F. Berrouk[1],
H.R.E.H. Bouchekara [2,*]
A.E. Chaib[3],
M.A. Abido[4],
K. Bounaya[1]
M.S. Javaid [2]

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A New Multi-objective Jaya Algorithm for Solving the Optimal Power Flow Problem

A new multi-objective Jaya (MOJaya) algorithm for solving optimal power flow (OPF) problem is developed in this paper. The developed MOJaya algorithm has been implemented to solve the multi-objective OPF (MOPF) problem with conflicting objectives, which are generating fuel cost minimization, voltage deviation improvement, voltage stability enhancement, active power losses reduction and system security enhancement. The developed algorithm is applied to find a set of Pareto-optimal solutions. Moreover, an algorithm based on fuzzy logic is implemented to identify the best compromise solution among the Pareto optimal set of solutions. Results are obtained by running the simulation on IEEE 30-bus test system which confirms the efficacy of the developed algorithm in solving real MOPF cases and also in ascertaining well-distributed Pareto optimal set of solutions.

Keywords: Optimal power flow; Power system optimization; Multi-objective optimization; Jaya.

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1. Introduction

The Optimal Power Flow (OPF) problem has been a subject of interest since Carpentier introduced this term in 1962 [1] and later it was developed by Dommel and Tinney [2], and since then it has been a topic of considerable research in the domain of power system operation and planning. The sole purpose of OPF is to optimize a certain objective function, say fuel cost, by determining the optimal operational strategy of a power system, while simultaneously satisfying a set of physical and operational constraints as imposed by equipment, physics of electricity and network limitations [3] [4].

After scanning the recent literature about OPF, it can be noticed that there are many papers that have contributed to solve the OPF problem using either classical optimization algorithms or metaheuristic algorithms (sometimes called also computational intelligence algorithms). As reported in many research works, classical optimization algorithms that make use of derivatives and gradients need some simplifying assumptions. However, the OPF deals with the objective functions that are generally non-smooth, non-convex and non-differentiable [5]. Therefore, a need arises to develop new optimization algorithms that are efficient to handle such complexities. Metaheuristics have been extensively and successfully used over the last decade to solve the OPF problem. However, there is a relatively low number of papers that are devoted to the multi-objective OPF (MOPF) problem.

Some example of metaheuristics used for solving the MOPF problem are discussed here. In [6] an Enhanced Genetic Algorithm (EGA) is used along with Strength Pareto Evolutionary Algorithm (SPEA) based approach having set of strongly dominated solutions in order to determine Pareto optimal set. The objective functions considered were fuel cost,

*Corresponding author: Bouchekara.houssem@gmail.com`, Tel: (+966)561277130
[1]LGEG Laboratory, University of Guelma, BP 401 Guelma, 24000, Algeria
[2]Department of Electrical Engineering, University of Hafr Al Batin, Hafr Al Batin 31991.
[3]Constantine Electrical Engineering Laboratory, LEC, Department of Electrical Engineering, University of Freres Mentouri Constantine, 25000 Constantine, Algeria.
[4]Electrical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

losses, and a voltage stability index. In [7] a Multi-Objective Differential Evolution (MODE) is used in order to solve the MOPF problem considering fuel cost, emission and losses of flexible AC transmission systems (FACTS) device-equipped power systems. In [8] another MODE Pareto-based approach algorithm is used in order to optimize fuel cost, losses and voltage stability. In [9] an Improved Particle Swarm Optimisation (IPSO) algorithm is used to solve the MOPF problem considering fuel cost, losses, emission and voltage stability index where an aggregation of objectives is used to convert the set of objectives into one objective. In [10] the Gravitational Search Algorithm (GSA) is applied considering fuel cost, voltage profile and losses where the objective functions are aggregated and the problem is converted into a single objective optimization problem. In [4] a modified Shuffle Frog Leaping Algorithm (MSLFA) using Pareto-based approach is applied to optimize fuel cost and emission. In [11] the Artificial Bee Colony (ABC) algorithm is used to optimize fuel cost, voltage profile, voltage stability index, losses, and emission via aggregation of objective functions. In [12] a fuzzy-based Modified Artificial Bee Colony (MABC) algorithm is employed for simultaneous optimization of fuel cost, emission, losses, and voltage profile. In that study the objectives are combined using fuzzy logic to form one single objective function. In [13] a Pareto-based approach using an hybrid algorithm based on PSO and SFLA algorithms is utilized where the objective functions considered are fuel cost and emission. In [14] a new Multi-objective Modified Imperialist Competitive Algorithm (MOMICA) is used in order to optimize fuel cost, emission, voltage profile and losses using a Pareto-based approach. In [15] ICA with some modified techniques (MICA) are used to solve the MOPF problem considering fuel cost, losses and voltage profile using a Pareto-based approach. In [16], a Pareto-based approach using a Modified Teaching–Learning Based Optimization (MTLBO) algorithm is proposed to solve the MOPF problem considering fuel cost and emission. In [17] a Pareto-based approach based on an Adaptive Group Search Optimization (AGSO) algorithm is used to optimize fuel cost, emission and security index. In [18] the Grenade Explosion Method (GEM) is used along with different aggregations functions to optimize different objectives which are: fuel cost, voltage profile, voltage stability index, emission and losses.

In [19] a new metaheuristic called Jaya (a Sanskrit word meaning victory) is developed. Jaya is a population based optimization algorithm inspired from the idea that an optimal solution of a certain problem tends to move away from the worst solution and, simultaneously, finding its way to the best solution [19].

The main contribution of the paper is to develop and implement of a new multi-objective Jaya (MOJaya) algorithm for solving the MOPF problem. The MOPF is formulated in this paper using the following objective functions: fuel cost minimization, voltage profile improvement, voltage stability enhancement, active power losses reduction and system security enhancement.

The remaining of this paper is organized as follows: section 2 describes the single objective OPF and MOPF problems, then, section 3 describes the Jaya algorithm and the developed MOJaya algorithm, while section 4 exposes the results obtained in this work along with a discussion about these results, and finally, conclusions are drawn in section 5.

2. The OPF Problem

Mathematically stating, the aim of the OPF is to minimize a particular objective function by optimizing a set of certain control variables, and simultaneously satisfying both equality and inequality constraints.

2.1. Formulation

There are two formulations of the OPF problem, based on number and nature of objectives: single objective OPF and multi-objective OPF.

2.1.1. Single objective OPF

IWhen only one objective function is optimized, the OPF is called a single objective one and it is noted as OPF in this paper. The single objective OPF problem can be formulated as follows [20],[21]:

$$\begin{aligned} \text{Minimize} \quad & \mathrm{f}(\mathrm{x},\mathrm{u}) \\ \text{Subject to} \quad & g(\mathrm{x},\mathrm{u}) = 0 \\ \text{and} \quad & h(\mathrm{x},\mathrm{u}) \le 0 \end{aligned} \tag{1}$$

Where: $\mathrm{f}(\mathrm{x},\mathrm{u})$ is the objective function, $\mathrm{g}(\mathrm{x},\mathrm{u})$ is the set of equality constraints, $\mathrm{h}(\mathrm{x},\mathrm{u})$ is the set of inequality constraints, x is the vector of dependent variables or state variables and u is the vector of independent variables or control variables.

2.1.2. Multi-objective OPF

When more than one objective function are optimized at a time, the OPF is called a multi-objective one and it is noted in this paper as (MOPF).

Therefore, the MOPF will take following mathematical formulation [18]:

$$\begin{aligned} \text{Minimize} \quad & \mathrm{F}(\mathrm{x},\mathrm{u}) = [\mathrm{f}_1(\mathrm{x},\mathrm{u}), \mathrm{f}_2(\mathrm{x},\mathrm{u}), \dots, \mathrm{f}_k(\mathrm{x},\mathrm{u})]^T \\ \text{Subject to} \quad & g(\mathrm{x},\mathrm{u}) = 0 \\ \text{and} \quad & h(\mathrm{x},\mathrm{u}) \le 0 \end{aligned} \tag{2}$$

where: F(x, u) and k represent the vector and total number of objective functions, respectively.

2.2. Design Variables

2.2.1. Control Variables

In the OPF problem, following can be accounted as control variables: V_G is the PV buses voltage magnitude, P_G is the active power generation at PV buses (except slack bus), Q_C is the shunt VAR compensation, and T is the transformers tap settings.

Hence, u can be expressed as:

$$\mathrm{u}^{\mathrm{T}} = \left[\mathrm{P}_{\mathrm{G}_2} \cdots \mathrm{P}_{\mathrm{G}_{\mathrm{NG}}}, \mathrm{V}_{\mathrm{G}_1} \cdots \mathrm{V}_{\mathrm{G}_{\mathrm{NG}}}, \mathrm{Q}_{\mathrm{C}_1} \cdots \mathrm{Q}_{\mathrm{C}_{\mathrm{NC}}}, \mathrm{T}_1 \cdots \mathrm{T}_{\mathrm{NT}}\right] \tag{3}$$

where NT, NG, and NC are the number of transformers, generators and VAR compensators, respectively.

2.2.2. State Variables

State variables for the OPF problem, generally, are: V_L is the voltage magnitudes at PQ buses or load buses, P_{G1} is the active power generation at slack bus, S_l is the transmission line loadings (or line flow) and Q_G is the reactive power output of all generators.

Hence, x takes following expression

$$x^T = [P_{G_1}, V_{L_1} \cdots V_{L_{NL}}, Q_{G_1} \cdots Q_{G_{NG}}, S_{l_1} \cdots S_{l_{nl}}] \tag{4}$$

where, NL and nl represent the number of load buses number of transmission lines, respectively.

It is worth to mention that, it is assumed that G1 is the slack bus, if this is not the case the number of the slack bus must be changed for both x and u.

2.3. Objective functions

In this paper, following five objective functions are taken into consideration.

2.3.1. Objective function 1: Cost

Primary objective of solving an OPF problem is to minimize generation fuel cost. This cost can be expressed as a quadratic function as follow:

$$\text{Cost} = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{5}$$

where: P_{G_i} is the active power of the ith generator, NG is the number of generators and a_i, b_i and c_i are the cost coefficients of the i^{th} generator. Equation (5) represents a convex objective function. However, it can be non-convex in some cases, for instance, while considering multi-fuels option, it happens to be non-convex problem [22], [23].

2.3.2. Objective function 2: Voltage deviation

To ensure power system's safety and service quality, regulating bus voltage is a crucial requirement. Therefore, minimizing voltage deviation (VD) from 1.0 p.u. is the second objective function, as expressed below:

$$VD = \sum_{i=1}^{NL} \left| V_{L_i} - 1.0 \right| \tag{6}$$

2.3.3. Objective function 3: Voltage stability index

Predicting events of voltage instability is of prime importance for undisrupted operation of a power grid. In [24], a voltage stability index, L_{max}, is developed by Kessel and Glavitch. L_{max} is a function of local indicators L_j, as given below:

$$L_{max} = \max(L_j) \qquad j = 1,2, \dots, NL \tag{7}$$

where: L_j is the local indicator of bus *j*, given by:

$$\mathrm{L_j} = \left|1 - \sum_{\mathrm{i}=1}^{\mathrm{NG}} \mathrm{H_{LG_{ji}}} \frac{\mathrm{V_i}}{\mathrm{V_j}}\right| \qquad \mathrm{j} = 1,2, \dots, \mathrm{NL} \tag{8}$$

where matrix H is obtained by performing partial inversion on Y_{bus}. Details of voltage stability index are available in [24].

The range of L_{max} is from 0 to 1. Lower value indicates a more stable system. Thus, minimizing L_{max} to enhance the voltage stability is another objective function.

2.3.4. Objective function 4: Active power transmission losses

Following expression accounts for the total active power loss:

$$\mathrm{P_{Losses}} = \sum_{i=1}^{NB} P_{\mathrm{i}} = \sum_{i=1}^{NB} P_{Gi} - \sum_{i=1}^{NB} P_{Di} \tag{9}$$

where, P_D is real load demand and NB denotes the total number of busses.

2.3.5. Objective function 5: Security index (SI)

The security index, proposed in this paper, is given by:

$$\mathrm{SI} = \sum_{i=1}^{nl} \left(\frac{S_{l_i}}{S_{l_i}^{\max}}\right) \tag{10}$$

where: S_{l_i} and $S_{l_i}^{\max}$ are the apparent and maximum power flow in transmission line i, respectively. For enhances system security, SI must be minimized.

2.4. Constraints

In this paper, two types of OPF constraints are considered - equality and inequality constraints.

2.4.1. Equality constraints

Real power constraints are:

$$P_{Gi} - P_{Di} - V_i \sum_{j=i}^{NB} V_j\left[G_{ij}\cos(\theta_{ij}) + B_{ij}\sin(\theta_{ij})\right] = 0 \tag{11}$$

However, reactive power constraints are given by:

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=i}^{NB} V_j\left[G_{ij}\sin(\theta_{ij}) - B_{ij}\cos(\theta_{ij})\right] = 0 \tag{12}$$

where $\theta_{ij} = \theta_i - \theta_j$, G_{ij} and B_{ij} represent conductance and susceptance, respectively, between bus *i* and bus *j*. Both belong to the admittance matrix $(Y_{ij} = G_{ij} + j\, B_{ij})$.

2.4.2. Inequality constraints

a) Generator constraints

$$V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max}, \quad i = 1, \dots, NG \tag{13}$$

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}, \quad i = 1, \dots, NG \tag{14}$$

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max}, \quad i = 1, \dots, NG \tag{15}$$

b) Transformer constraints

$$T_i^{\min} \leq T_i \leq T_i^{\max}, \quad i = 1, \dots, NT \tag{16}$$

c) Shunt VAR compensator constraints

$$Q_{C_i}^{\min} \leq Q_{C_i} \leq Q_{C_i}^{\max}, \quad i = 1, \dots, NC \tag{17}$$

d) Security constraints

$$V_{L_i}^{\min} \leq V_{L_i} \leq V_{L_i}^{\max}, \quad i = 1, \dots, NL \tag{18}$$

$$S_{l_i} \leq S_{l_i}^{\max}, \quad i = 1, \dots, nl \tag{19}$$

2.4.2. Constraints handling

Power flow, self-satisfies equality constraints, whereas, the optimization algorithm handles the inequality constraints imposed on control variables. However, the inequality constraints imposed on dependent quantities are handled using the penalty method. It consists of adding a measure of violation of considered quantities multiplied by penalty factors. The measure of violation is null if constraints are satisfied.

3. The Optimization Algorithm

3.1. Jaya Algorithm

As aforesaid, Jaya algorithm is a newly developed optimization algorithm [19]. This algorithm is inspired by the fact that the candidates of the population should move towards the best solution of the population and avoid the worst one. Moreover, Jaya has a major distinction over other optimization algorithms because it has no specific parameters which must be carefully selected, and needs only common parameters like population size and the maximum number of iterations [19].

The main steps of the Jaya algorithm are described below:

Step 1: Initialization: In this step a population of 'n' candidates that has a predefined size is randomly generated in the search space.

Step 2: Identification of best and worst solutions: After the initialization of the population, the best and worst candidates among the population in terms of objective functions are identified.

Step 3: In this step, the candidates of the solution are moved using the following expression:

$$\begin{aligned} \mathrm{x_{New}}(i) = {} & \mathrm{x_{Old}}(i) + r_1 \cdot (\mathrm{X_{Best}}(i) - |\mathrm{x_{Old}}(i)|) - r_2 \\ & \cdot (\mathrm{X_{Worst}}(i) - |\mathrm{x_{Old}}(i)|) \\ & \forall i = 1{:}\, n \end{aligned} \tag{20}$$

where: r_1 and r_2 are two random numbers in the range [0, 1], $X_{Best}(i)$ and $X_{Worst}(i)$ are the best and worst candidates obtained at the it^{th} iteration, respectively.

For a given candidate, if the new solution (after moving) is better than the old one (before moving), the solution is accepted, and the corresponding candidate is updated. Otherwise, the new solution is discarded and the old one is kept.

The process in step 2 and step 3 is repeated until a termination criterion is reached. The termination criterion chosen for Jaya is the maximum number of iterations and this criterion can be changed, and any other criterion can be implemented.

3.2. The developed Multi-objective Jaya algorithm (MOJaya)

3.2.1. Overview

The As previously mentioned, a multi-objective Jaya algorithm noted as MOJaya is developed in this paper. MOJaya is based on SPEA2 (improving strength Pareto evolutionary algorithm) [25].

3.2.2. MOJaya algorithm

The main steps of the MOJaya algorithm are:

Step 1: Initialization: in this step an initial population noted as $\mathrm{Pop}(0)$ is randomly generated in the search space. Moreover, an empty external archive $\mathrm{Pop}_{\mathrm{archive}}(0) = \emptyset$ is created.

Step 2: Fitness assignment: the fitness values of all candidates of an overall population ($\mathrm{POP} = \mathrm{Pop} \cup \mathrm{Pop}_{\mathrm{archive}}$) composed of $\mathrm{Pop}(\mathrm{it})$ and $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it})$ is calculated using the following procedure:

For each candidate 'i', in the population $\mathrm{Pop}(\mathrm{it})$ and in the archive $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it})$ a strength S(i) is assigned which represents the number of candidates it dominates. Based on S(i), the raw fitness R(i) of a candidate 'i' is determined by following expression:

$$\mathrm{R(i)} = \sum \mathrm{S(j)} \tag{21}$$

It is worth to mention that, since the MOPF problem is formulated as a minimization one, R(i)=0 corresponds to a nondominated candidate (a solution from the Pareto front) while a high value of R(i) is synonym to that this candidate is dominated by many candidates.

After that, a density D(i) is calculated using the following expression:

$$\mathrm{D(i)} = \frac{1}{\sigma_i^k + 2} \tag{22}$$

where σ_i^k is the k-th nearest neighbor (based on the distance in the objective space), $k = \sqrt{\mathrm{n} \cdot \mathrm{n_A}}$. The 2 is added in the expression of D(i) to ensure that this one is comprised between 0 and 1.

Finally, the fitness F(i) is calculated using the following expression:

$$\mathrm{F(i)} = \mathrm{R(i)} + \mathrm{D(i)} \tag{23}$$

Step 3: Environmental selection: in this step, the nondominated candidates in $\mathrm{Pop}(\mathrm{it})$ and in the archive $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it})$ are copied into $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it}+1)$. If the size of $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it}+1)$ is superior than n_A, $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it}+1)$ is reduced using the truncation operator, otherwise if the size of $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it}+1)$ is less than n_A, then $\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it}+1)$ is completed by less dominated candidates in $\mathrm{Pop}(\mathrm{it})$ and in

$\mathrm{Pop}_{\mathrm{archive}}(\mathrm{it})$. This will allow the size of $\mathrm{Pop}_{\mathrm{archive}}$ to be constant over all iteration whatever the number of nondominated candidates found is.

Step 4: Identification of best and worst solutions in POP based on fitness F.

Step 5: Moving the candidates of POP using (20). Then, for a candidate in POP, if a new solution (after moving) dominates the old one (before moving) this solution is updated. Otherwise the new solution is discarded.

This process in step 2 to step 5 is repeated until a termination criterion is reached.

3.2.3. Best compromise solution via fuzzy decision

For decision making, i.e. in order to help the decision maker, it is necessary to identify the best compromise solution among the set of nondominated solution found. Using the Fuzzy Set Theory, the best compromise solution is determined as follows. First, each objective function from the nondominated solution is replaced by a membership function defined as [8], [26], [27]:

$$\mu_i = \begin{cases} 1 & F_i < F_i^{\max} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i^{\min} < F_i \end{cases} \tag{24}$$

where $F_i^{\max}$ and $F_i^{\min}$ denote the maximum and minimum of the corresponding objective function, respectively. A normalized membership function for each k is evaluated as under:

$$\mu^k = \max\left(\frac{\sum_{i=1}^{\mathrm{Nobj}} \mu_i^k}{\sum_{k=1}^{\mathrm{Nnds}} \sum_{i=1}^{Nobj} \mu_i^k}\right) \tag{25}$$

where N_{obj} and N_{nds} are the number of objective functions treated and the number of nondominated solutions found, respectively.

4. Applications and Results

Effectiveness of the developed MOJaya has been evaluated by testing it on the IEEE 30-bus test system. This system has a generation capacity of 900.2 MW and it is composed of 30 buses, 41 branches, 9 shunt capacitors, 6 generators and 4 tap changing transformers. Therefore, this system has 24 design variables. More details about this system are in [28].

The investigated cases in this paper are shown in Table 1. First, five single objective OPF cases have been solved corresponding the five selected objective functions. Second, eleven MOPF cases combining the selected objective functions have been investigated.

Table 1: Summary of investigated cases.

Cases	Type	Cost	VD	L_{max}	P_{loss}	SI
CASE-1	Single objective	☑				
CASE-2	Single objective		☑			
CASE-3	Single objective			☑		
CASE-4	Single objective				☑	
CASE-5	Single objective					☑
CASE-6	Multi-objective	☑	☑			

CASE-7	Multi-objective	☑		☑		
CASE-8	Multi-objective	☑			☑	
CASE-9	Multi-objective	☑				☑
CASE-10	Multi-objective	☑	☑	☑		
CASE-11	Multi-objective	☑	☑		☑	
CASE-12	Multi-objective	☑	☑			☑
CASE-13	Multi-objective	☑		☑	☑	
CASE-14	Multi-objective	☑		☑		☑
CASE-15	Multi-objective	☑			☑	☑
CASE-16	Multi-objective	☑	☑	☑	☑	☑

The developed program has been implemented using the commercial MATLAB software and the open source MATPOWER software. The simulation runs were performed using the proposed MOJaya approach with n = 100, n_A=100, and a maximum of 500 iterations.

4.1 Single Objective Problem

The obtained results of this single objective OPF study are displayed in Table 2. Moreover, the convergence of the objectives is shown in Figure 1, Figure 2, Figure 3, Figure 4 and Figure 5. It can be noticed from these figures that the objective function converges quickly to the optimum value while the penalty term reaches zero after some iterations.

This study is very useful since it helps to identify the range of variation of each objective function and will help to analyze the best compromise solution later.

Table 2: Optimal results found for the single objective OPF cases using Jaya.

Variables	CASE-1	CASE-2	CASE-3	CASE-4	CASE-5
P_{G1}	177.0386	89.0808	53.4323	51.2433	78.5505
P_{G2}	48.6817	78.6206	79.4068	79.9994	79.9934
P_{G5}	21.3210	49.8306	49.6937	50.0000	49.9996
P_{G8}	21.0966	34.6289	34.2490	34.9999	34.9847
P_{G11}	11.8740	23.9941	29.9464	30.0000	29.9922
P_{G13}	12.0001	12.0077	39.7724	39.9999	13.5290
V_{G1}	1.1000	1.0248	1.0991	1.1000	1.0999
V_{G2}	1.0807	1.0143	1.0925	1.0932	1.0914
V_{G5}	1.0541	1.0127	1.0868	1.0752	1.0584
V_{G8}	1.0619	1.0071	1.0783	1.0822	1.0704
V_{G11}	1.1000	1.0441	1.0998	1.1000	1.1000
V_{G13}	1.1000	1.0004	1.0999	1.1000	1.0948
$T_{11(6\text{-}9)}$	1.0216	1.0646	0.9791	1.0526	0.9799
$T_{12(6\text{-}10)}$	0.9000	0.9010	0.9063	0.9000	0.9797
$T_{15(4\text{-}12)}$	0.9645	0.9574	0.9746	0.9836	0.9815
$T_{36(28\text{-}27)}$	0.9530	0.9699	0.9437	0.9686	0.9794
QC_{10}	4.9998	4.4080	4.3023	4.9936	4.9830
QC_{12}	5.0000	0.0000	4.0689	4.9955	5.0000
QC_{15}	4.9955	4.8290	3.4300	3.8780	2.8708
QC_{17}	4.9999	0.0773	4.2433	5.0000	4.9847
QC_{20}	4.2670	4.9988	4.7195	3.6541	3.7408

QC_{21}	4.9998	4.8611	0.0426	5.0000	4.9775
QC_{23}	2.6187	4.9784	0.1934	2.4078	1.1458
QC_{24}	5.0000	4.9206	0.0277	4.9988	4.9916
QC_{29}	2.3064	2.5858	0.1018	2.0461	2.5062
Cost ($/h)	**799.0343**	907.2475	963.1270	967.0467	919.9918
VD (pu)	1.9737	**0.0935**	2.0425	2.0418	1.7959
L_{max}	0.1260	0.1488	**0.1245**	0.1258	0.1293
P_{Losess} (MW)	8.6121	4.7626	3.1006	**2.8425**	3.6494
SI	14.3861	13.1574	13.0120	12.6494	**11.2312**

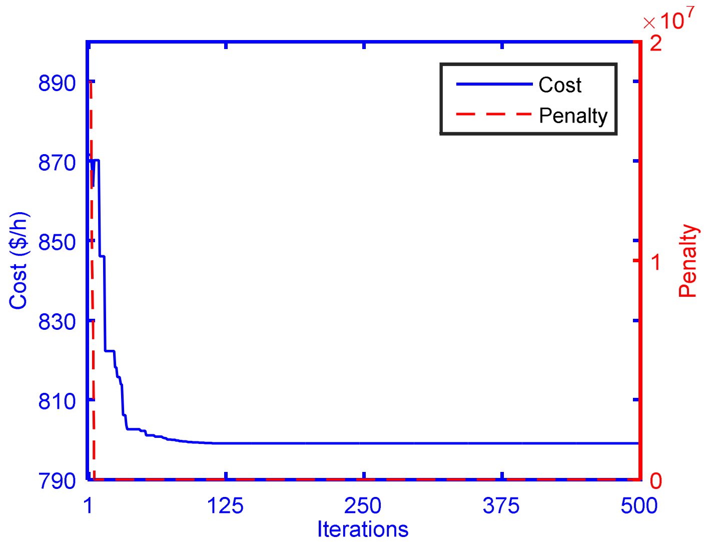

Figure 1 : Fuel cost minimization.

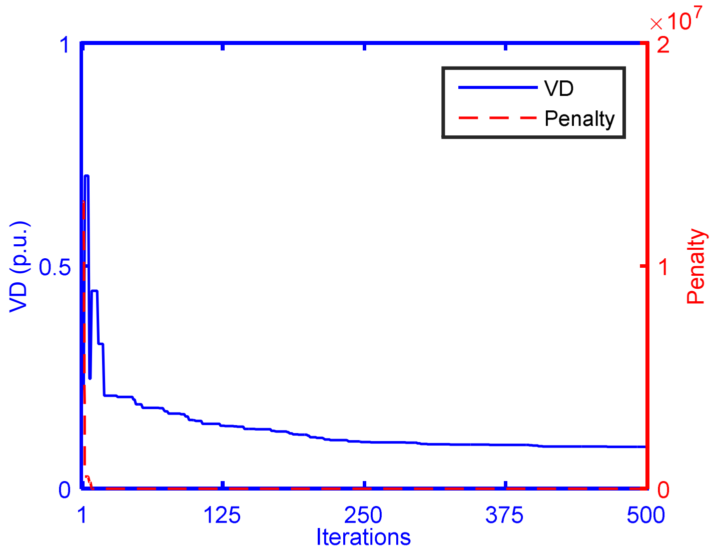

Figure 2 : Voltage deviation minimization.

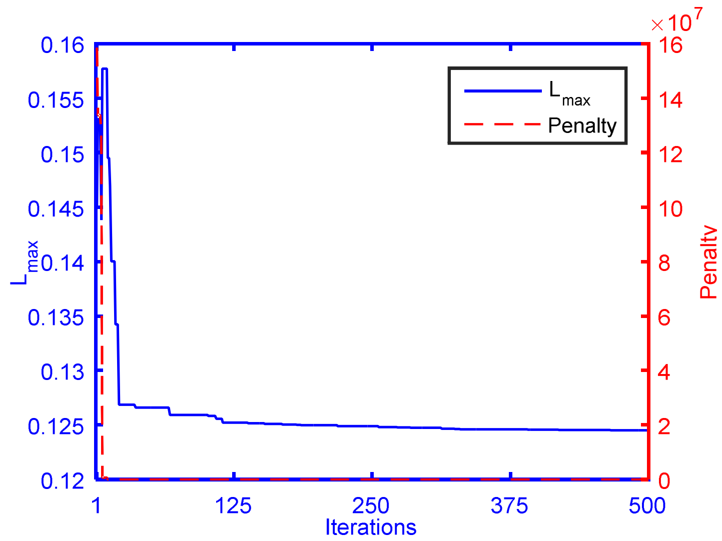

Figure 3 : L_{max} minimization.

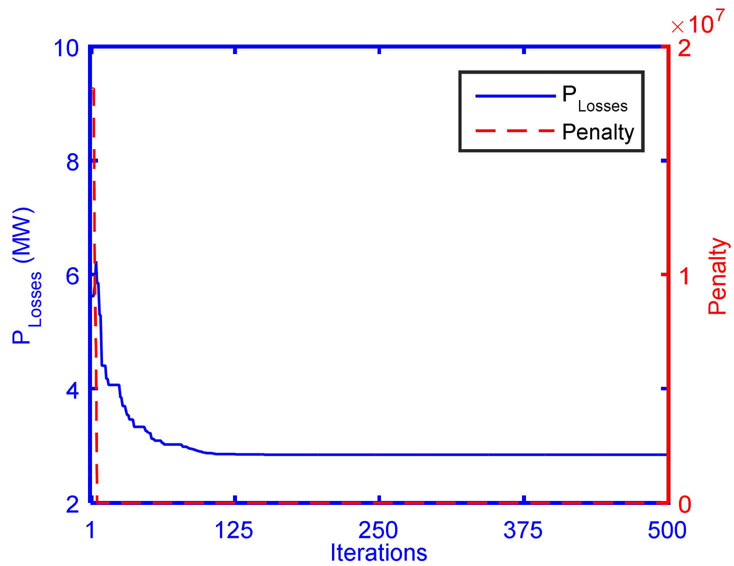

Figure 4 : Active power losses minimization.

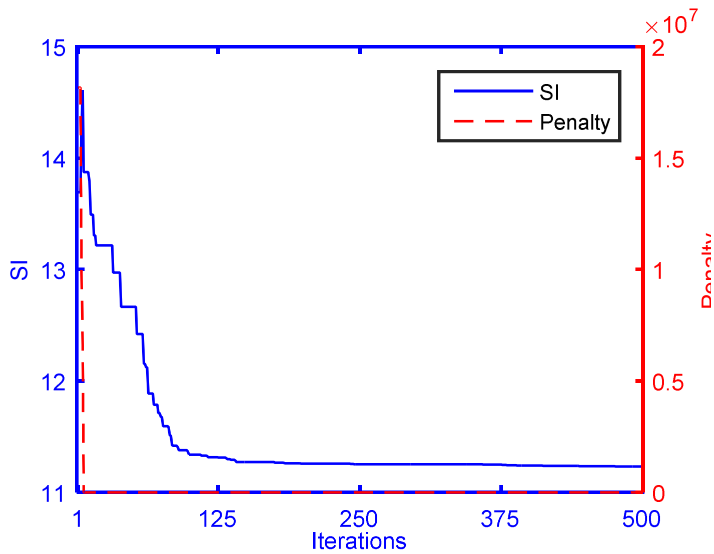

Figure 5 : SI minimization.

From Table 2, it can be seen that the best value of Cost is 799.0343 $/h and the worst one is 967.046 $/h obtained when the P_{Losses} is minimized. The best value of VD obtained is 0.0935 and the worst one which is obtained when L_{max} is minimized. For L_{max} the best value obtained is 0.1245 while the worst one is 0.1488 obtained when VD is optimized. Regarding losses, the best and worst values obtained are 2.8425 MW and 8.6121 MW, respectively. Finally, for SI, the best value reached after optimization is 11.2312 while the worst one that is obtained when the cost is minimized is 14.3861.

In order to show the efficiency of the Jaya algorithm, the results obtained for the first case (since this case is the most widely investigated case) are compared with many other algorithms as shown in Table 3. It can be seen that, Jaya outperforms many other optimization algorithms in terms of the objective function found.

Table 3: Comparison of CASE-1 simulation results with existing literature.

Cost	Optimization algorithm (abbreviation)	Reference
799.0343	Colliding Bodies Optimization (CBO)	
799.0349	Enhanced Colliding Bodies Optimization (ECBO)	[23]
799.0352	Improved Colliding Bodies Optimization (ICBO)	[23]
799.0353	Grenade Explosion Method (GEM)	[23]
799.0463	Teaching-Learning-Based Optimization (TLBO)	[18]
799.0715	Backtracking Search Optimization Algorithm (BSA)	[22]
799.0760	Biogeography-Based Optimization (BBO)	[20]
799.1116	Improved Electromagnetism-Like Mechanism (IEM)	[29]
799.1821	League Championship Algorithm (LCA)	[30]
799.1974	Differential Evolution (DE)	[3]
799.2891	Simulated Annealing (SA)	[31]
799.45	Black-Hole-Based Optimization (BHBO)	[32]
799.9217	Electromagnetism-Like Mechanism (EM)	[21]
800.078	Genetic Evolving Ant Direction HDE (EADHDE)	[30]
800.1579	Evolving Ant Direction Differential Evolution (EADDE)	[33]
800.2041	Particle Swarm Optimization (PSO)	[34]
800.41	Fuzzy Particle Swarm Optimization (FPSO)	[35]
800.72	Improved Genetic Algorithms (IGA)	[36]
800.805	Particle Swarm Optimization (PSO)	[37]
800.96	Fuzzy Genetic Algorithm (GAF)	[36]
801.21	Imperialist Competitive Algorithm (ICA)	[36]
801.843	Enhanced Genetic Algorithm (EGA)	[38]
802.06	Tabu Search (TS)	[39]
802.2900	Modified Differential Evolution Algorithm (MDE)	[40]
802.376	Improved Evolutionary Programming (IEP)	[41]
802.465	Evolutionary Programming (EP)	[42]
802.62	Refined Genetic Algorithm (RGA)	[43]
804.02	Gradient Method (GM)	[44]
804.853	Genetic Algorithm (GA)	[45]
805.94	Colliding Bodies Optimization (CBO)	[44]

4.2. Multi Objective Problem

After having solved single objective OPF cases in the previous section, MOPF cases are considered in this section. It is important to highlight that since cost is the most important objective, it is considered as an objective function in all MOPF cases. The best compromise solutions found for all investigated MOPF cases are displayed in Table 4.

CASE-6 gives the best compromise solution, which can be represented by the pair (Cost, VD) is (803.8962, 0.1648) and it can be compared with CASE-1 and CASE-2 represented by (799.0343, 1.9737) and (907.2475, 0.0935), respectively. It can be seen that this solution offers a good compromise between the two objectives. Moreover, the Pareto optimal set obtained for this case and sketched in Figure 6 has a good distribution between the two objectives. The points vary between (800.7102, 0.7323) and (824.4804, 0.1551).

Table 4: Best compromise solutions found for MOPF cases using MOJaya.

	CASE-6	**CASE-7**	**CASE-8**	**CASE-9**	**CASE-10**	**CASE-11**	**CASE-12**	**CASE-13**	**CASE-14**	**CASE-15**	**CASE-16**
P_{G1}	174.7	179.0	129.1	145.6	159.6	118.0	158.5	130.8	146.8	119.4	125.1
P_{G2}	48.5	48.5	50.9	43.9	55.6	65.0	36.9	42.0	55.1	59.3	52.9
P_{G5}	18.4	19.8	29.8	24.9	20.0	29.2	22.3	35.3	25.2	40.7	22.9
P_{G8}	29.3	18.6	35.0	35.0	35.0	22.1	35.0	30.3	32.0	31.3	32.5
P_{G11}	10.0	14.4	30.0	26.9	10.0	29.9	26.9	20.7	19.4	25.9	30.0
P_{G13}	12.0	12.0	14.3	14.4	12.0	25.6	12.0	29.9	12.0	12.0	26.7
V_{G1}	1.057	1.100	1.100	1.038	1.100	1.046	1.020	1.098	1.100	1.100	1.039
V_{G2}	1.039	1.081	1.085	1.023	1.082	1.034	1.001	1.080	1.086	1.088	1.020
V_{G5}	0.996	1.059	1.055	0.965	1.053	1.006	0.952	1.054	1.040	1.054	0.999
V_{G8}	1.000	1.061	1.070	0.988	1.024	0.994	0.979	1.059	1.045	1.060	1.010
V_{G11}	1.001	1.100	1.072	1.100	1.080	1.027	1.049	1.079	1.096	1.100	1.062
V_{G13}	1.036	1.100	1.071	1.096	1.045	1.004	1.044	1.100	1.100	1.095	1.018
$T_{11(6\text{-}9)}$	1.014	0.998	1.028	0.900	0.982	0.990	0.968	1.041	0.961	0.953	0.979
$T_{12(6\text{-}10)}$	0.919	0.900	0.947	0.900	0.980	0.969	0.951	0.943	0.900	1.018	0.992
$T_{15(4\text{-}12)}$	1.018	0.969	0.999	0.905	1.086	0.977	0.992	0.954	0.969	0.988	0.993
$T_{36(28\text{-}27)}$	0.978	0.932	1.022	0.900	0.900	0.947	0.951	0.922	0.917	0.994	0.900
QC_{10}	3.984	0.755	3.480	0.177	1.059	5.000	5.000	2.247	1.935	5.000	0.429
QC_{12}	3.066	3.706	4.298	0.000	5.000	2.591	0.000	0.279	0.000	2.718	1.738
QC_{15}	5.000	0.000	0.980	3.657	2.959	4.701	4.965	4.855	0.189	1.006	4.387
QC_{17}	5.000	5.000	5.000	5.000	0.000	2.664	3.080	2.541	0.000	4.289	2.045
QC_{20}	5.000	4.582	5.000	4.410	0.000	2.306	1.605	4.681	2.346	0.788	5.000
QC_{21}	0.586	5.000	0.000	5.000	4.531	4.839	4.973	4.027	3.677	2.745	2.866
QC_{23}	4.927	5.000	2.080	2.228	0.665	5.000	4.958	2.808	1.880	0.000	2.465
QC_{24}	3.835	0.000	5.000	4.606	0.236	3.392	3.101	0.280	0.010	5.000	4.035
QC_{29}	4.539	0.000	3.351	2.593	3.395	2.396	4.330	0.067	0.000	1.630	5.000
Cost ($/h)	**803.9**	**799.8**	**824.6**	**816.1**	**807.2**	**839.3**	**815.4**	**834.5**	**808.7**	**845.6**	**830.8**
VD (pu)	**0.165**	1.866	1.150	1.513	**0.814**	**0.157**	**0.266**	1.630	1.668	1.389	**0.458**
L_{max}	0.149	**0.125**	0.139	0.131	**0.130**	0.147	0.149	**0.126**	**0.126**	0.135	**0.135**
P_{Losses} (MW)	9.489	8.885	**5.620**	7.328	8.814	**6.347**	8.228	**5.649**	7.122	**5.173**	**6.663**
SI	14.308	14.836	12.846	**12.637**	16.537	13.549	**13.151**	14.228	**13.759**	**12.491**	**14.329**

The best compromise solution for CASE-7 is found to be (Cost=799.7642 and L_{max}=0.1254) and it can be compared with CASE-1 and CASE-3 represented by (799.0343, 0.1260) and (963.1270, 0.1245), respectively. The Pareto optimal set of solutions obtained for this case is sketched in Figure 7

The best compromise solution found for CASE-8 is (Cost=824.5752 and P_{Losses}=5.6196) and it can be compared with CASE-1 and CASE-4 represented by (799.0343, 8.6121) and (967.0467, 2.8425), respectively. The Pareto optimal set of solutions obtained for this case is plotted in Figure 8.

The best compromise solution found for CASE-9 is (Cost=816.1213 and SI=12.6369) and it can be compared with CASE-1 and CASE-5 represented by (799.0343, 14.3861) and (919.9918, 11.2312), respectively. The Pareto optimal set of solutions obtained for this case is plotted in Figure 9.

The same analysis can be made for the remaining cases.

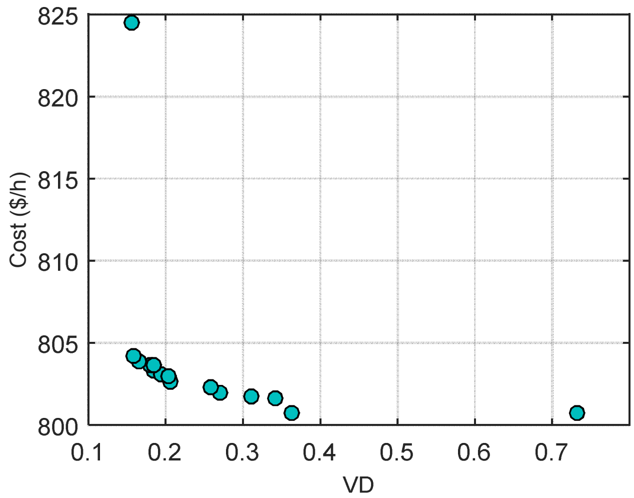

Figure 6 : Pareto optimal set of solutions for CASE-6.

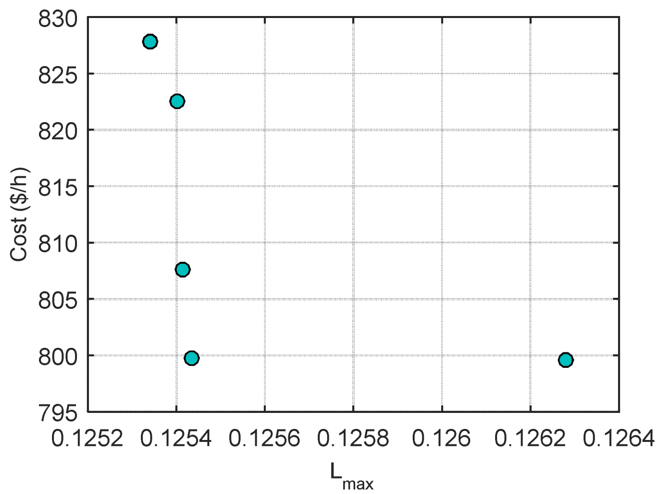

Figure 7 : Pareto optimal set of solutions for CASE-7.

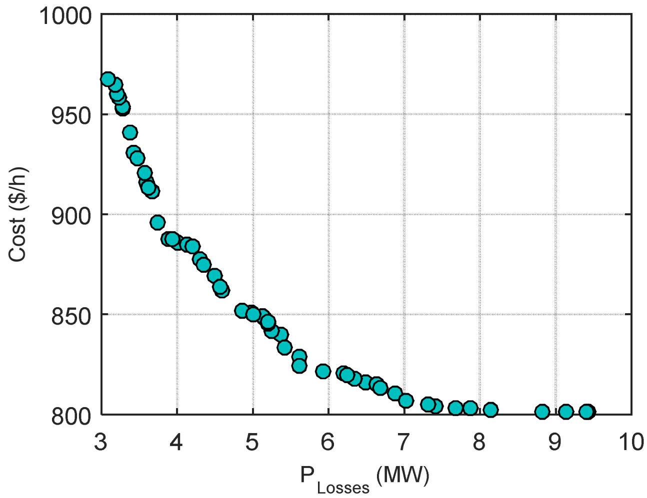

Figure 8 : Pareto optimal set of solutions for CASE-8.

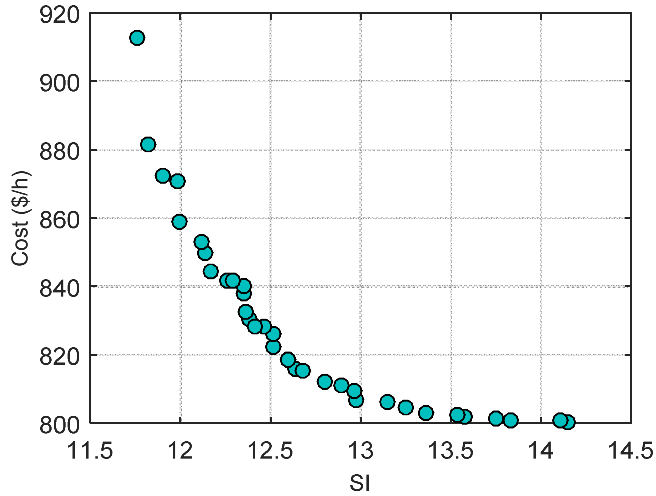

Figure 9 : Pareto optimal set of solutions for CASE-9.

5. Conclusion

In this paper, a new multi-objective optimization algorithm has been developed based on Jaya algorithm and SPEA2 for solving the MOPF problem. The developed algorithm has been successfully implemented and applied to solve the OPF where sixteen cases have been investigated (5 single objective cases and 11 multi-objective cases). For single objective cases five objective functions have been considered. They include minimized fuel cost, enhanced voltage profile, increased voltage stability, active power losses reduction and improved system security. For multi-objective cases, the minimization of the total generation fuel cost is considered along with one or two other objectives. The Pareto optimal sets obtained for these cases has been sketched to show the performance of the developed algorithm. The obtained results show the quality of the solutions when one, two or three objective functions are considered.

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