# Multi-objective Optimization in Power Systems Including UPFC Controller with NSGA III

Ahmed Merah and Mohamed Adjabi

*Abstract*— **In this paper, the third Version of Non-dominated Sorting Genetic Algorithm (NSGA III) inspired by nature is presented and used for the problem of optimal power flow (OPF) in power systems with a unified power flow controller (UPFC). The total cost of production, emission and active loss in a power system with the UPFC that sets the load bus voltage and controls the power transits across the transmission line are minimized and validated optimally with the use of NSGA III.**

**The NSGA III algorithm is an extension of NSGA I and II that is based on natural selection, it is also recently proposed multi-objective optimization (MOO) algorithms. The performances of NSGA III have been tested and verified on the IEEE 30-bus power system by comparing them to several other methods multi objective particle swarm optimization (MOPSO) and Strength Pareto Evolutionary Algorithm (SPEA II). In addition, NSGA III are used not only to optimize contradictory objectives such as total production cost, emission and active power losses, but also to improve the voltage profile of the power system. Our results illustrate that NSGA III can be used successfully to solve non-linear power system problems in the presence of UPFC, the most powerful and dynamic device of the third generation of the FACTS family.**

*Index Terms*—**Front de Pareto, multi-objective optimisation, NSGA III, UPFC.**

## I. Introduction

When the energy transmitted in the various transmission lines and branches out over large geographical areas, the challenge is to reach the optimal operating point of the operating system, this is done by respecting all the maximum and minimum capabilities of all devices and machines connected to the transport network. In addition, this, while respecting the constraints imposed by the customers. The data becomes very formidable with large operating systems and interconnection with each other. The equations become very difficult to solve and in some ways contradictory solutions. Optimization has become a science in itself and has attracted many researchers and scientists from around the world, not only in electrical systems, but also in many sensitive specialties [1].

Many sciences overlap in order to develop intelligent algorithms that derive from the study and careful consideration of humans in natural phenomena. Many objectives have been set and developed by researchers where each objective aims to reach an optimal operational point. Often, you find many solutions and it is impossible to try them all, to contradict each other. A solution gives a good result for a particular purpose. But gives a bad result in another goal in the same network. Here, the application of logic becomes necessary, and many solutions must be removed with only good solutions being shown in the different objectives to be optimized. GA is one of these algorithms, has evolved a lot since it was invented and published by John Holland in 1975. GA is based on the tradition of the work of nature from a Darwinian point of view [2]. Uses a technique inspired by the biology of evolution, such as selection, crossover, mutation to obtain approximate optimal solutions. Srinivas & Deb proposed NSGA in 1995, then it came an NSGA II extension by Deb et al in 2002 [3]. Later NSGA III by Deb and Jain in 2014 with a multi-objective non-domination approach based on several reference points.

In this article, the utility of NSGA III is to provide optimized solutions by satisfying the active and reactive power balance, voltage profile, safety margin index, transmission losses, emission index, while Power generators operate within its allowable limits. All this with minimizing as much as possible the total cost of energy production. We aim to take advantage of the benefits of UPFC to improve power flow and achieve the best results that achieve the greatest number of goals.

UPFC is the most complete and practical of the FACTS family. Combine the advantages of the series types and the advantages of the parallel types. Where it consists of a serial part and another shunt connects to each other by a capacitor. It can switch between several control modes. In this work, the inclusion of UPFC is by adding two fictitious buses (n + 1) represents the serial part, and (n + 2) represents the shunted part. All this by modifying the Jacobian matrix in Newton Raphson's algorithm [5], [6].

The results in this article are divided into 5 cases. Start with the first case with Simple-Objective Optimization (SOO) without UPFC, followed directly by case 2 SOO with UPFC. Cases 3 and 4 contain Bi-objective Optimization (BOO) without and with UPFC compared with multi-objective particle swarm optimization (MOPSO) and Strength Pareto Evolutionary Algorithm (SPEA II) respectively. Finally MOO with and without UPFC in case 5.

## II. Formulations of the Optimal Power Flow Problem with UPFC

Each network has its own personality. The functions in the research documents vary according to the objectives to be optimized. In this paper, take into account three functions. The first function is to reduce the fuel cost, which reflects the economic and investment face [4].

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$$\min C_P=\sum_{i=1}^{m}(a_i+b_iP_{Gi}+c_i P_{Gi}^2)+d_i sine_i(P_{Gi}^{min}-P_{Gi}) \quad (1)$$

The second function is to reduce emission index from generation plants that reflect the environmental side.

$$min\ E_P=\sum_{i=1}^{m}\left(\alpha_i+\beta_i P_{Gi}+\gamma_i P_{Gi}^2\right)+\zeta_i e^{(\lambda_i P_{Gi})} \quad (2)$$

Finally, reduce power losses that reflect the performance of the network.

$$min\ P_{loss}=\sum_{i=1}^{nl}P_{Li} \quad (3)$$

These objectives are subject to a set of equality constraints as follows:

$$\sum P_{Gi}-\sum P_{Di}-\sum P_{loss}=0 \quad (4)$$
$$\sum Q_{Gi}-\sum Q_{Di}-\sum Q_{loss}=0 \quad (5)$$

They are also subject to a set of inequality constraints

$$V_i^{min}\le V_i\le V_i^{max} \quad (6)$$
$$\theta_i^{min}\le\theta_i\le\theta_i^{max} \quad (7)$$
$$P_{Gi}^{min}\le P_{Gi}\le P_{Gi}^{max} \quad (8)$$
$$Q_{Gi}^{min}\le Q_{Gi}\le Q_{Gi}^{max} \quad (9)$$

Without neglecting the side of protection

$$S_{Li}\le S_{Li}^{max} \quad (10)$$

The Equivalent Circuit of UPFC in this article is taken from reference [5]. For a better control regime in the transmission line $L_{ij}$ in to bus i, UPFC also subject to a set of limit constraints considered as follows: Active power exchange limit between the two sides (series and shunt), Current limit through the serial side, Shunt side current limit and amplitude limit of the voltage injected by the series side. We summarize it mathematically as follows [6]:

$$PE\le PE^{lim} \quad (11)$$
$$I_{se}\le I_{se}^{lim} \quad (12)$$
$$I_{sh}\le I_{sh}^{lim} \quad (13)$$
$$V_{se}\le V_{se}^{lim} \quad (14)$$

The performance and reliability of multi-objective power flow optimization algorithms with and without FACTS device remain important issues in the field of electrical system control and planning. A new application of NSGA III for solving multi-objective optimization problems requires particularly high performance. In other ways, it is impossible to define an optimal solution to a multi-objective optimization problem in general. Instead, there is a set of optimal solutions forming a Pareto front (FP).

## III. Pareto Front

The Pareto front is a set of non-dominated solutions chosen as optimal if no objective can be improved without sacrificing at least one other objective. On the other hand, a solution $X_1$ is considered to be dominated by another solution $X_2$ if, and only if, $X_2$ is also good or better than $X_1$ with respect to all objectives. Most multi-objective optimization algorithms practice this concept invented by the Pareto economist to obtain the non-dominated set of solutions, hence the Pareto front [7]. Fig.1 illustrates a Pareto front typical of a minimization optimization problem of two objectives where the arrow in the figure indicates the Pareto-optimal region.

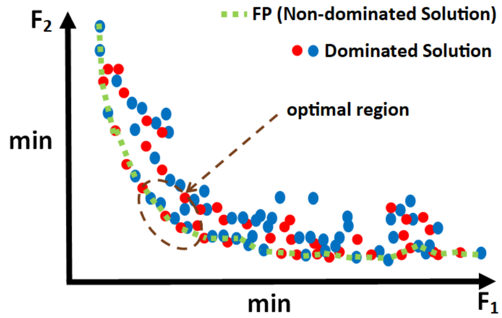



Fig. 1. Pareto Front (min-min).

## IV. NSGA II

In the first step of the algorithm of NSGA II is to choose the best N member of the population of the offspring $R_t$ of size 2N among the combined population of parents and descendants $P_t \cup Q_t$ if $P_t$ is of size N. This step thus preserve the elite members of the parents' population. To do this, the combined $R_t$ population is first sorted according to different levels of non-domination of the different objective functions. Then, each non-denomination level is selected one at a time to construct a new population $S_t$, starting from $F_1$, until the size of $S_t$ is equal to N or for the first time greater than N. Let's say that the last level included is the l. Thus, all solutions from level (l + 1) are rejected from the combined population $R_t$ . In most situations, the last level accepted is only partially accepted. In such a case, only the solutions that maximize the diversity of the front are chosen. This is achieved through an efficient but approximate niche preservation operator that calculates crowding distance for each member of the last level as a summation of the objective normalized distance between two neighboring solutions. Subsequently, solutions that have larger crowding distance values are chosen [8].

## V. NSGA III

The identification of non-dominant fronts in NSGA III by the use of usual dominance principle. The reference points are chosen during optimization by the use of systematic techniques of Das and Dennis [5] to ensure the diversity of solutions obtained. The members of the population are associated with each of these points of reference [9].

$$H=\binom{M+p-1}{p} \quad (15)$$

where H is the total number of reference points and M is the number of objectives. If the reference points are widely distributed throughout the hyperplane normalized, the resulting solutions are being widely distributed on the front of Pareto optimal. The ideal point of the population $S_t$ is determined by identifying the minimum value for each objective function $z_i^{min}$ . Each objective value of $S_t$ is then translated so that the ideal point of $S_t$ translated becomes a null vector by the deference between the objective value $f_i$ and the minimum value of each objective as follows [10]:

$$f_i'(x) = f_i(x) - z_i^{min} \text{ ou } i = 1 \dots M \tag{16}$$

The association of each member of the population (yellow points in fig.2) to a reference point (black points) by a reference line (blue rights) corresponding to each reference point. In the hyperplane, the reference point whose reference line is closest to a member of the population in the standardized objective space is considered to be associated with members of the population, this is determined by the vertical distance between each member of the population $S_t$ and each of the reference lines. Where the black square point represents the ideal point or the optimal solution [10] [11].

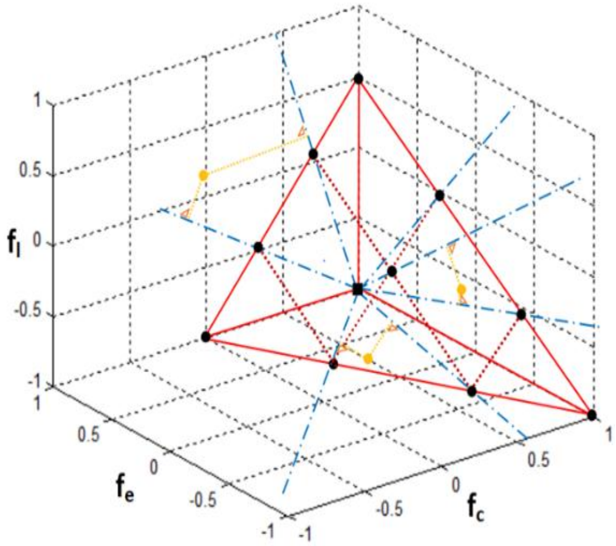



Fig. 2. Association of members of the population with reference points.

The reference points need not be associated with a member of the population. Subsequently, a niche preservation operation is performed by counting the number of individuals of $P_t + 1 = S_t / F_l$ that are associated with each reference point, and defining a set of reference points containing the reference points having the number of minimal niches ρ. If this set contains no points, we choose one at random.

If ρ is zero, the front $F_l$ has no associated member at the reference point. In this case, the reference point is excluded. Other scenario, there is one or more members in front of $F_l$ associated with the reference point. In this case, the one with the shortest perpendicular distance from the reference line is added to $P_t + 1$.

The size N of the population depends on H, NSGA III does not require new parameters other than the usual GA parameters. In NSGA III, elite solutions are carefully selected while maintaining the diversity of solutions by focusing on the closest solutions to the reference line for each reference point. All of these steps can be simplified in Fig. 2. The Steps of the gray zone have been presented in detail in [10] .

We apply now it to the multi-objective power flow optimization problem in next section.

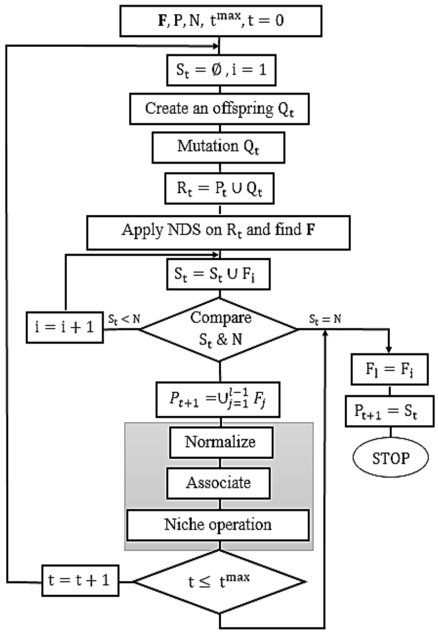



Fig. 3. Flowchart of NSGA III.

## VI. Results and Discussions

In this section, the simulations were performed in the MATLAB R2017a environment on a 1.70 GHz CPU i3-4005U PC with 4 GB of RAM. To show the capabilities of NSGA III and UPFC, 3 objective functions $C_p$, $E_p$ and $P_{loss}$ were studied using an IEEE 30-bus [12] system taking into account all the imposed constraints. The minimum and maximum capacity of the generators, the fuel cost coefficients and the emission factors are presented in appendix in Table VI and VII. The parameters of the NSGA III, MOPSO and SPEA II methods used in this article are presented in Table 8, 9 and 10.

### A. *CASE 1*

Simple Objective Optimization (SOO) without UPFC of fuel cost, emissions and power loss using NSGA III. The best solution for each optimal objective function is listed in Table 1. The other two functions were monitored and placed in the same table with control of the voltages and their angles, as well as the active and reactive power control generated by the 6 generators installed in the IEEE 30-Bus network. As indicated in this table, it is clear that the reduction of a particular goal results in an increase of another goal or both.

### B. *CASE 2*

SOO of fuel cost, emissions and power loss with UPFC installed in transmission line 27-30 with $V_{30}^{ref} = 1.01$ and $P_{27-30}^{sp} = 7.5$ MW using NSGA III. Followed by two diagrams in Fig. 4 showing the voltages and their angles in the different buses, and this for case 1 and 2. A slight improvement in the fuel cost is indicated in Table 2. There is also a decrease in power loss, which is due to the benefits of UPFC in improving the power flow and thus a slight decrease in losses. As shown in Fig. 4, the ability of UPFC to set the voltage in the bus 30 is one of its main advantages. As shown in Fig.4, there is also an improvement of the voltage angles not only in the bus 30, but also in the buses adjacent thereto. This is due to the dynamics of reactive energy generation by

UPFC.

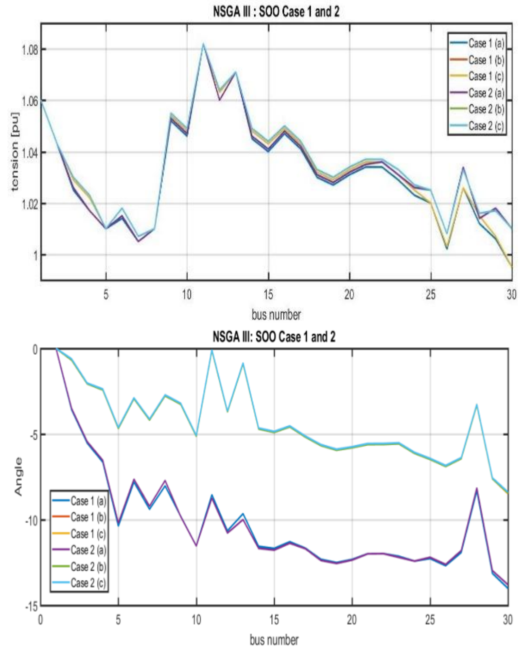



Fig. 4. The voltages and angles for Case 1 and 2.

TABLE I: RESULTS OBTAINED IN CASES 1 WITHOUT UPFC

| | Case 1 : SOO with UPFC | | |
|---|---|---|---|
| | Cost | Emission | Loss |
| $V_1$ | 1,060 | 1.060 | 1.060 |
| $V_2$ | 1,043 | 1.043 | 1.043 |
| $V_5$ | 1.010 | 1.010 | 1.010 |
| $V_8$ | 1.010 | 1.010 | 1.010 |
| $V_{11}$ | 1.082 | 1.082 | 1.082 |
| $V_{13}$ | 1.071 | 1.071 | 1.071 |
| $\theta_1$ | 0.000 | 0.000 | 0.000 |
| $\theta_2$ | -3,579 | -0,623 | -0.620 |
| $\theta_5$ | -10,381 | -4,630 | -4.627 |
| $\theta_8$ | -8,026 | -2,730 | -2.728 |
| $\theta_{11}$ | -8,541 | -0,092 | -0.090 |
| $\theta_{13}$ | -9,652 | -0,874 | -0.872 |
| $P_{G1}$ | 176.905 | 52.020 | 51.897 |
| $P_{G2}$ | 49.475 | 79.878 | 80.000 |
| $P_{G5}$ | 20.141 | 50.000 | 50.000 |
| $P_{G8}$ | 20.228 | 35.000 | 35.000 |
| $P_{G11}$ | 12.031 | 30.000 | 30.000 |
| $P_{G13}$ | 14.096 | 40.000 | 40.000 |
| $Q_{G1}$ | -1.647 | 28.770 | 28.808 |
| $Q_{G2}$ | 29.254 | 4.019 | 3.979 |
| $Q_{G5}$ | 26.584 | 14.484 | 14.484 |
| $Q_{G8}$ | 16.757 | 3.996 | 3.996 |
| $Q_{G11}$ | 15.196 | 15.281 | 15.281 |
| $Q_{G13}$ | 8.266 | 6.873 | 6.873 |
| $C_p$ [$/h] | **802.182** | 968.302 | 968.562 |
| $E_P$ [ton/h] | 0.336 | **0.197** | 0.197 |
| $P_{loss}$ [MW] | 9.476 | 3.498 | **3.497** |

TABLE II: RESULTS OBTAINED IN CASES 1 WITHT UPFC

| | Case 1 : SOO with UPFC | | |
|---|---|---|---|
| | Cost | Cost | Cost |
| $V_1$ | 1.060 | 1.060 | 1.060 |
| $V_2$ | 1.043 | 1.043 | 1.043 |
| $V_5$ | 1.010 | 1.010 | 1.010 |
| $V_8$ | 1.010 | 1.010 | 1.010 |
| $V_{11}$ | 1.082 | 1.082 | 1.082 |
| $V_{13}$ | 1.071 | 1.071 | 1.071 |
| $\theta_1$ | 0.000 | 0.000 | 0.000 |
| $\theta_2$ | -3.505 | -0.682 | -0.614 |
| $\theta_5$ | -10.195 | -4.679 | -4.618 |
| $\theta_8$ | -7.714 | -2.770 | -2.717 |
| $\theta_{11}$ | -8.746 | -0.124 | -0.072 |
| $\theta_{13}$ | -9.998 | -0.896 | -0.846 |
| $P_{G1}$ | 173.768 | 54.091 | 51.650 |
| $P_{G2}$ | 49.456 | 77.576 | 80.000 |
| $P_{G5}$ | 21.187 | 50.000 | 50.000 |
| $P_{G8}$ | 26.658 | 35.000 | 35.000 |
| $P_{G11}$ | 10.203 | 30.000 | 30.000 |
| $P_{G13}$ | 11.054 | 40.000 | 40.000 |
| $Q_{G1}$ | -0.882 | 28.013 | 28.758 |
| $Q_{G2}$ | 28.777 | 4.433 | 3.625 |
| $Q_{G5}$ | 26.148 | 14.323 | 14.320 |
| $Q_{G8}$ | 14.296 | 2.742 | 2.751 |
| $Q_{G11}$ | 14.960 | 15.030 | 2.751 |
| $Q_{G13}$ | 8.243 | 6.555 | 6.558 |
| $C_p$ [$/h] | **801.328** | 962.895 | 967.972 |
| $E_P$ [ton/h] | 0.331 | **0.197** | 0.197 |
| $P_{loss}$ [MW] | 9.126 | 3.467 | **3.450** |

### C. CASE 3

The results of bi-objective optimization (BOO) without UPFC of $C_p$ and $E_p$ as two main objectives are represented in Fig.5.a, $C_p$ and $P_{loss}$ as two main objectives are represented in the Fig.5.b. and $E_p$ and $P_{loss}$ are drawn in Fig.5.c. Note that in all three figures the algorithm provided well-distributed solutions across the entire Pareto front. It is not possible to improve a goal without degrading others, so the objectives are contradictory. In Fig.5.a, the maximum solution horizontally (912.748, 0.201) vertically contradicts the maximum solution (802.509, 0.325). The same thing in Fig.5.b, the solution (963.291, 3.517) goes against the solution (803.167, 9.021). For the two solutions in Fig.5.c, (0.197, 3.497) and (0.197, 3.537) there is a very small margin of contradiction. The algorithm also offers solutions that belong to the area Pareto optimal solutions, these solutions are the best solutions taking into account the two objectives, they are closest to the ideal points (800, 0.2), (800.3) and (0.197, 3.490) of the three landmark respectively. The results presented numerically in Table 3. The results were compared to the BOPSO method with the parameters presented in appendix in Table 9. The results were very close, but the BOPSO method could not determine the Pareto front with the parameters provided in the third bi-objective optimization $E_p$ and $P_{loss}$ and the figure obtained is presented in Fig.5.f.

### D. CASE 4

in this case we apply the same previous BOO but in the presence of UPFC. Despite the increasing complexity of the network and the opposition of objectives and modifications of the Jacobian matrix in the presence of UPFC. However, the algorithm was able to provide well-distributed solutions on the Pareto front. The results clearly show, comparing Tables 3 and 3, that in the presence of UPFCs there is a minimization of all objectives.

### E. CASE 5

The optimization here is done taking into consideration the three objectives at the same time without and with UPFC in fig.7.a and b respectively. In many research articles like[13], the objectives are combined, gathered or subtractive by multiplying them by special coefficients limited between 0 and 1 according to the importance of the objective to be improved, this method does not reflect the real optimization. Here the algorithmproposes solutions representing the Pareto multi-dimension front. The MOO with the installation of UPFC with the same parameters mentioned above gives better solutions closer to the ideal point (800, 0.200, 3) as shown in Table V.

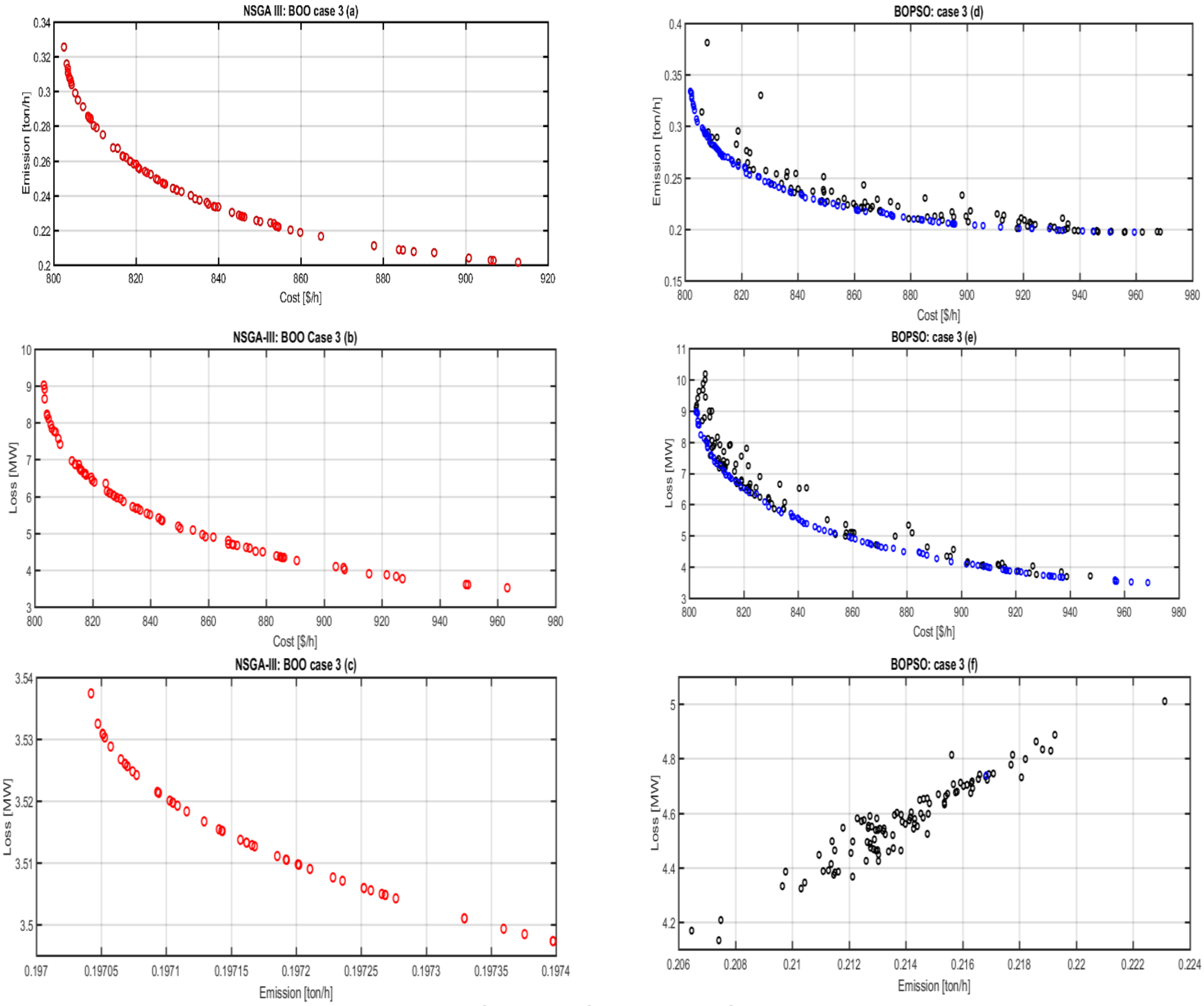
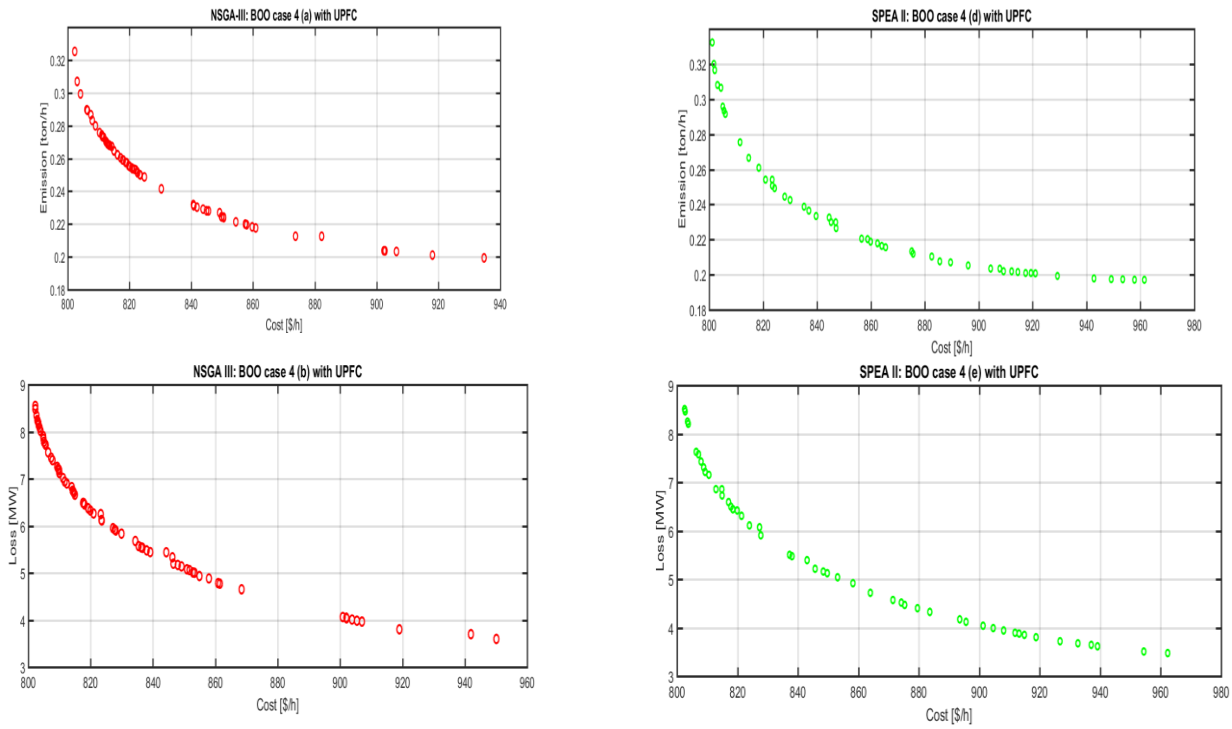



Fig. 5. BOO without UPFC by NSGA III and BOPSO in case 3.



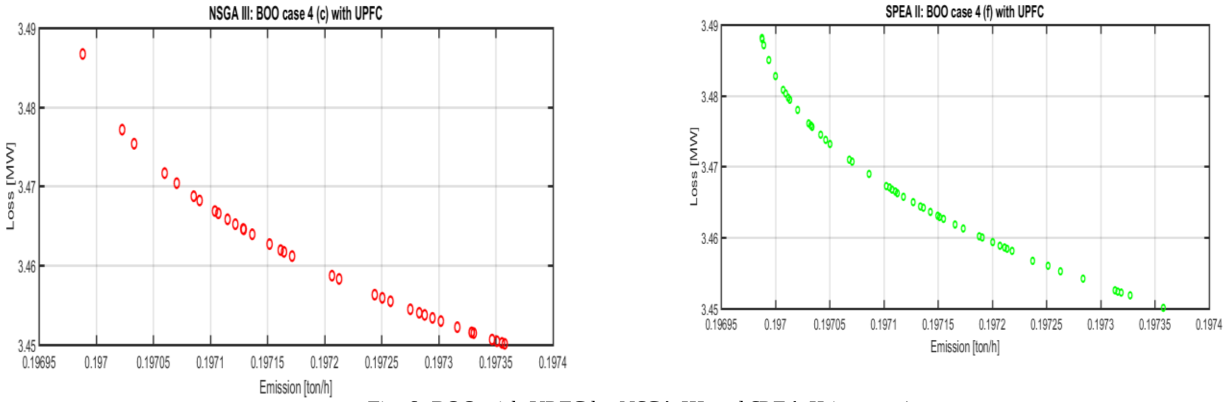



Fig. 6. BOO with UPFC by NSGA III and SPEA II in case 4.

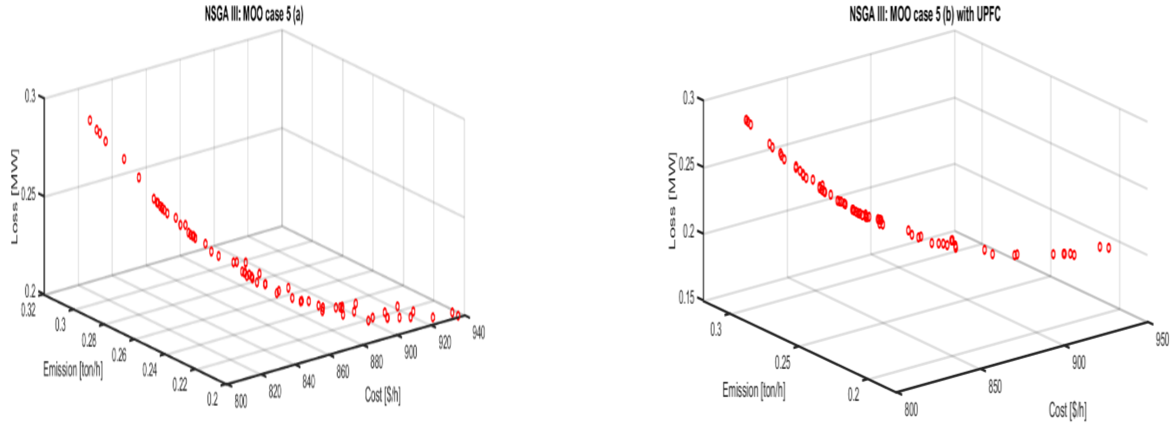



Fig. 7. MOO optimization by NSGA III for case 5

TABLE III: RESULTS OBTAINED FOR CASE 3 COMPARED WITH BOPSO

| | **BOO NSGA III** | | | | | | **BOPSO** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Case 3 (a) | | Case 3 (b) | | Case 3 (c) | | Case 3 (e) | | Case 3 (e) | | Case 3 (f) | |
| | $C_p$ | $E_p$ | $C_p$ | $P_{loss}$ | $E_p$ | $P_{loss}$ | $C_p$ | $E_p$ | $C_p$ | $P_{loss}$ | $E_p$ | $P_{loss}$ |
| Min | 802.509 | 0.201 | 803.167 | 3.517 | 0.197 | 3.497 | 802.301 | 0.197 | 802.553 | 3.691 | 0.206 | 4.132 |
| Max | 912.748 | 0.325 | 963.291 | 9.021 | 0.197 | 3.537 | 968.562 | 0.381 | 947.434 | 10.181 | 0.223 | 5.010 |
| Range | 110.238 | 0.124 | 160.124 | 5.504 | 0.00035577 | 0.040 | 166.261 | 0.184 | 144.881 | 6.49 | 0.016651 | 0.877 |
| Std | 30.7734 | 0.033 | 41.596 | 1.450 | 0.00012963 | 0.012 | 48.006 | 0.034418 | 41.787 | 1.771 | 0.002613 | 0.153 |
| Mean | 836.520 | 0.250 | 849.581 | 5.753 | 0.197 | 3.512 | 878.083 | 0.231 | 841.547 | 6.563 | 0.21402 | 4.573 |

TABLE IV: RESULTS OBTAINED FOR CASE 4 COMPARED WITH SPEA II

| | **BOO NSGA III** | | | | | | **SPEA II** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Case 4 (a) | | Case 4 (b) | | Case 4 (c) | | Case 4 (e) | | Case 4 (e) | | Case 4 (f) | |
| | $C_p$ | $E_p$ | $C_p$ | $P_{loss}$ | $E_p$ | $P_{loss}$ | $C_p$ | $E_p$ | $C_p$ | $P_{loss}$ | $E_p$ | $P_{loss}$ |
| Min | 802.275 | 0.199 | 802.237 | 3.596 | 0.196 | 3.450 | 801.135 | 0.197 | 802.497 | 3.474 | 0.196 | 3.450 |
| Max | 934.764 | 0.325 | 950.104 | 8.548 | 0.197 | 3.486 | 961.429 | 0.332 | 962.289 | 8.509 | 0.197 | 3.488 |
| Range | 132.489 | 0.125 | 147.866 | 4.951 | 0.00036939 | 0.036588 | 160.293 | 0.135 | 159.791 | 5.034 | 0.00037004 | 0.038021 |
| Std | 32.666 | 0.028 | 34.532 | 1.346 | 0.00010413 | 0.00757 | 48.569 | 0.038 | 47.791 | 1.53 | 0.00010423 | 0.01044 |
| Mean | 836.454 | 0.247 | 834.247 | 6.195 | 0.197 | 3.454 | 863.801 | 0.235 | 858.271 | 5.493 | 0.197 | 3.467 |

TABLE V: MOO OPTIMIZATION BY NSGA III FOR CASE 5

| | **MOO NSGA III** | | | **MOO NSGA III** | | |
|---|---|---|---|---|---|---|
| | **case 5 (a)** | | | **case 5 (b)** | | |
| | $C_p$ | $E_p$ | $P_{loss}$ | $C_p$ | $E_p$ | $P_{loss}$ |
| Min | 803.102 | 0.200 | 3.710 | 802.490 | 0.198 | 3.628 |
| Max | 936.742 | 0.319 | 8.621 | 942.480 | 0.311 | 8.436 |
| Range | 133.64 | 0.119 | 4.910 | 139.989 | 0.113 | 4.807 |
| Std | 36.924 | 0.0316 | 1.33 | 35.169 | 0.028 | 1.199 |
| Mean | 851.088 | 0.246 | 5.912 | 840.350 | 0.239 | 5.628 |

The algorithms have generally given converging results. However, NSGA III algorithm excelled in most cases. This is shown in Table 3 and 4 by the Mean values. Standard deviations also show stability of this superiority. One of the biggest problems with multi-objective metaheuristic algorithms is to group solutions in one area and not distribute them on the Pareto front. This is where the MOPSO algorithm failed in case 3 (f). Here, in NSGA III the importance of the reference lines in the distribution of solutions and the prevention of their regrouping in a single small area is clearly demonstrated. The Normalize, Associate and Niche operators can adapt to changing the number of functions and modifying their algebraic expressions. In addition, no settings are changed when you switch from single objective optimization (Case 1 and 2) or higher (Case 3,4 and 5). It has therefore been applied to our problem in a simpler and less complicated way and this leads to a lot of the time profit by comparing it to previous versions I and II. the distribution of solutions is very uniform from the Pareto front. The results show that NSGA III is able to approach the optimal Pareto multidimensions front with reasonable convergence and coverage even in the presence of the UPFC controller. The results in Cases 2, 4 and 5 (b) show that they were better in the presence of the UPFC controller and this is reflected in its positive and flexible characteristics for the control of power flow and bus voltage with its positive impact on power generated from power stations and losses in transmission lines. In addition to reducing the emission rate resulting from a small reduction in the power generated. To a large extent in this work, these results show that the NSGA III algorithm in the presence of UPFC used to solve multiobjective optimization problems with obscure search locations is extremely efficient at finding a very good approximation and the solutions of highly optimized distribution of Pareto multi-dimensions.

## VII. Conclusion

The optimization problems were solved as a multi-constrained optimization problem where the fuel cost, emissions and power losses are minimized. The well distributed solutions across the Pareto front because of the reference points. The proposed NSGA III algorithm based on a dominant multi-objective Pareto front with a most complicated FACTS device has been successfully implemented by testing on the IEEE 30-Bus network to solve the SOO problem, BOO and MOO. UPFC controls real-time power flow in transmission lines by adjusting on line parameters, including node voltage, phase angle, and line impedance. It also contributes to the reduction of the three objectives: cost, emission and active loss, as evidenced by the results of this article. Compared to the results obtained by MOPSO and SPEA II frequently used, the results show that the proposed NSGA III can be highly competitive for selected cases. Therefore, it is reasonable to assume that the NSGA III algorithm is an effective method for solving multi-objective optimization problems including FACTS devices with high accuracy.

Future work will consist of providing more practical results of the Pareto front obtained from multi-objective optimization algorithms for power grid operators, with adapted to help them choose the best solution and make appropriate and correct decisions.

## Appendix

TABLE VI: Limits and Fuel Cost Coefficients of Generators

| | $P^{min}$ | $P^{max}$ | $10^4.a_i$ | $b_i$ | $c_i$ |
|---|---|---|---|---|---|
| $G_1$ | 50 | 200 | 037.5 | 2.00 | 0 |
| $G_2$ | 20 | 80 | 175.0 | 1.75 | 0 |
| $G_5$ | 15 | 50 | 625.0 | 1.00 | 0 |
| $G_8$ | 10 | 35 | 083.0 | 3.25 | 0 |
| $G_{11}$ | 10 | 30 | 250.0 | 3.00 | 0 |
| $G_{13}$ | 12 | 40 | 250.0 | 3.00 | 0 |

TABLE VII: Emission Coefficients of Generators

| | $10^5.\alpha_i$ | $10^3.\beta_i$ | $10.\gamma i$ |
|---|---|---|---|
| $G_1$ | 6.490 | -5.554 | 4.091 |
| $G_2$ | 5.638 | -6.047 | 2.543 |
| $G_5$ | 4.586 | -5.094 | 4.258 |
| $G_8$ | 3.380 | -3.550 | 5.326 |
| $G_{11}$ | 4.586 | -5.094 | 4.258 |
| $G_{13}$ | 5.151 | -5.555 | 6.131 |

TABLE VIII: Parameters of NSGA III

| NSGA III | |
|---|---|
| Max iterations | 50 |
| Population Size | 100 |
| Crossover Percentage | 0.5 |
| Number of Parents | 40 |
| Mutation Percentage | 0.5 |
| Number of Mutants | 40 |
| Mutation Rate | 0.02 |
| Mutation Step Size | 0.2 |
| number of division | 10 |

TABLE VIX: Parameters of BOPSO

| BOPSO | |
|---|---|
| Max iterations | 50 |
| Population Size | 100 |
| Repository Size | 100 |
| Inertia Weight | 0.5 |
| Inertia Weight Damping Rate | 0.99 |
| Personal Learning Coefficient | 1 |
| Global Learning Coefficient | 2 |
| Number of Grids per Dimension | 7 |
| Inflation Rate | 0.1 |
| Leader Selection Pressure | 2 |
| Deletion Selection Pressure | 2 |
| Mutation Rate | 0.1 |

TABLE VX: Parameters of SPEA II

| SPEA II | |
|---|---|
| Max iterations | 50 |
| Population Size | 50 |
| Archive Size | 50 |
| KNN Parameter | 30 |
| Crossover Percentage | 0.7 |
| Number of Parents (Offspring's) | 36 |
| Mutation Percentage | 0.3 |
| Number of Mutants | 14 |

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