{w_i^j | f_i(x) - z_i^*\}$, with $w^j = \{w_1^j, \dots, w_k^j\}$ and $j = 1, \dots, N$. The proposed approach looks for the sequential minimization of these sub-problems. Similar to MOEA/D [16], neighborhood relationships among these sub-problems are defined by computing Euclidean distances among weighting vectors. A neighborhood to the weighting vector w^j is defined as a set of its closest weighting vectors in $\{w^1, \dots, w^N\}$.

In MOTLA/D, for the j -th sub-problem, the size of the neighborhood becomes the number of learners in the class. This class can be expressed as,

$$C_{jth} = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,D} \\ x_{2,1} & x_{2,2} & \dots & x_{2,D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{T_{size},1} & x_{T_{size},2} & \dots & x_{T_{size},D} \end{bmatrix} \quad (3)$$

where the subscript D is the number of design variables, and T_{size} is the size of the neighborhood Ω_T . T_{size} is the main control parameter in MOTLA/D. If T_{size} is too small, the algorithm lacks the ability to explore new regions in the searching space. On the other hand, if T_{size} is too large, the exploitation ability of the algorithm is weakened.

Within the *teacher phase*, the mean of the class (M_{class}) for each design variable is evaluated,

$$M_{class} = [m_1, m_2, \dots, m_D] \quad (4)$$

The *teacher* (M_{new}) for the j -th sub-problem represents the best learner of the class C_{jth} . Thus, the teacher is determined by,

$$M_{new} = \{x_j | \min_{x_j \in \Omega_T} g(x_j | w^j, z^*)\} \quad (5)$$

The solutions are updated according to the difference between the mean of the class (M_{class}) and the new mean (M_{new}) by,

$$x_{newT,i} = x_{j,i} + r_i (M_{new,i} - T_F M_{class,i}) \quad (6)$$

where index j corresponds to the current index of j -th sub-problem, r_i is a random number within the range $[0, 1]$. T_F is the teaching factor. It may be either 1 or 2, which is decided randomly with uniform probability as $T_F = \text{round}[1 + \text{rand}(0, 1)]$.

The *learner phase* generates a new solution (x_{newL}) by randomly selecting another learner x_i , such that $i \neq j$. This can be expressed by,

$$\begin{aligned} & \text{if } f(x_j) < f(x_i) \\ & \quad x_{newL} = x_j + r_i (x_j - x_i) \\ & \text{else} \\ & \quad x_{newL} = x_j + r_i (x_i - x_j) \\ & \text{end} \end{aligned} \quad (7)$$

MOTLA/D generates one offspring by the recombination of the solutions generated by both phases: the *teacher phase* and the *learner phase*. Particularly, the algorithm of MOTLA/D crosses each vector as follows:

$$\begin{aligned} & \text{for } i = 1 \text{ to } D \\ & \quad \text{if } \text{rand} \leq 0.5 \\ & \quad \quad x_{new,i} = x_{newT,i} \\ & \quad \text{else} \\ & \quad \quad x_{new,i} = x_{newL,i} \\ & \quad \text{end if} \\ & \text{end for} \end{aligned} \quad (8)$$

Crossover is performed for each of the D variables. Additionally, a polynomial mutation operator is applied to maintain the solutions' diversity. The operator uses the polynomial distribution,

$$\delta_i = \begin{cases} (2r_i)^{\frac{1}{\mu+1}} - 1, & \text{if } r_i < 0.5 \\ 1 - [2(1-r_i)]^{\frac{1}{\mu-1}}, & \text{if } r_i \geq 0.5 \end{cases} \quad (9)$$

where r_i is a uniformly distributed random number in the range $[0, 1]$, and μ is a mutation distribution index. The mutated element is given by,

$$x_{new,i} = x_{new,i} + [x_{ub,i} - x_{lb,i}] \delta_i \quad (10)$$

where $x_{lb,i}$ and $x_{ub,i}$ are the lower and upper limits for the i -th decision variable, respectively. If one or more variables within the new solution (x_{new}) lies outside Ω , the i -th value of x_{new} is reset as follows:

$$x_{new,i} = \begin{cases} x_{lb,i}, & \text{if } x_{new,i} \leq x_{lb,i} \\ x_{ub,i}, & \text{if } x_{new,i} \geq x_{ub,i} \end{cases} \quad (11)$$

The new solution (x_{new}) is accepted if it improves the function value and replaces the old solution (x_j).

The procedure for the implementation of MOTLA/D may be summarized as follows.

A) Initialization

A.1) Set $t = 0$ and generate a well-distributed set of N weighting vectors $w^j = (w_1^j, \dots, w_k^j)$, $j = 1, \dots, N$.

A.2) Compute the Euclidian distances between any two weighting vectors in order to define the neighborhood Ω_T for each vector.

A.3) Generate an initial population of N points $\{x_1, \dots, x_N\}$ and evaluate its individuals $F(x_1), \dots, F(x_N)$.

A.4) Initialize the reference point z^* . $z^* = (z_1^*, \dots, z_k^*)$ where $z_i^* = \min\{f_i(x) | x \in \Omega\}$, for $i = 1, \dots, k$.

B) Teaching-learning scheme

For $j = 1$ to N do

B.1) Generate a solution x_{newT} from the *teacher phase* according to (6). Then, generate a solution x_{newL} from the *learner phase* according to (7).

B.3) Crosses solution x_{newT} and x_{newL} in order to generate a new solution x_{new} according to (8). Then, perform a mutation operator (10). If an element of x_{new} lies outside Ω , its value is reset according to (11).

B.4) Update the reference point z^* : if $f_i(x_{new}) < z_i^*$ then $z_i^* = f_i(x_{new})$ for each $i = 1, \dots, k$.

B.5) Update the population: if $g(x_{new} | w^j, z^*) \leq g(x_j | w^j, z^*)$, then $x_j = x_{new}$ and $F(x_j) = F(x_{new})$.

C) Stopping Criterion: If $t < N_{gen}$ (number of generations), then $t = t + 1$ and go to **Step B**. Otherwise, stop MOTLA/D and report as the output of the algorithm: x_1, \dots, x_N and $F(x_1), \dots, F(x_N)$.

The major computational burden lies on Step B, where MOTLA/D generates N new solutions. Step B.1 just randomly picks two solutions for the *learner phase*. Step B.4 performs $O(k)$ comparisons and assignments, where k is the number of objectives. Step B.5 requires $O(kT_{size})$ basic operations since its major cost are to compute the value of $g(x | w, z^*)$ for T_{size} solutions; the computation of such value requires $O(k)$ basic operations. Therefore, the computational complexity of step B is $O(kNT_{size})$.

IV. FORMULATION

In this paper, a reactive power system problem is approached, which may be stated as an optimization problem where two objective functions are minimized, while satisfying a number of equality and inequality constraints. The following objective functions are minimized: (i) the reactive power losses; and (ii) the voltage stability index [19].

A. Objective functions

A.1 Reactive power losses

One important issue in power transmission is the high reactive power losses on the highly loaded lines, with the consequent transmission capacity reduction. Therefore, the reactive power losses minimization is selected as one objective function. Losses are evaluated by the following expression,

Losses for a single line

$$Q_{VAR,i} = X_i |I_i|^2 = X_i \left| \frac{(V_{ei} - V_{ri})^2}{X_i^2} \right| \quad (12)$$

where V_{ei} and V_{ri} are the sending and receiving voltages, respectively; X_i is the line reactance; I_i is the current through the transmission line.

Objective function for the power system losses:

$$R_{Loss} = \sum_{i=1}^{nl} Q_{VAR,i} \quad (13)$$

where nl is the number of lines. Reducing the reactive power losses enables more active power to be transferred over a single line.

A.2 Voltage stability index

A conventional way for the voltage stability assessment is the use of indexes, which estimate the proximity to the voltage instability and determine those buses exhibiting weak stability.

There is a variety of indexes that help to assess the steady state voltage stability. In this case, the voltage stability index L_{index} is used [19]. This index is able to evaluate the steady state voltage stability margin of each bus. The L_{index} value lies between zero (no load) and one (voltage collapse). This value implicitly includes the load effect. The bus with the highest L_{index} value will be the most vulnerable, and therefore, this method helps to identify weak areas that require a critical support of reactive power. The L_{index} is calculated in the following way [19].

For the j -th load bus, the voltage stability index is defined by [19],

$$L_j = \left| 1 - \frac{\sum_{i \in \alpha_G} F_{ji} V_i}{V_j} \right| \quad (14)$$

where (α_G) represents the set of generator buses; F_{ji} is a term evaluated through the partial inversion of the admittance matrix Y_{bus} [19]; V represents complex voltages. For stable conditions, $0 \leq L_j \leq 1$ must not be violated for any j . Hence,

a global indicator L_{index} describing the whole system's stability is defined by [19],

$$L_{index} = \max_{j \in \alpha_L} (L_j) \quad (15)$$

where (α_L) is the set of load buses. Pragmatically, L_{index} must be lower than a given threshold value. The predetermined threshold value is specified depending on the system configuration and on the utility policy regarding service quality and allowable margin. Thus, the L_{index} in (15) is associated with the worst bus in the sense of voltage stability. The minimization of L_{index} implies to move such bus toward a less stressed condition.

B. Constraints

B.1 Equality constraints

The equality constraints are the balance of the active and reactive power described by the set of power flow equations. They may be expressed as follows,

$$P_{gi} - P_{di} - \sum_{j=1}^{N_b} |V_i| |V_j| |Y_{ij}| \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \quad (16)$$

$$Q_{gi} - Q_{di} - \sum_{j=1}^{N_b} |V_i| |V_j| |Y_{ij}| \sin(\delta_i - \delta_j - \theta_{ij}) = 0 \quad (17)$$

where, N_b is the number of buses, P_{gi} is the i -th active power generation, Q_{gi} is the i -th reactive power generation, P_{di} is the i -th active power load, Q_{di} is the i -th reactive power load, and $|Y_{ij}|$ is the ij -th element of the admittance matrix. These equality constraints are handled by running the power flow program.

B.2 Inequality constraints

The following inequality constraints are taken into account: (i) generators' voltage (V_g), active power (P_g), and reactive power (Q_g); (ii) Transformer's tap position.

In this paper, to test the algorithms, the generator voltages are allowed to vary within the interval [0.95, 1.05]. Actually, both limits will depend on the operating point, reactive power availability, tap positions, etc., thus, this interval may be modified. The active/reactive minimization losses tend to take the voltages to the upper limits. If actually this fact leads to inconveniences (as insulations' stress), as mentioned above, one alternative could be to limit the generator voltage upper bound.

C. Decision variables

The decision variables include the generator voltages V_G , and the tap ratio of transformers (T),

$$x = [V_{g_1}, \dots, V_{g_{N_g}}, T_1, \dots, T_{N_t}] \quad (18)$$

It is worth noting that the decision variables are self-constrained by the optimization algorithm.

D. Case of study

This paper compares the effectiveness and performance of the proposed algorithm respect to the MOEA/D. Both MOTLA/D and MOEA/D have been applied to an equivalent of the Mexican electrical grid; this system consists of 190-buses, 260-lines, and 46-generating units. The system model and data are summarized in [20-21].

E. Performance measures

In order to assess the algorithms' performance, two indicators are utilized.

E.1 Coverage of two sets

This performance measure was proposed by Zitzler et al. [22]. It compares two sets of non-dominated solutions (A, B) and outputs the percentage of individuals in one set dominated by the individuals of the other set. This performance measure is defined as,

$$C(A, B) = \frac{|\{b \in B \mid \exists a \in A : a \preceq B\}|}{|B|} \quad (19)$$

The value $C(A, B) = 1$ means that all points in B are dominated by or equal to all points in A . The opposite, $C(A, B) = 0$ represents the situation when none of the solutions in B are covered by the set A . Note that both $C(A, B)$ and $C(B, A)$ have to be considered, since $C(A, B)$ is not necessarily equal to $1 - C(B, A)$. When $C(A, B) = 1$ and $C(B, A) = 0$ then, we say that the solutions in A completely dominate the solutions in B (i.e., this is the best possible performance for A).

E.2 Spacing

This performance measure was proposed by Schott [23], and it quantifies the spread of solutions (i.e., how uniformly distributed the solutions are) along a Pareto front approximation. This performance measure is defined by,

$$S = \sqrt{\frac{1}{|n-1|} \sum_{i=1}^n (\bar{d} - d_i)^2} \quad (20)$$

where n is the number of non-dominated solutions, $d_i = \min_{i, i \neq j} \sum_{m=1}^k |f_m^i - f_m^j|$, $i, j = 1, 2, \dots, n$, where k denotes the number of objectives, and $\bar{d} = \frac{\sum_{i=1}^n d_i}{|n|}$. A value of zero implies that all solutions are uniformly spread (i.e., the best possible performance).

V. RESULTS

An equivalent of the Mexican electrical grid is used for testing the algorithms. In this study, 20 independent runs were performed by each algorithm.

The control parameter settings utilized by the MOTLA/D and MOEA/D are summarized in Table I, where T_{size} defines the neighborhood size, N_{pop} is the population size, μ indicates the distribution index used in the polynomial mutation, F_s is an algorithm's parameter representing the amount of perturbation added to the main parent, P_c is the crossover rate, and it determines the quantity of elements to be exchanged by the crossover operator, and $P_m = 1/n$ is the mutation rate, where n is the number of decision variables of the problem. It indicates the probability that each variable has of being changed. It is worth mentioning that the stop condition of each algorithm is the number of generations (N_{gen}).

TABLE I PARAMETER SETTINGS FOR MOTLA/D AND MOEA/D

Parameters	MOTLA/D	MOEA/D
N_{pop}	100	100
N_{gen}	50	50
T_{size}	30	30
μ	20	20
F_s	-	0.5
P_c	0.5	1
P_m	1/n	1/n

The optimal results for the reactive power losses (R_{loss}) and voltage stability index (L_{index}) obtained by both algorithms are summarized in Table II. This Table indicates that the proposed MOTLA/D estimates $R_{loss} = 64.78$ p.u and $L_{index} = 0.4926$, this means that MOTLA/D reaches a 16.74% reduction in losses and a 12.19% reduction in L_{index} . Meanwhile, the MOEA/D algorithm attains $R_{loss} = 69.72$ p.u and $L_{index} = 0.5118$. This means a 10.39% reduction in losses and 8.77% reduction in L_{index} with respect to the base case.

TABLE II: SUMMARY OF MAIN RESULTS

Objective functions	Base Case	MOTLA/D	MOEA/D
R_{loss}	77.81 p.u	64.78 p.u	69.72
L_{index}	0.561	0.4926	0.5118

TABLE III: OPTIMAL VOLTAGES

Variables	MOTLA/D	MOEA/D
V_{g1} (p.u)	1.05	1.0016
V_{g2} (p.u)	1.05	0.9766
V_{g3} (p.u)	1.0374	0.9534
V_{g4} (p.u)	1.05	1.0076
V_{g5} (p.u)	1.05	1.05
V_{g6} (p.u)	1.05	0.95
V_{g7} (p.u)	1.05	0.9534
V_{g8} (p.u)	1.05	1.05
V_{g9} (p.u)	0.9836	1.0299
V_{g10} (p.u)	0.9667	1.0385

TABLE IV: OPTIMAL TAP POSITION

Sending Bus	Receiving Bus	MOTLA/D	MOEA/D
53	54	1.05	1.05
59	60	1.05	1.0484
64	65	1.05	1.0496
64	66	1.0474	1.0469
84	85	1.05	1.0403
86	87	1.05	1.0403
78	88	0.9524	1.0209
89	90	1.05	1.0388
92	93	1.05	1.0453
98	100	1.027	0.9586

Table III, shows the optimal values of some generators' voltages from the optimal solutions obtained by the algorithms. Likewise, Table IV indicates the tap-position for some transformers with one-line tap changers. It means that moving the corresponding elements toward the optimal values specified in the Tables, the power system will attain an improved operating condition, more secure, economical, and efficient. For the sake of brevity not all voltage generators and taps' positions were included in Tables III and IV. The one-line diagram is depicted in reference [21].

The Pareto fronts obtained by MOTLA/D and MOEA/D are shown in Figure. 1. These figures represent the best case, according to the performance measures defined in (19) and (20). It can be observed from Figure 1 that MOTLA/D obtained better convergence as well spread solution over the decision space than the MOEA/D algorithm.

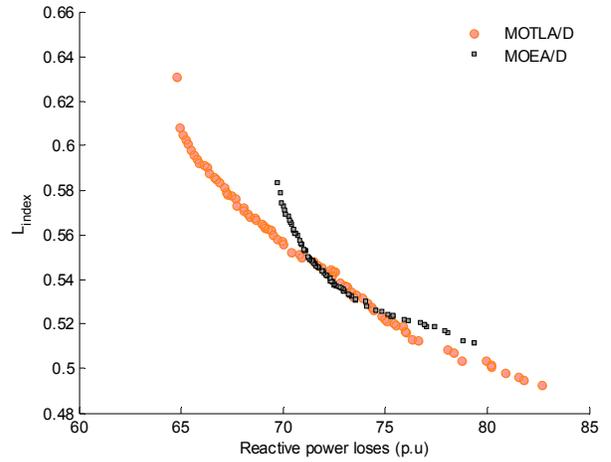


Figure 1. Pareto Front obtained by the algorithms

The MOTLA/D and the MOEA/D were evaluated using the two performance measures previously described. The results are summarized in Tables V and VI. Each of these Tables presents the average of each performance measure. The best results are displayed in **boldface**.

As noticed in Table V and VI, the proposed approach (MOTLA/D) outperformed MOEA/D regarding the Coverage of two sets. This indicates that our proposed approach produces more solutions that dominate the solutions produced by MOEA/D. Regarding Spacing, MOEA/D attains relatively better results. However, since convergence has precedence over spread, we can conclude that our proposed MOTLA/D outperformed MOEA/D in the analyzed case of study.

TABLE V: COVERAGE OF TWO SETS (C) PERFORMANCE MEASURE

TEST	C(MOTLA/D,MOEA/D)	C(MOEA/D,MOTLA/D)
	Average	Average
Mexican Grid	0.58	0.207

TABLE VI: SPACING PERFORMANCE MEASURE

TEST	MOTLA/D	MOEA/D
	Average	Average
Mexican Grid	0.01762	0.0099

CONCLUSIONS

This paper presented a multi-objective teaching learning algorithm based on decomposition (MOTLA/D) for solving a reactive power system problem. The effectiveness and performance of MOTLA/D was compared with respect to the MOEA/D, which represents a state-of-the-art algorithm. These two approaches were applied over an equivalent of the Mexican electrical grid. The results indicated that the proposed algorithm was able to obtain better solutions than MOEA/D. Therefore, MOTLA/D is able to achieve an optimal handling of reactive power by optimizing the reactive power losses and the voltage stability index. Thus, it may be concluded that the proposed algorithm may be a reliable choice for power systems applications.

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