

FUZZY MULTI-OBJECTIVE OPTIMAL POWER FLOW USING GENETIC ALGORITHMS APPLIED TO ALGERIAN ELECTRICAL NETWORK

Ahmed SALHI¹, Djemai NAIMI¹, Tarek BOUKTIR²

¹Laboratory of Electrical Engineering (LGEB), Department of Electrical Engineering, University Mohamed Khider of Biskra, BP 145, 070 00 Biskra, Algeria

²Department of Electrical Engineering, Faculty of Technology, University Ferhat Abbas of Setif, Cite Mabouda, 190 00 Setif, Algeria

a_salhi_m@yahoo.fr, d.naimi@univ-biskra.dz, tarek.bouktir@esrgroups.org

Abstract. *This paper presents a mathematical model for solving Multi-Objective Optimal Power Flow problem considering uncertainties modeled by fuzzy numbers affecting three objective functions given by total generation cost, total gas emission and voltage profile index. The presented resolution approach is based on Genetic Algorithm (GA), where the parameters of this algorithm are determined and optimized after many tests of execution. A model for analyzing trade-off between profit and security constraint is developed. The probabilities of crossover and mutation optimized for GA parameters, dedicated to the presented approach are used to demonstrate a performance and effectiveness of the algorithm compared to other approaches mentioned in this paper. The mathematic model is applied in the Algerian electrical network for 59-bus test system.*

Keywords

Fuzzy logic, gas emission, generation cost, genetic algorithms, optimal power flow, voltage profile index.

1. Introduction

Modern power grids are facing many paradigms that directly affect their state of planning and operations, while being affected by several uncertain variables. Under the influence of market processes and operating constraints, the decision-making for power utilities is influenced mainly by the volatility of fuel prices, fluctuating pollutant gas emission and instability of the voltage caused by load changes from time to another. For such reasons, the Optimal Power Flow (OPF) problem must deal with three problems men-

tioned above as an optimization problem under uncertainties, where objective functions are handled as fuzzy numbers. We are faced a Multi-Objective Optimal Power Flow (MOOPF) issue for three objectives, the fuel cost minimization (economic generation), less polluted environment with minimization of total emission of environmental pollutants (can be caused by nitrogen oxides NOx and sulphur oxides emitted from generation units based on fuel fossil) and best security of power system described by flatter voltage profile (safety operation of equipments in power system is considered for preferred voltage magnitude at buses closer to 1 p.u).

The ordinary applications of the traditional OPF optimize only a single objective function and the rest of objectives functions must be dealt as constraints [1]. Nevertheless, when such objective functions describe trade-off statements with each other, the development of an efficient algorithm of MOOPF becomes a necessity to solve the problem [2].

Many deterministic optimization techniques in the literature have been applied for solving OPF problems [3], [4], [5], [6], they depend to the convex form of the objective function to find the global optimal solution. Nevertheless, the most OPF problems are non-linear, non-convex and non-differential, where the previous techniques do not ensure a global optimal solution. Furthermore, those traditional methods used to optimize specific aspects of power system operations are not efficient, because they are not appropriate to deal with many practical aspects encountered in recent electrical networks, including the uncertainties of the objective functions and operational constraints [7]. According to these issues, it is necessary to extend the problem to Fuzzy MOOPF (FMOOPF) problem using Artificial Intelligence (AI) [8]. The application of AI in the recent years has undergone a significant evolution

[9], they include for example Differential Evolution [10], Particle Swarm Optimization (PSO) [11] and Genetic Algorithms (GA) [12].

In this paper, the study is based on the optimization of three objective functions previously cited, while taking into the account the adjustment devices in the electrical network. We describe three cases for the optimization problem. In the first case, each objective function is optimized independently to another one, with determination of maximal and minimal values in order to define the membership function for each one. In the second case, FMOOPF problem is solved to get the best compromise solution for all membership functions using maximization of Degree of Satisfaction (DS). In the third case, the optimization problem is extended for various scenarios by increasing the load to 20 % and 30 % compared to the base case. The problem resolution is based on the optimal choice of GA parameters (crossover and mutation probability), considered as key factors for efficiency and accuracy of the algorithm. The GA parameters adjustment is determined with respect to our own experimental tests (crossover probability with two points). The mathematical optimization model proves its efficiency to overcome other metaheuristic methods. The mathematical algorithm application is interested in the Algerian electrical network for 59 bus test system. For this aim, our paper is structured as follows: After the introduction, section 2 presents the problem formulation that focuses on the FMOOPF Problem describing the approach and the objective functions. Section 3 is devoted to GA dedicated to the resolution of the FMOOPF problem. Section 4 illustrates the optimization strategy and its application on the mathematical model. Simulation, results and discussions are reserved to the Section 5 with comparison of the algorithm to some other methods. Finally, we finished with conclusion.

2. Problem Formulation

The problem formulation is based on fuzzy quantification of objective functions in the aim to define the Multi-Objective Problem.

2.1. Fuzzy Multi-Objective Problem

Regarding human ambiguity, it is more convenient for the Decision Maker (DM) to have such fuzzy targets as, "it is desirable to make each objective function below a certain value f_o " and "it is necessary for each objective function to have a desirable limit value f_m " Fig. 1.

Then the quantitative implementation can be made by defining a membership function for each objective function. For the multi-objective problem formulated

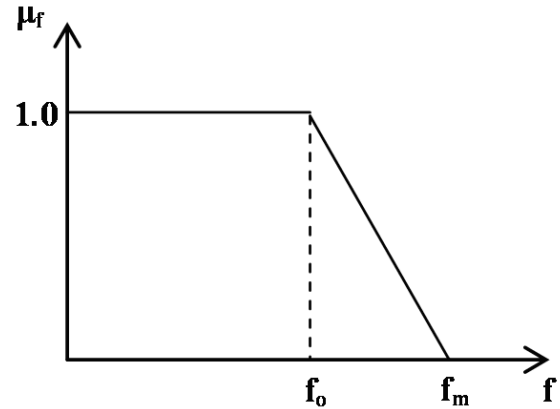


Fig. 1: Membership function for one objective function.

as a vector minimization, it becomes a vector of maximization of all membership functions and evaluation of membership function can be expressed as formulating the DS of DM by changing the problem to conventional OPF with the aim to maximize the DS [13]. The work in this paper is based on the above formulation using GA. We adopt a fuzzy linear distribution for each objective function as shown in the following expression.

$$\mu_{f_i}(x) = \begin{cases} 1 & 0 \leq f_i(x) \leq f_{i(o)} \\ \frac{f_i(x) - f_{i(m)}}{f_{i(o)} - f_{i(m)}} & f_{i(o)} \leq f_i(x) \leq f_{i(m)} \\ 0 & f_i(x) \geq f_{i(m)} \end{cases} \quad (1)$$

2.2. Objective Functions

The three most important problems considered in the power system operation are economy, environment, and security conflicts selected as the evaluation of three functions described as below:

1) Total Cost Generation Function

The most commonly used objective in the OPF problem formulation is the minimization of the total operating cost of the fuel consumed in producing electric power. The generation cost related to each thermal unit is considered as an economic function with respect to real power, describing a curve in second order and expressing a quadratic function. The total cost of power generation can be calculated as:

$$f_c = \sum_{i=1}^{n_g} (a_i + b_i P_{gi} + c_i P_{gi}^2) \quad [$/h], \quad (2)$$

P_{gi} : active power generation at unit i . n_g : number of total units for active power generation. a_i , b_i and c_i : are the cost coefficients of the i th generator.

2) Total Gas Emission Function

The Kyoto Protocol, adopted in 1997, has forced electricity power companies to reduce their pollutant gases emitted by power plants to keep a clean environment. The objective function of total emission gases is expressed as a function of active power generation and can be summarized as follows:

$$f_E = \sum_{i=1}^{n_g} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \delta_i \exp(\varepsilon P_{gi})) [Ton/h], \quad (3)$$

$\alpha_i, \beta_i, \gamma_i, \delta_i$ and ε_i are coefficients of the i^{th} generator emission characteristics.

3) Function of Voltage Profile Index

The voltage magnitude of load buses must be in proximity of 1 p.u (nominal values), which means a flattened voltage profile for a security issue. The function of Voltage Profile Index (VPI) is as below:

$$f_{VPI} = \sqrt{\sum_{i=1}^{N_{pg}} (V_i - 1)^2}, \quad (4)$$

V_i - Voltage magnitude in p.u at PQ bus i , N_{pg} - Number of PQ buses.

2.3. Fuzzy Multi-Objective Optimization

The generalized problem optimization can be formulated in the following manner:

$$\begin{aligned} & \min(f_C, f_E, f_{VPI}) \\ \text{Subject to} & \quad g(x) = 0, \quad (5) \\ & \quad h(x) \leq 0 \end{aligned}$$

where $g(x)$ and $h(x)$ are respectively the set of equality and inequality constraints described respectively in Eq. (6) and Eq. (7).

We have two types of equality constraints; the first is the necessity to keep at each moment, the total generation power equal to the total load demand plus transmission line losses. The second and third equality constraints are described by the power flow equations reflected by the injection of active and reactive powers at each bus.

$$\begin{cases} \sum_{i=1}^{n_g} P_{gi} - \sum_{k=1}^{n_{ld}} P_{dk} - P_{loss} = 0 \\ Q_i = Q_{gi} - Q_{di} = \sum_{j=1}^{n_b} V_i V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\ P_i = P_{gi} - P_{di} = \sum_{j=1}^{n_b} V_i V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \end{cases} \quad (6)$$

P_{gi} and P_{di} , are the active powers of generation and demand respectively of the i -th bus, Q_{gi} and Q_{di} are the reactive powers of generation and demand respectively of the i -th bus. The voltage magnitudes of the i -th and j -th buses are V_i and V_j respectively. The angle θ_{ij} signify the difference of voltage angles for i -th and j -th buses, while the transfer admittance is modeled by real and imaginary parts G_{ij} and B_{ij} for the same buses. The parameters n_b is the number of buses and n_{ld} is the number of loads in power system, P_{loss} is the total active losses.

The inequality constraints are reflected by the operating limits of electrical network components which are considered for secure power system operation. The most adopted inequality constraints in OPF problem are the limited active and reactive powers at generation buses, voltage limits corresponding to voltage generators at PV-buses and the limited interval of transformer tap setting.

$$\begin{cases} P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} & i = 1, 2, \dots, n_g \\ Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} & i = 1, 2, \dots, n_g \\ V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max} & i = 1, 2, \dots, r \\ T_i^{min} \leq T_i \leq T_i^{max} & i = 1, 2, \dots, p \end{cases}, \quad (7)$$

where: p and r are the number of transformer tap settings and the number of generators with controlled voltages respectively. \vec{x} is the vector of control and state variables. The control variables are:

- Unit active power output.
- Generation bus voltage magnitude.
- Transformer-tap settings.

The state variables are voltage and angle of load buses.

For the optimization in fuzzy set theory, objectives and constraints are modeled as membership functions. The decision making of Bellman and Zadeh [14] in fuzzy environment is adopted to get the overall degree of membership using the minimum operator with conjunction of all membership functions. The intersection of all fuzzy sets must lead to the optimal solution (optimal decision for the DM) [13]. If $\mu_{f(x)}$ is the membership function of all fuzzy objective functions and $\mu_{h(x)}$

is the membership function of all fuzzy constraints, the overall degree of membership is given as follows :

$$\begin{aligned} \mu_{DS} &= \min(\mu_{f(x)}, \mu_{h(x)}) \\ \mu_{f(x)} &= \min(\mu_{FC(x)}, \mu_{FE(x)}, \mu_{VPI(x)}) , \\ \mu_{h(x)} &= \min(\mu_{h1(x)}, \mu_{h2(x)}, \dots, \mu_{hm(x)}) \end{aligned} \tag{8}$$

m: number of inequality constraints.

The maximization of the overall degree of membership μ_{DS} leads to the optimal solution defined with the highest degree of membership, subject to the crisp and fuzzy constraints. The multi-objective optimization problem Eq. (5) can be transformed as:

$$\begin{aligned} \max_{x \in X} (z = \mu_{DS}(x)) \\ z \leq \mu_{fi}(x) \\ z \leq \mu_{hk}(x) \\ 0 \leq z \leq 1 \end{aligned} \tag{9}$$

with $i = 1, \dots, N_{obj}$; $k = 1, \dots, m$ and X denotes the feasible region satisfying all goals and constraints of the problem. N_{obj} is the number of objective functions.

3. Genetic Algorithms

The GA is proposed as a computational model inspired from the natural evolution of survivals by Holand [15] in 1970. It is an optimization procedure to find the globally optimal solution using natural selection process, in which stronger individuals of the population have the highest probability to reproduce based on their level of goodness. Each individual represents a potential solution reflecting a chromosome structure.

In the beginning of GA algorithm, an initial population (encoded in chromosome) satisfying all constraints of the problem is selected. The evaluation of fitness function based on the objective function value is accomplished to rank all members of the population in the goodness order and to perform the selection process of chromosomes that must be reproduced. The combination of the current solutions of the population (pairs from subsets) is achieved based on a crossover process to create a new population of children (called offspring) and mutation mechanism describing occasional interchanges on the genes of chromosomes (particular variables of the problem). The process continues with the same reasoning described previously in every generation until the number of generations is reached. The genetic operators; number of generations, crossover and

mutation forms the key factors to find the optimum solution efficiently and accurately [16]. GA increases the probability to achieve an absolute optimum point of the optimization problem without trapping in local optimum points [17]. The parameters of GA for this paper are given as follows:

3.1. Chromosome Type

Each variable of the optimization problem plays as a gene and a set of genes form a chromosome [18]. In the presented paper approach, the chromosome is an answer to the optimization problem as it is represented in Fig. 2.

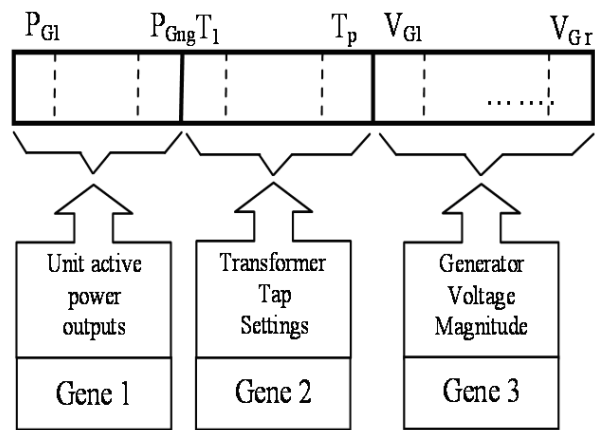


Fig. 2: Chromosome structure described by genes.

3.2. Crossover Type

We must specify a crossover type to produce children from one pair of parents. Among crossover type used in GAs, we choose crossover two points cleared as below: for example, choose randomly two integers pi and qi from 1 to variables number. The process must select:

- Sub-vector from the parent number 1, for entries numbered less than or equal to pi .
- Sub-vector from the parent number 2, for entries numbered from $pi+1$ to qi .
- Sub-vector from the parent number 1, numbered greater than qi .

The Fig. 3 illustrates two point crossover process with $pi = 2$ and $qi = 5$.

3.3. Mutation Type

The mutation is an essential process of the genetic algorithm, by applying random changes to a single in-

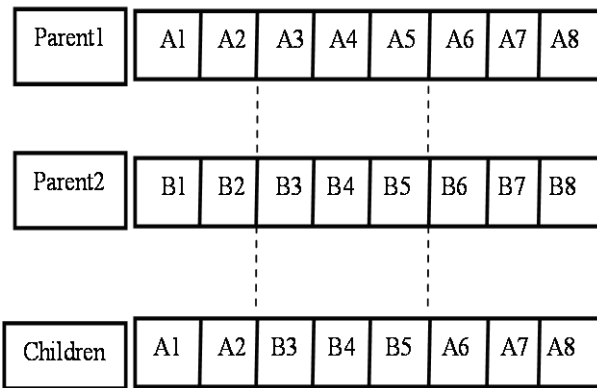


Fig. 3: Two points crossover process illustration.

dividual in the current generation to create a child. It is a mechanism which ensures the diversity of the population and thereby increases the likelihood that the algorithm will generate individuals with better fitness function values. In this paper, a uniform mutation is used and defined in a two-step process. First, the algorithm selects a fraction of the vector entries of an individual for mutation, where each entry has a probability rate of being mutated. In the second step, the algorithm replaces each selected entry by a random number selected uniformly from the range for that entry [19].

3.4. Fitness Function

GAs are usually designed so as to maximize the Fitness Function (FF), which is a measure of the quality of each candidate solution. In this paper the fitness function is defined as follows:

$$FF = \frac{1}{F_{obj} + WP_{fun}}, \quad (10)$$

F_{obj} : Objective Function. P_{fun} : Penalty function for violating constraint in the first equation of system (6). W : Penalty factor.

4. Optimization Strategy

The strategy of optimization aims at the maximization of the DS for the problem formulated in Eq. (9) by GA while being based on the couple (f_o, f_m) for each objective function f , resulting from DM. For this objective, three cases are presented:

- Case1: Each objective function is optimized independently to another one and the couple $(f_o,$

$f_m)$ is extracted. f_o : optimal value of the objective function f given independently to another one. f_m : maximum value of the objective function f imposed during the optimization of another objective functions. The membership function for each objective function is defined based on the couple (f_o, f_m) . The objective function in Eq. (10) becomes f_C, f_E or f_{VPI} .

- Case 2: The couple (f_o, f_m) is introduced for each objective function in problem Eq. (9), the DS is maximized by GA and the objective function in Eq. (10) becomes

$$F_{obj} = \frac{1}{DS}. \quad (11)$$

- Case 3: The optimization is focused on various load levels with different scenarios given by:

$$\begin{aligned} P_D &= \lambda P_{DO} \\ Q_D &= \lambda Q_{DO} \end{aligned}, \quad (12)$$

where, P_{DO} and Q_{DO} are active and reactive power demands at base case. λ : is the load factor. ($\lambda=1$ for the base case).

5. Simulation and Results

Simulation is applied on the Algerian electrical network for 59-bus test system represented in Fig. 4. The model has 9 generators (except 13th generator bus, no generation power at output), 83 branches (lines and transformers) and 50 load buses. Number of control variables is 22 with $n_g = 9$, $p = 5$ and $r = 8$. The first type of control variables is reserved to the power generation output at buses 1, 2, 3, 4, 27, 37, 41, 42 and 53 the second type is devoted to tap setting transformers at branches 20–22, 29–30, 33–34, 52–53 and 58–59, while the third type is addressed to voltage of generating buses (except the slack bus). Upper and lower active power generating limits, reactive power limits and unit cost coefficients are given in Tab. 1. Emission characteristics of generators for the test system are presented in [20]. Lower and upper limits of voltage magnitude for generator buses are 0,95 and 1,05 p.u respectively. Permissible range related to tap setting transformers is considered from 0,9 to 1,1 p.u.

The proposed approach is developed by the use of MATLAB 7.9 tested with Pentium (R) - Dual-Core CPU 3 GHz, 1 GHz DDR RAM, consistently acceptable results were observed. For base case $\lambda=1$, the total active and reactive load are $P_{dt}=684,1$ [MW] and $Q_{dt}=311,6$ [MVAR].

Tab. 1: Lower and upper limits of parameters related to generators with cost coefficients.

Bus Gen	Pg min [MW]	Pg max [MW]	Qg min [MVAR]	Qg max [MVAR]	a [\$/h]	b [\$/MWh]	c [\$/MW ² h]
1	8	72	-10	15	0	1,5	0,0085
2	10	70	-35	45	0	2,5	0,0170
3	30	510	-35	55	0	1,5	0,0085
4	20	400	-60	90	0	1,5	0,0085
27	10	100	-20	35	0	2,5	0,0170
37	10	100	-20	35	0	2	0,0030
41	15	140	-35	45	0	2	0,0030
42	18	175	-35	55	0	2	0,0030
53	30	450	-100	160	0	1,5	0,0085

Tab. 2: Optimization of one objective function independently to another one at base case.

Control Variables & Objectives	Load level $\lambda=1$ (base case)		
	<i>Min FC</i>	<i>Min FE</i>	<i>Min VPI</i>
Pg(1)[MW]	57,4753	70,1355	34,6141
Pg(2)[MW]	24,0218	66,2597	65,6863
Pg(3)[MW]	101,2526	97,1995	73,1261
Pg(4)[MW]	109,7631	91,7974	100,0925
Pg(27)[MW]	26,6854	92,1636	68,4728
Pg(37)[MW]	51,8554	58,2120	49,8656
Pg(41)[MW]	95,8106	68,7312	15,2855
Pg(42)[MW]	142,5365	74,2913	60,6954
Pg(53)[MW]	103,8911	88,6956	250,0076
T ₂₀₋₂₂	0,9677	0,9812	0,9510
T ₂₉₋₃₀	0,9938	0,9949	0,9512
T ₃₃₋₃₄	1,0499	1,0496	0,9503
T ₅₂₋₅₃	0,9501	0,9597	0,9506
T ₅₈₋₅₉	1,0008	0,9895	0,9512
Vg ₂ [p.u]	1,0490	1,0470	1,0136
Vg ₃ [p.u]	1,0499	1,0496	1,0006
Vg ₄ [p.u]	1,0179	1,0102	1,0246
Vg ₂₇ [p.u]	1,0169	1,0115	1,0260
Vg ₃₇ [p.u]	1,0500	1,0469	1,0319
Vg ₄₁ [p.u]	1,0500	1,0453	1,0247
Vg ₄₂ [p.u]	1,0500	1,0485	1,0479
Vg ₅₃ [p.u]	1,0498	1,0422	1,0260
F _c [\$/h]	1693,69	1840,8	2118,2
F _e [Ton/h]	0,4918	0,3970	0,8824
F _{VPI} [p.u]	0,2921	0,2811	0,1718
P _{loss} [MW]	29,1918	23,3859	33,7459

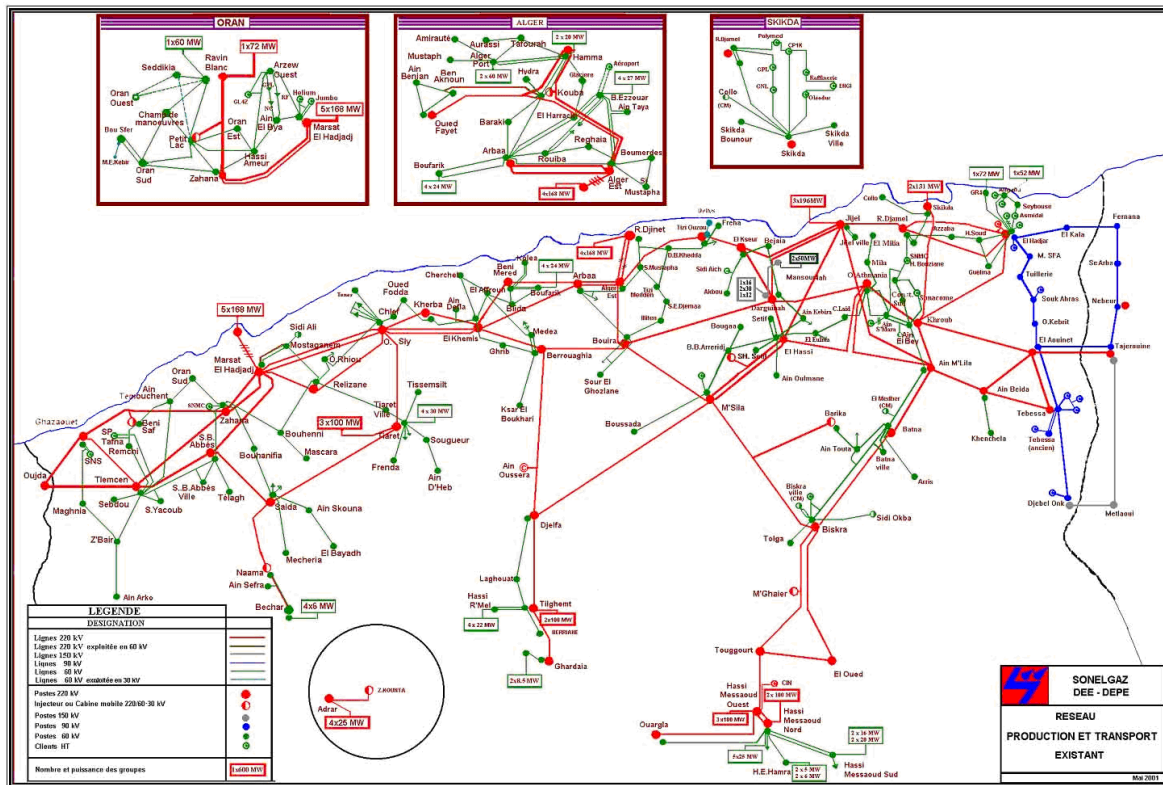


Fig. 4: Topology of the Algerian production and transmission network.

5.1. First Case

The optimal results of several objective functions independently of the one to another are illustrated in Tab. 2 in the base case, specifying the optimal values of the parameters of the adjusting devices. Generation’s number, population’s size, crossover probability (two points) and mutation probability are respectively 250, 200, 0,7 and 0,061. These parameters are optimized based on our own experimental results (after several tests of execution).

For the fuel cost minimization, our approach gives a more important profit of 1693,6 \$/h compared to three other approaches Genetic Algorithm/Fuzzy Rules (FGA) [21], Decomposed Parallel GA (PGA) [22] and Ant Colony Optimization (ACO) [23], given in Tab. 3. The good simulation results show the best choice of the probabilities of crossover and mutation for the presented approach (compared to the choice of the same parameters indicated in [21] and [22]). Ploss have an acceptable value of 29,19 MW and acceptable voltage profile with minimal value of voltage magnitude 0,9166 p.u referred to Fig. 5. The previous figure describes the voltage profile for each case of optimization.

Best situation of electrical power system security is assigned to the voltage profile index minimization with

value of 0,1718 and relatively higher active total losses 33,74 MW, but maximal values of the total cost generation 2118,2 \$/h and emission level 0,882 ton/h referred to other functions minimization. Such remark shows the trade-off between security and cost-benefits problems.

In the case of emission level minimization, 0,3970 ton/h is the better results assigned to our approach compared to optimal emission values for PGA method in [22] with 0,4213 ton/h and for Fast Successive Linear Programming method (FSLP) with 0,4329 ton/h in [24] based on Tab. 4. Medium values of generation cost 1840,8 \$/h and Ploss of 23,3859 MW with violation of voltage magnitude (0,8891 p.u at 35th bus noticed in Fig. 5). All control variables are in their allowable limits referred to declared values in the beginning of this section. It is clearly remarked the trade-off between market benefits, gas emission and voltage security issues.

5.2. Second Case

The couple (f_o , f_m) to define each membership function related to each objective function is shown in Tab. 5 referred to Tab. 2.

The DS is optimized using GA (maximizing the fitness function i.e optimization of three functions simultaneously). The crossover probability pc chosen from four values 0,6; 0,7; 0,8 and 0,9 based on simulation results taken at base case with fixed mutation probability at 0,061. The best value of F_{obj} to maximize the DS is observed for simulation results in Fig. 6 and for pc equal to 0,7 (which proves the best choice previously indicated), where it is established in following simulations. The previous figure exposes the change of the objective function at each generation, with a multitude of crossover probability values and mutation probability of 0,061. Control variables are extracted after simulation for the optimization of three functions simultaneously, DS is maximized and optimal values of objective functions are obtained in the base case and results are arranged in Tab. 6. The convergence has been achieved after 226,116 seconds with 250 iterations.

Voltage magnitudes are closer to 1 p.u for the optimization of three functions simultaneously than the optimization of the cost function and emission function Fig. 5 and Fig. 7 (voltage profile index has the best value in optimization of f_{VPI}). Based on Fig. 7, voltage profile is assigned to the DS maximization without voltage violation (minimal voltage magnitude 0,9005 at 35th bus).

In the base case and for the optimization of three functions simultaneously, we remark based on simulation results in Tab. 6 intermediary's values of three conflicting functions. The tap setting transformers and generation bus voltage magnitudes have contributed to the improvement of the objective functions. As seen in Tab. 7, the presented approach is significantly better than PGA [22] and FSLP [24] methods (for simultaneous minimization of fuel cost and gas emission). The optimized choice of GA parameters confirms the efficiency of the proposed approach which makes it promising to solve the FMOOPF.

5.3. Third Case

For this case, the load level $\lambda=1,2$ and $\lambda=1,3$ (load is increased by 20 % and 30 %), we extend the code of simulation to obtain the state of the test system in such cases. For the same reasoning as described in the base case, results are detailed in Tab. 8, Tab. 9 and Tab. 10. Increased values are assigned to our objective functions due to expansion of demand (active and reactive total load). Results appear in Tab. 8 for each couple (f_o , f_m). Tab. 9 and Tab. 10 show simulation results at such cases obtained by the proposed approach for DS maximization (control variables are between lower and upper limits).

Tab. 3: Comparison of the proposed approach with other techniques for the total cost minimization case.

Generation [MW]	FGA [21]	PGA [22]	ACO [23]	Our Approach
Pg(1)	11, 193	41, 272	64, 01	57, 4753
Pg(2)	24, 000	37, 319	22, 75	24, 0218
Pg(3)	101, 70	133, 83	82, 37	101, 2526
Pg(4)	84, 160	142, 32	46, 21	109, 7631
Pg(27)	35, 220	24, 80	47, 05	26, 6854
Pg(37)	56, 800	39, 70	65, 56	51, 8554
Pg(41)	121, 38	39, 54	39, 55	95, 8106
Pg(42)	165, 520	119, 78	154, 23	142, 5365
Pg(53)	117, 32	123, 46	202, 36	103, 8911
P_{dt} [MW]	684, 1	684, 1	684, 1	684, 1
P_{loss} [MW]	33, 1930	17, 921	39, 98	29, 19
Min Cost [\$ /h]	1768, 5	1769, 7	1815, 7	1693, 6

Tab. 4: Comparison of the proposed approach with other techniques for total gas emission minimization case.

Generation [MW]	PGA [22]	FSLP [24]	Our Approach
Pg(1)	30, 5995	28, 558	70, 1355
Pg(2)	70, 00	70, 000	66, 2597
Pg(3)	109, 40	114, 200	97, 1995
Pg(4)	79, 80	77, 056	91, 7974
Pg(27)	80, 58	87, 575	92, 1636
Pg(37)	34, 86	32, 278	58, 2120
Pg(41)	70, 04	63, 176	68, 7312
Pg(42)	100, 62	95, 645	74, 2913
Pg(53)	128, 02	135, 540	88, 6956
P_{dt} [MW]	684, 1	684, 1	684, 1
P_{loss} [MW]	19, 8195	19, 93	23, 3859
Min Emission [Ton/h]	0, 4213	0, 4329	0, 3970

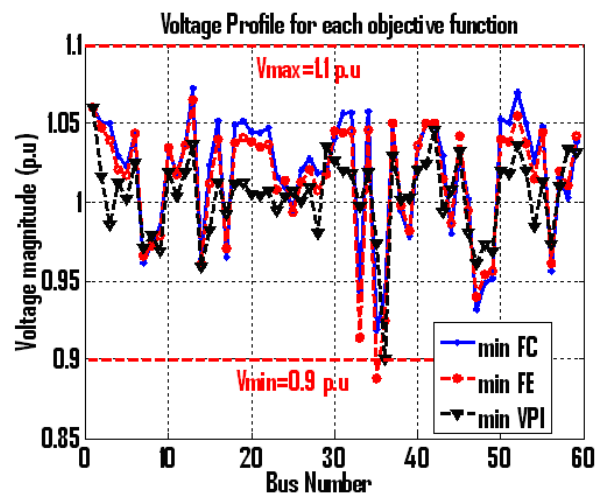


Fig. 5: Voltage profile for the optimization of one objective function at base case.

We obtain the Pareto solutions in wide case, they will be increased by percentage ΔF (%) (for each objective function) related to the base case (for DS maximiza-

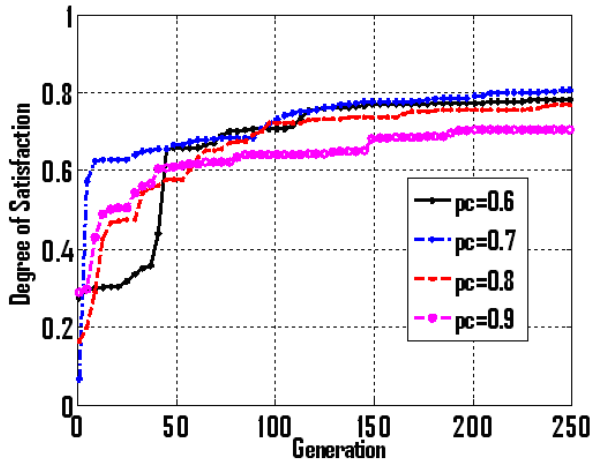


Fig. 6: Evolution of DS with respect to crossover probability at base case $\lambda=1$.

Tab. 5: f_o and f_m values for each objective function at base case.

Load level	Base case $\lambda=1$	
Function	f_o	f_m
f_C [\$/h]	1693.6	2118.2
f_E [Ton/h]	0.3970	0.8824
f_{VPI} [p.u]	0.1718	0.29214

Tab. 6: Optimization of three functions simultaneously (best compromise solution) at base case.

Control Var. & Objectives	Load level $\lambda=1$ (base case)	Control Var. & Objectives	Load level $\lambda=1$ (base case)
	Max DS		Max DS
Pg(1)[MW]	57, 1366	Vg ₂ [p.u]	1, 0131
Pg(2)[MW]	47, 3324	Vg ₃ [p.u]	1, 0179
Pg(3)[MW]	120, 6109	Vg ₄ [p.u]	1, 0146
Pg(4)[MW]	79, 1477	Vg ₂₇ [p.u]	1, 0159
Pg(27)[MW]	41, 3378	Vg ₃₇ [p.u]	1, 0324
Pg(37)[MW]	52, 7766	Vg ₄₁ [p.u]	1, 0438
Pg(41)[MW]	68, 9375	Vg ₄₂ [p.u]	1, 0500
Pg(42)[MW]	103, 4737	Vg ₅₃ [p.u]	1, 0247
Pg(53)[MW]	139, 8473	F _c [\$/h]	1759, 9
T ₂₀₋₂₂	0, 9509	F _e [Ton/h]	0, 4669
T ₂₉₋₃₀	0, 9579	F _{VPI} [p.u]	0, 1905
T ₃₃₋₃₄	0, 9519	P _{loss} [MW]	26, 50
T ₅₂₋₅₃	0, 9510	DS	0, 8438
T ₅₈₋₅₉	0, 9537	P _{dt} [MW]	684, 1

tion) described in Tab. 11. Simulation model allows us to have a database of several best compromise solutions for different load scenarios, without recourse to a Pareto front.

6. Conclusion

An efficient algorithm of Multi-Objective Optimal Power Flow with Fuzzy Logic using Genetic Algorithms

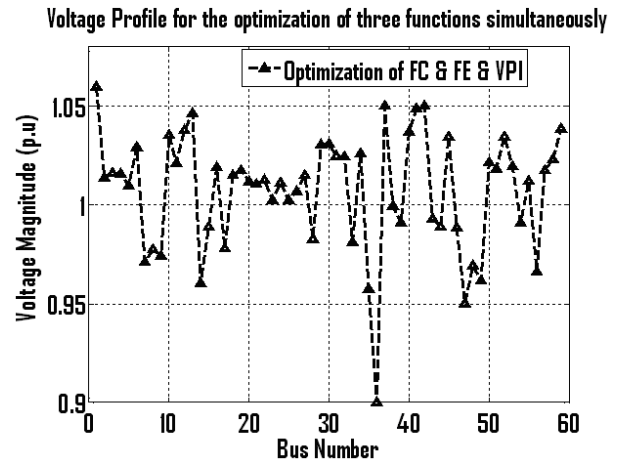


Fig. 7: Voltage profile for the optimization of three functions simultaneously at base case.

Tab. 7: Comparison of the proposed approach with other techniques for DS maximization case.

Generation [MW]	PGA [22]	FSLP [24]	Max DS Approach
Pg(1)	36, 8311	37, 464	57, 1366
Pg(2)	53, 170	52, 675	47, 3324
Pg(3)	119, 06	116, 080	120, 6109
Pg(4)	138, 32	141, 490	79, 1477
Pg(27)	22, 860	28, 286	41, 3378
Pg(37)	39, 800	34, 565	52, 7766
Pg(41)	59, 900	56, 644	68, 9375
Pg(42)	109, 52	101, 800	103, 4737
Pg(53)	122, 92	133, 920	139, 8473
F _C [\$/h]	1765, 7	1786, 000	1759, 9
F _E [Ton/h]	0, 4723	0, 4746	0, 4669
P _{loss} [MW]	18, 2811	18, 83	26, 50

Tab. 8: f_o and f_m values for each objective function at wide cases $\lambda=1,2$ and $\lambda=1,3$.

Load level	Wide case $\lambda=1,2$		Wide case $\lambda=1,3$	
	Value of f_o	Value of f_m	Value of f_o	Value of f_m
f_C [\$/h]	2161, 8	2571, 8	2421, 9	3020, 1
f_E [Ton/h]	0, 4964	1, 1347	0, 5709	1, 8284
f_{VPI} [p.u]	0, 2244	0, 3471	0, 2737	0, 3393

is applied on Algerian electrical network with accurate results and best solutions compromise to deal with different types of objective functions.

The optimized GA parameters of the proposed approach show its effectiveness to enhance the solution quality in comparison to other Algorithms PGA, FSLP and ACO presented in this paper. The security constraints are satisfied for voltage magnitudes ($0,9 < V < 1,1$ p.u) for the optimization of three functions simultaneously at the base and wide cases. Results

Tab. 9: Optimization of three functions simultaneously in wide case $\lambda=1,2$ (maximization of DS).

Control Var. & Objectives	Load level $\lambda=1,2$ (base case)	Control Var. & Objectives	Load level $\lambda=1,2$ (base case)
	<i>Max DS</i>		<i>Max DS</i>
Pg(1)[MW]	64,0361	Vg ₂ [p.u]	1,0213
Pg(2)[MW]	44,5210	Vg ₃ [p.u]	1,0395
Pg(3)[MW]	157,2404	Vg ₄ [p.u]	1,0194
Pg(4)[MW]	151,6268	Vg ₂₇ [p.u]	1,0175
Pg(27)[MW]	51,2728	Vg ₃₇ [p.u]	1,0500
Pg(37)[MW]	59,2180	Vg ₄₁ [p.u]	1,0500
Pg(41)[MW]	66,2862	Vg ₄₂ [p.u]	1,0500
Pg(42)[MW]	113,6315	Vg ₅₃ [p.u]	1,0307
Pg(53)[MW]	141,6863	F _c [\$/h]	2241,5
T ₂₀₋₂₂	0,9697	F _e [Ton/h]	0,6213
T ₂₉₋₃₀	0,9502	F _{VPI} [p.u]	0,2477
T ₃₃₋₃₄	0,9589	P _{loss} [MW]	28.599
T ₅₂₋₅₃	0,9500	DS	0,8043
T ₅₈₋₅₉	0,9517	P _{dt} [MW]	820,92

Tab. 10: Optimization of three functions simultaneously in wide case $\lambda=1,3$ (maximization of DS).

Control Var. & Objectives	Load level $\lambda=1,3$ (base case)	Control Var. & Objectives	Load level $\lambda=1,3$ (base case)
	<i>Max DS</i>		<i>Max DS</i>
Pg(1)[MW]	65,5808	Vg ₂ [p.u]	1,0281
Pg(2)[MW]	41,0067	Vg ₃ [p.u]	1,0433
Pg(3)[MW]	154,0971	Vg ₄ [p.u]	1,0361
Pg(4)[MW]	165,9475	Vg ₂₇ [p.u]	1,0372
Pg(27)[MW]	63,0611	Vg ₃₇ [p.u]	1,0500
Pg(37)[MW]	62,5830	Vg ₄₁ [p.u]	1,0500
Pg(41)[MW]	69,3981	Vg ₄₂ [p.u]	1,0500
Pg(42)[MW]	140,0954	Vg ₅₃ [p.u]	1,0451
Pg(53)[MW]	159,1458	F _c [\$/h]	2490,5
T ₂₀₋₂₂	0,9592	F _e [Ton/h]	0,7152
T ₂₉₋₃₀	0,9512	F _{VPI} [p.u]	0,2812
T ₃₃₋₃₄	0,9625	P _{loss} [MW]	31,585
T ₅₂₋₅₃	0,9500	DS	0,8853
T ₅₈₋₅₉	0,9633	P _{dt} [MW]	889,33

Tab. 11: Rate of increase of each objective function (in wide cases) referred to base case.

Load level	$\lambda=1,2$	$\lambda=1,3$
Function	ΔF (%)	ΔF (%)
f_C [\$/h]	27,36	41,51
f_E [Ton/h]	34,55	53,18
f_{VPI} [p.u]	30,02	47,61

signal the trade-off between economic environmental dispatch and voltage security constraints.

For the case of DS maximization, a best compromise solution can be obtained without resort to Pareto front. Uncertainties about constraints, ambiguities about practical data description language provide an interactive algorithm with decision maker. The proposed approach creates a platform of relationship analysis between objective functions denoted by the trade-off to get a set of Pareto solutions (best compromise solutions).

References

- [1] MOMOH, J. A., M. E. EL-HAWARY and R. ADAPA, Ramababu. A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods. *IEEE Transactions on Power Systems*. 1999, vol. 14, iss. 1, pp. 105–111. ISSN 0885-8950. DOI: 10.1109/59.744492.
- [2] XUEBIN L. Study of multi-objective optimization and multi-attribute decision-making for economic and environmental power dispatch. *Electric Power Systems Research*. 2009, vol. 79, iss. 5, pp. 789–795. ISSN 0378-7796. DOI: 10.1016/j.epsr.2008.10.016.
- [3] YANG, Xin-She. *Engineering optimization: an introduction with metaheuristic applications*. Hoboken, N.J.: John Wiley, 2010. ISBN 04-705-8246-4.
- [4] RAO, S. *Engineering optimization: theory and practice*. 4th ed. Hoboken, N.J.: John Wiley, 2009. ISBN 978-0-470-18352-6.
- [5] ZHU, Jizhong. *Optimization of power system operation: Theory and practice*. 4th ed. Chichester: John Wiley, 2009. IEEE. ISBN 04-702-9888-X.
- [6] CAPITANESCU F., M. GLAVIC, D. ERNST and L. WEHENKEL. Interior-Point based Algorithms for the Solution of Optimal Power Flow Problems. *Electric Power Systems Research*. 2007, vol. 77, iss. 5–6, pp. 508–517. ISSN 0378-7796. DOI: 10.1016/j.epsr.2006.05.003.
- [7] BEDRINANA, M. F., J. A. BOSCO, C. A. F. MURARI and C. A. CASTRO. Decisions in Power System Operation based on Fuzzy Economic and Environmental Dispatch. In: *IEEE Power Tech 2007*. Lausanne: IEEE: 2007, pp. 1296–1301. ISBN 978-1-4244-2189-3. DOI: 10.1109/PCT.2007.4538503.
- [8] HAIDAR, Ahmed M. A., A. MOHAMED and F. MILANO. A computational intelligence-based suite for vulnerability assessment of electrical power systems. *Simulation Modelling Practice and Theory*. 2010, vol. 18, iss. 5, pp. 533–546. ISSN 1569-190X. DOI: 10.1016/j.simpat.2009.12.009.
- [9] ABIDO M. A. *Multiobjective Evolutionary Algorithms for Electric Power Dispatch Problem*. Berlin: Springer Berlin Heidelberg, 2009. ISBN 978-3-642-01798-8. DOI: 10.1007/978-3-642-01799-5.3.

- [10] ABOU EL ELA, A. A., M. A. ABIDO and S. R. SPEA. Optimal power flow using differential evolution algorithm. *Electric Power Systems Research*. 2010, vol. 80, iss. 7, pp. 878–885. ISSN 0378-7796. DOI: 10.1016/j.epsr.2009.12.018.
- [11] SAFARI, A. and H. SHAYEGHI. Iteration particle swarm optimization procedure for economic load dispatch with generator constraints. *Expert Systems with Applications*. 2011, vol. 38, iss. 5, pp. 6043–6048. ISSN 0957-4174. DOI: 10.1016/j.eswa.2010.11.015.
- [12] RAHUL, J., Y. SHARMA and D. BIRLA. A New Attempt to Optimize Optimal Power Flow Based Transmission Losses Using Genetic Algorithm. In: *2012 Fourth International Conference on Computational Intelligence and Communication Networks*. Mathura: IEEE, 2012, pp. 566–570. ISBN 978-1-4673-2981-1. DOI: 10.1109/CICN.2012.212.
- [13] LIANG, Ruey-Hsun, Sheng-Ren TSAI, Yie-Tone CHEN and Wan-Tsun TSENG. Optimal power flow by a fuzzy based hybrid particle swarm optimization approach. *Electric Power Systems Research*. 2011, vol. 81, iss. 7, pp. 1466–1474. ISSN 0378-7796. DOI: 10.1016/j.epsr.2011.02.011.
- [14] ABOU EL-ELAA A. A., M. BISHRA, S. ALLAMA and R. EL-SEHIEMY. Optimal Preventive Control Actions using Multi-Objective Fuzzy Linear Programming Technique. *Electric Power Systems Research*. 2005, vol. 74, iss. 1, pp. 147–155. ISSN 0378-7796. DOI: 10.1016/j.epsr.2004.08.014.
- [15] MAN, K. F., K. S. TANG and S. KWONG. Genetic algorithms: concepts and applications. *IEEE Transactions on Industrial Electronics*. 1996, vol. 43, iss. 5, pp. 519–534. ISSN 0278-0046. DOI: 10.1109/41.538609.
- [16] SIVANANDAM, S. *Introduction to genetic algorithms*. Berlin: Springer, 2008. ISBN 978-3-540-73189-4.
- [17] KUMARI, M. S. and S. MAHESWARAPU. Enhanced Genetic Algorithm based computation technique for multi-objective Optimal Power Flow solution. *International Journal of Electrical Power*. 2010, vol. 32, iss. 6, pp. 736–742. ISSN 0142-0615. DOI: 10.1016/j.ijepes.2010.01.010.
- [18] LAKSHMI, G. Venkata and K. AMARESH. Optimal Power Flow with TCSC using Genetic Algorithm. In: *2012 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*. Bengaluru: IEEE, 2012, pp. 1–6. ISBN 978-1-4673-4506-4. DOI: 10.1109/PEDES.2012.6484394.
- [19] User's Guide. *Global Optimization Toolbox*. Mathworks Inc, 2011.
- [20] MAHDAD B., T. BOUKTIR and K. SRAIRI. OPF with environmental constraints with SVC controller using decomposed parallel GA: Application to the Algerian network. In: *Power & Energy Society General Meeting (PES'09)*. Calgary, AB: IEEE, 2009, pp. 1–8. ISSN 1944-9925. ISBN 978-1-4244-4241-6. DOI: 10.1109/PES.2009.5275817.
- [21] MAHDAD B., T. BOUKTIR and K. SRAIRI. Optimal power Flow of the Algerian Network using Genetic Algorithm/Fuzzy Rules. In: *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, IEEE General Meeting 2008*. Pittsburgh: IEEE, 2008, pp. 1–8. ISSN 1932-5517. ISBN 978-1-4244-1905-0. DOI: 10.1109/PES.2008.4596656.
- [22] MAHDAD B., T. BOUKTIR and K. SRAIRI. OPF with Environmental Constraints with Multi Shunt Dynamic Controllers using Decomposed Parallel GA: Application to the Algerian Network. *Journal of Electrical Engineering & Technology*. 2009, vol. 4, iss. 1, pp. 55–65. ISSN 1975-0102.
- [23] BOUKTIR T. and L. SLIMANI. Optimal Power Flow of the Algerian Electrical Network using an Ant Colony Optimization Method. *Leonardo Journal of Sciences*. 2005, vol. 4, iss. 7, pp. 43–57. ISSN 1583-0233.
- [24] ZEHAR K. and S. SAYAH. Optimal Power Flow with Environmental Constraint using a Fast Successive Linear Programming Algorithm: Application to the Algerian Power System. *Energy Conversion and Management*. 2008, vol. 49, iss. 11, pp. 3362–3366. ISSN 0196-8904. DOI: 10.1016/j.enconman.2007.10.033.

About Authors

Ahmed SALHI was born in Biskra, Algeria in 1967. He received the B.Sc. degree in Electrical Engineering Power system from Biskra University Algeria in 1992, his M.Sc. degree from Batna University in 2003. He is spirit to prepare his Ph.D. degree in power system. His areas of interest are the application of the meta-heuristic methods in optimal power flow, FACTS control and improvement in electric power systems, Multi-Objective Optimization for power systems, and Voltage Stability and Security Analysis.

Djemai NAIMI was born in Batna, Algeria in 1967. He is a professor in the department of electrical engineering in Biskra University, Algeria. He received

his M.Sc. degree in electrical engineering on 2003 from Constantine University, Algeria. He is also a member of LGEB laboratory. His research activities include integration of renewable energy in power system grid, optimization, and power flow and power system stability. His teaching includes modeling and optimization in power system and power system stability.

Tarek BOUKTIR was born in Ras El-Oued, Algeria in 1971. He received the B.Sc. degree in Electrical Engineering Power system from Setif University (Algeria) in 1994, his M.Sc. degree from Annaba University in 1998, his Ph.D. degree in power system from Batna University (Algeria) in 2004. He is with the Department of Electrical Engineering in Ferhat

Abbes University (Setif), ALGERIA. His areas of interest are the application of the meta-heuristic methods in linebreak optimal power flow, FACTS control and improvement in electric power systems, Multi-Objective Optimization for power systems, and Voltage Stability and Security Analysis. He is the Editor-In-Chief of Journal of Electrical Systems (Algeria), He currently serves on the editorial boards of TELKOMNIKA Journal, Indonesia. He serves as reviewer with the Journals: IEEE Transactions on SYSTEMS, MAN, AND CYBERNETICS, IEEE Transactions on Power Systems (USA), ETEP-European Transactions on Electrical Power Engineering. He is also the head of the research team "Algerian Smart Grid".