TVAC based PSO for Solving Economic and Environmental Dispatch considering Security constraint

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***Abstract*—This paper presents Multi Objective Optimization for Economic and Environmental Dispatch (EED) problem considering security constraint described by Voltage Profile Index (VPI). The fuzzy set theory is used for the modeling of uncertainties about objective functions in the practical environment of poorly defined data. In the beginning, each objective function is optimized independently with an extraction of minimal and maximal values for each one. The membership functions are defined, fuzzy set theory is used to formulate the new standard nonlinear problem and max-min operator for maximizing the Degree of Satisfaction (DS) of all membership functions and to get Pareto solution. Conventional Particle Swarm Optimization (PSO) and Time Varying Acceleration Coefficients (TVAC) based PSO methods are used to solve the problem and demonstrating the effectiveness and capability of the second method over the first one. For both algorithms, IEEE 30 bus test system is applied to verify objectives cited above.**

Keywords-Degree of Satisfaction; Economic and Environmental Dispatch; Fuzzy Set Theory; Particle Swarm Optimization; Time Varying Acceleration Coefficients; Voltage Profile Index.

I. INTRODUCTION

Due to increased requirements for a best quality of modern power system, there is a great need to develop Optimal Power Flow (OPF) algorithms in the sense to get sophisticated power system operations in which several claims stemming from economic, environmental and security aspects are simultaneously satisfied. A straightforward application of the conventional OPF optimizes only one objective and the remaining objectives must be treated as constraints [1]. However, since such objectives are in trade-off relationships with each other, it is necessary to develop efficient Multi Objective OPF (MOOPF) Algorithms [2]. A number of conventional optimization techniques have been applied to solve the OPF problems; they rely on convexity to find the global optimum. However, due to the non-differential, nonlinearity and non-convex nature of the OPF problems, classical methods based on these assumptions do not guarantee to find the global optimum. Those traditionally OPF methods, used to optimize specific aspects of power system operations are not efficient, because they are not suitable to handle many practical considerations encountered in power systems. According to these issues, the interest in applying Artificial Intelligence (AI) in optimization has grown rapidly [3]. Including the uncertainty of the objective functions and ambiguities about operational constraints, it is necessary to extend the problem to MOOPF using fuzzy set theory and AI [4]. Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart, [5] is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems.

In this paper, we describe a MOOPF problem applied on Economic and Environmental Dispatch (EED) [6] considering security constraint, solved by conventional PSO and Time Varying Acceleration Coefficients based PSO (TVAC-PSO) [7] for three objects, the fuel cost minimization (economic generation), less polluted environment with minimization of total emission of atmospheric pollutants (such as sulphur oxides SO_x and nitrogen oxides NO_x caused by the operation of fossil-fuelled thermal generation) and best security of power system described by the flatter voltage profile defined by Voltage Profile Index (VPI) (safety operation of power system with minimal voltage deviations referred to 1 p.u magnitude).

The fuzzy set theory is used for the modeling of uncertainties about objective functions in the practical environment of poorly defined data. Firstly, the Fuel cost, total emission and VPI objectives are optimized individually in order to define the membership of the objective function, then, the multi-objective problem is reformulated into a new standard nonlinear problem by the fuzzy sets theory and max-min operator. Finally, it is solved by PSO and TVAC-PSO approaches. The model is applied on IEEE 30 bus test system.

For this target, our paper is structured as follows: After the introduction, section II describes the problem formulation that focuses the Multi-Objective Problem with Objective Functions and the Optimization Problem. Section III is devoted to the conventional PSO, section IV is dedicated to TVAC based PSO. Section V illustrates the Optimization Strategy and its application to the mathematic model. Simulation, results and discussions are reserved to Section VI. Finally, we finished with a conclusion.

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II. Problem Formulation

A. Multi-Objective Problem using fuzzy set theory

Regarding to human ambiguity, it is natural to consider that the Decision Maker (DM), will 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 functional limit value f_m" Fig. 1, Then the quantitative implementation can be made by defining a membership function for each objective function.

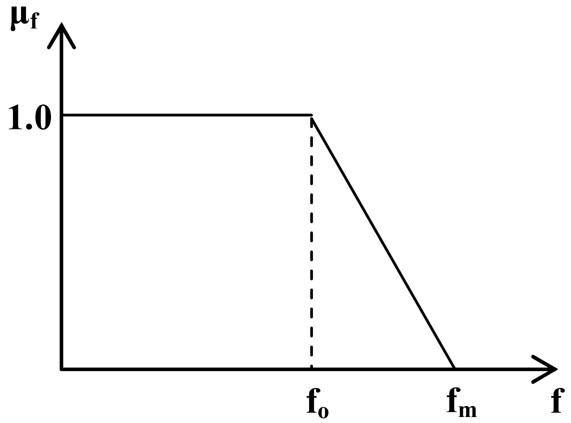

Figure 1. Membership function for one objective function

For the multi-objective problem formulated as a vector minimization, it becomes a vector of maximization for all membership functions and membership function value can be interpreted as expressing the Degree of Satisfaction (DS) of the DM, by changing the problem to conventional OPF with the aim to maximize the DS [8] and to get a Pareto solution (best compromise solution). The work in this paper is based on the above formulation using conventional PSO and (TVAC-PSO). We adopt a fuzzy linear distribution for each objective function as shown in (1).

$$\mu_{fi}(x)=\begin{cases}1 & 0\le f_i(x)<f_{i(o)}\\ \dfrac{f_i(x)-f_{i(m)}}{f_{i(o)}-f_{i(m)}} & f_{i(o)}\le f_i(x)\le f_{i(m)}\\ 0 & f_i(x)>f_{i(m)}\end{cases} \tag{1}$$

B. Objective Functions

The three most important concerns considered in the power system operation are economical, environmental and security problems to define the EED problem, selected as the evaluation of three functions describe as bellow:

1) Total cost generation function

$$f_C=\sum_{i=1}^{ng}(a_i+b_iP_{Gi}+c_iP_{Gi}^2)\qquad (\$/h) \tag{2}$$

P_{Gi} : active power generation at unit i.

ng : 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

$$f_E=\sum_{i=1}^{ng}(\alpha_i+\beta_iP_{Gi}+\gamma_iP_{Gi}^2+\delta_i\exp(\varepsilon_iP_{Gi}))\quad (Ton/h) \tag{3}$$

α_i, β_i, γ_i, δ_i and ε_i are the coefficients of the i^{th} generator emission characteristics.

3) Function of Voltage profile (security index)

$$f_{VPI}=\sqrt{\sum_{i=1}^{Npq}(V_i-1)^2} \tag{4}$$

f_{VPI} : Voltage profile function.
V_i : Voltage magnitude at PQ bus i,
N_{pq} : Number of PQ buses.

C. Multi-Objective Optimization using fuzzy set theory

$$\min\,(f_C, f_E, f_{VPI})$$
$$g(x)=0 \tag{5}$$
$$h(x)\le 0$$

where:
x is the vector of the control variables such as generator real power Pg, generator voltage at PV bus Vg and transformer tap setting T. Therefore, it can be expressed as:

$$x=[P_{g1}\quad Pg_{ng}, V_{g1}\quad Vg_{ng}, T_1\quad T_{nt}] \tag{6}$$

nt is the number of transformer branches.

$g(x)$: represents the equality constrains described as below :

$$P_{Ti}+P_{Li}-P_{gi}=0 \tag{7}$$
$$Q_{Ti}+Q_{Li}-Q_{gi}=0 \tag{8}$$

P_{gi}, P_{Li} and P_{Ti} indicate active power generation, load, and injection in bus i respectively.
Q_{gi}, Q_{Li} and Q_{Ti} indicate reactive power generation, load, and injection in bus i respectively

$h(x)$: represents inequality constrains described as below :

$$\begin{aligned}&P_{gi}(\min)\le P_{gi}\le P_{gi}(\max)\quad i=1,2,...ng\\&Q_{gi}(\min)\le Q_{gi}\le Q_{gi}(\max)\quad i=1,2,...ng\\&T_{i(\min)}\le T_i\le T_{i(\max)}\quad i=1,2,...nt\\&V_{gi(\min)}\le V_{gi}\le V_{gi(\max)}\quad i=1,2,....ng\end{aligned} \tag{9}$$

In fuzzy set, objective functions and constraints can be characterized by membership functions. The optimal solution

(fuzzy decision) is given as an intersection of the fuzzy sets describing the constraints and the objectives [9].
As the conjunctive function, if we adopt the well-known fuzzy decision of Bellman and Zadeh [10] or minimum operator, the optimal solution is defined to be the one with the highest degree of DS membership function and the optimization problem becomes that of maximizing the Degree of Satisfaction μ_{DS}, subject to the crisp and fuzzy constraints, with the obtained Pareto solution. The multi-objective optimization problem (5) can be transformed as:

$$\max_{x \in X} (z = \mu_{DS}(x))$$

$$\begin{aligned} z(f_{mi} - f_{oi}) &\leq (f_i(x) - f_{oi}) \\ 0 \leq\ & z \leq 1 \end{aligned} \tag{10}$$

with $i=1,\ldots,Nobj$
f_i : is the i^{th} objective function with membership degree μ_{fi}.
X: denotes the feasible region satisfying all goals and constraints of the problem.

III. Conventional Particle Swarm Optimization

The PSO can be best understood through an analogy of a swarm of birds in a field. Without any prior knowledge of the field, the birds move in random locations with random velocities looking for foods.
In conventional PSO, particles change their positions (states) with time. Let 'X' and 'V' denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space respectively. The position vector Xi and the velocity vector Vi of the i th particle in the n-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, \ldots\ldots, x_{in})$ and $V_i = (v_{i1}, v_{i2}, \ldots\ldots, v_{in})$ respectively.
The best previous position of the i th particle is recorded and represented as $Pbest = (x_{i1}^{pbest}, x_{i2}^{pbest}, \ldots\ldots, x_{in}^{pbest})$. The index of the best particle among all the particles in the group is represented by the $Gbest = (x_1^{Gbest}, x_2^{Gbest}, \ldots\ldots, x_n^{Gbest})$. The modified velocity and position of each particle can be calculated as per following formulas [11]:

$$\begin{aligned} V_i^{(t+1)} = \underbrace{\omega V_i^{(t)}}_{Previous\ \ Velocity} + \underbrace{c_1 r_1 \times (Pbest_i^{(t)} - X_i^{(t)})}_{Cognitive\ \ Component} \\ + \underbrace{c_2 r_2 \times (Pgbest_i^{(t)} - X_i^{(t)})}_{Social\ \ Component} \end{aligned} \tag{11}$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \tag{12}$$

where $\omega, c_1, c_2 \geq 0$,
ω : is the inertia weight factor.
c_1 and c_2 : are the acceleration coefficients.
r_1 and r_2 : are two random numbers within the range [0,1].
$V_i^{(t)}$, $X_i^{(t)}$: are the velocity and the current position of particle i in the search space at iteration *iter*, respectively.
In general, the inertia weight ω provides a balance between global and local explorations (control the influence of the previous history of the velocities on the current one). It is set according to the following equation:

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{iter_{\max}} \times iter \tag{13}$$

ω_{min}, ω_{max} : initial and final inertia factor weights.
$iter_{max}$: maximum iteration number.
iter: current iteration number.
The position is updated with respect to (12).

IV. Concept of Time Varying Acceleration Coefficients

The time-varying inertia weight (TVIW) can locate a good solution at a significantly faster rate but its ability to fine tune the optimum solution is weak, due to the lack of diversity at the end of the search. It has been observed by most researchers that in PSO, problem-based tuning of parameters is a key factor to find the optimum solution accurately and efficiently [11]-[12]. In TVAC, this is achieved by changing the acceleration coefficients and with time in such a manner that the cognitive component is reduced while the social component is increased as the search proceeds. TVAC-PSO is successfully implemented for economic load dispatch (ELD) problem in [13].

$$\begin{aligned} V_i^{(t+1)} &= \omega^{(t)} V_i^{(t)} + c_1{}^{(t)} r_1 \times (Pbest_i^{(t)} - X_i^{(t)}) \\ &+ c_2{}^{(t)} r_2 \times (Pgbest_i^{(t)} - X_i^{(t)}) \end{aligned} \tag{14}$$

$$\begin{aligned} c_1^{(t)} &= (c_{1f} - c_{1i}) \times \frac{iter}{iter_{\max}} + c_{1i} \\ c_2^{(t)} &= (c_{2f} - c_{2i}) \times \frac{iter}{iter_{\max}} + c_{2i} \end{aligned} \tag{15}$$

where:

$c_i^{(t)}$ is the i^{th} acceleration coefficient at iteration *iter*.

c_{ii} and c_{if} are initial and final values of the i^{th} acceleration coefficient respectively.

$\omega^{(t)}$ is the same value of inertia weight in (13).

V. Optimization Strategy

The strategy of optimization aims to maximize the DS for the problem formulated in (10) by conventional PSO and TVAC-PSO. The optimization strategy is summarized in flowing steps:

Step1: Each objective function is optimized independently to another one, the minimal value is denoted by f_o, the optimal values for relationships in (2), (3) and (4) are denoted by f_{Co}, f_{Eo} and f_{VPIo} respectively.
Step 2: The maximal value of each objective function f_m is obtained during the optimization process of the other objective functions and the maximal values for the same relationships indicated in step1 are obtained, they are denoted by f_{Cm}, f_{Em} and f_{VPIm} respectively.
Step 3: For each objective function and after the extraction of f_o and f_m values, the membership function is defined.
Step 4: f_o and f_m values are introduced for each objective function in problem (10), the DS is maximized by conventional PSO and TVAC-PSO, the objective function (OF) becomes:

$$OF = \frac{1}{\mu_{DS}} \tag{16}$$

In this case, we obtain the Pareto solution for the minimization of OF (best compromise solution for the minimization of three functions simultaneously).

VI. SIMULATION AND RESULTS

Simulation is applied on IEEE 30 bus test system, under MATLAB environment. The model has 6 generators, 41 lines and 24 load buses. Upper and lower active power generating limits, reactive power limits, unit costs and emission characteristics of generators for the test system are presented in [14]. Lower and upper limits of voltage magnitude for generators are 0.95 and 1.1 p.u. Tap setting transformers limits are 0.9 and 1.1 p.u. The first type of control variables is reserved to the power generation output at buses 1, 2, 5, 8, 11 and 13, the second type is devoted to tap setting transformers at branches 6-9, 6-10, 4-12 and 28-27, while the third type is addressed to voltage of generating buses. Conventional PSO and TVAC-PSO parameters are exposed in Table I, w_{min} and w_{max} are the minimal and maximal values of inertia weight factor respectively.
The total active load was 283.4 MW. The optimization results of several objective functions independently of the one to another are illustrated in Table II for conventional PSO and Table III for TVAC-PSO.

TABLE I. CONVENTIONAL PSO AND TVAC-PSO PARAMETERS

Parameters	Conventional PSO	TVAC- PSO
Population size	200	200
Number of iterations	300	300
Acceleration Coefficients	c_1=2.05; c_2=2.05	c_{1i}=2.05 c_{1f}=0.5 c_{2i}=0.5 c_{2f}=2.05
ω_{min} and ω_{max}	0.4-0.9	0.4-0.9

Objective function values f_o and f_m related to each objective function are extracted from Table II and Table III, They are necessary objective values for maximizing the DS.
The Voltage profile (voltage magnitude at each bus) for the optimization of each objective function independently to another one is represented in Fig. 2. The Active Total Losses TL and CPU time are also presented for each case in tables cited above.
Proposed algorithms satisfy all system constraints, thereby validating the improved heuristic application of TVAC-PSO.
It is remarkable that results with TVAC-PSO are better than the ones obtained with conventional PSO for all objective functions.
The best situation of electrical power system security is assigned to voltage profile index minimization with a value of 0.0560 (Conventional PSO) and 0.0391 (TVAC-PSO), it is observed in Fig. 2.
Fig. 3 illustrates the effectiveness and the fast convergence to the best value with TVAC-PSO algorithm compared to a conventional PSO method for the cost minimization case.
CPU time of TVAC-PSO is reduced by comparison to conventional PSO referred to Table II and Table III.
Simulation results are obtained for the optimization of three functions simultaneously (maximization of DS) and represented in Table IV.

TABLE II. SIMULATION RESULTS WITH PSO METHOD

Control Variables & Objectives	Conventional PSO Method		
	Min FC	*Min FE*	*Min VPI*
Pg (1) (MW)	171.5715	70.0188	107.0830
Pg (2) (MW)	49.1229	71.7400	65.7839
Pg (5) (MW)	21.2407	50.0000	42.8962
Pg (8) (MW)	25.8099	35.0000	18.2297
Pg(11)(MW)	10.0000	30.0000	26.4638
Pg(13)(MW)	14.7566	31.4707	28.7817
T_{6-9}	1.1000	0.9452	1.0332
T_{6-10}	0.9488	1.1000	0.9118
T_{4-12}	1.1000	0.9000	1.0065
T_{28-27}	0.9898	0.9000	0.9621
Vg_1 (p.u)	1.0839	0.9902	1.0211
Vg_2 (p.u)	1.1000	0.9500	1.0129
Vg_5 (p.u)	1.0346	1.0043	1.0084
Vg_8 (p.u)	1.0808	0.9500	1.0425
Vg_{11} (p.u)	0.9500	0.9983	1.0055
Vg_{13} (p.u)	1.1000	1.1000	1.0695
F_c ($/h)	802.7879	935.8731	871.8805
F_e (Ton/h)	0.35486	0.21899	0.24435
F_{VPI} (p.u)	0.1580	0.1342	0.0560
Total Losses (Mw)	9.1015	4.8295	5.8383
CPU_Time (s)	295.1011	296.2719	346.2768

TABLE III. SIMULATION RESULTS WITH TVAC-PSO

Control Variables & Objectives	**TVAC-PSO Method**		
	Min FC	*Min FE*	*Min VPI*
Pg (1) (MW)	177.3614	67.6396	128.4062
Pg (2) (MW)	48.7124	71.2920	67.2948
Pg (5) (MW)	20.4398	50.0000	43.4828
Pg (8) (MW)	21.1180	35.0000	21.3491
Pg(11)(MW)	12.4687	30.0000	17.8262
Pg(13)(MW)	12.1533	33.1607	12.6567
T_{6-9}	0.9542	0.9970	1.0365
T_{6-10}	1.0576	0.9918	0.9013
T_{4-12}	1.0166	0.9899	0.9785
T_{28-27}	0.9879	0.9853	0.9492
Vg_1 (p.u)	1.0999	1.0568	0.9979
Vg_2 (p.u)	1.0839	1.0516	1.0469
Vg_5 (p.u)	1.0514	1.0222	1.0264
Vg_8 (p.u)	1.0629	1.0600	1.0084
Vg_{11} (p.u)	0.9576	0.9766	1.0198
Vg_{13} (p.u)	1.0848	1.0351	1.0311
F_c ($/h)	799.7911	935.7818	853.8796
F_e (Ton/h)	0.37011	0.21851	0.27223
F_{VPI} (p.u)	0.2294	0.1090	0.0391
Total Losses (Mw)	8.8537	3.6923	7.6158
CPU_Time (s)	282.5682	283.3196	285.3922

Table IV illustrates the best compromise solution obtained for both methods (Pareto solution for minimizing three functions simultaneously) and the best results obtained with TVAC-PSO for the maximization of DS, tuning the Pareto solution after extraction of the maximal and minimal values for each objective function. It is noted that all operating constraints are checked for both methods.

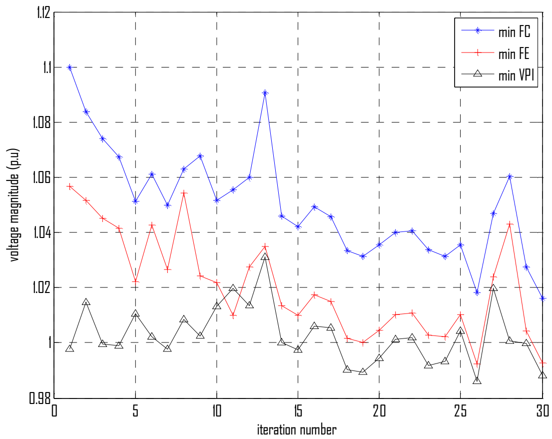

Figure 2. Voltage profile for each case of optimization using TVAC-PSO

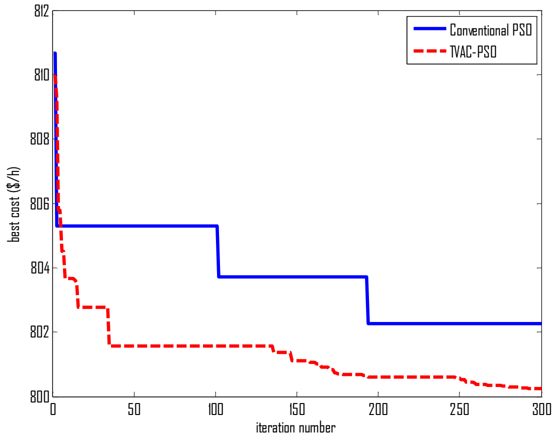

Figure 3. Convergence characteristics of TVAC-PSO and conventional PSO for cost minimization

TABLE IV. SIMULATION RESULTS FOR MAXIMIZATION OF DS WITH CONVENTIONAL PSO AND TVAC-PSO

Control Variables & Objectives	**Max DS**	
	Conventional PSO	*TVAC-PSO*
Pg (1) (MW)	123.4859	117.9153
Pg (2) (MW)	53.3348	60.8984
Pg (5) (MW)	36.2585	27.3071
Pg (8) (MW)	35.0000	35.0000
Pg(11)(MW)	30.0000	27.7174
Pg(13)(MW)	12.0000	20.7136
T_{6-9}	0.9353	0.9597
T_{6-10}	1.0729	1.0186
T_{4-12}	0.9000	0.9715
T_{28-27}	0.9000	0.9538
Vg_1 (p.u)	1.0374	1.0469
Vg_2 (p.u)	0.9500	1.0317
Vg_5 (p.u)	1.1000	1.0742
Vg_8 (p.u)	1.0041	1.0126
Vg_{11} (p.u)	0.9500	1.0195
Vg_{13} (p.u)	0.9500	1.0177
F_c ($/h)	841.7144	832.4987
F_e (Ton/h)	0.25948	0.25487
F_{VPI} (p.u)	0.0874	0.0538
Total Losses (Mw)	6.6792	6.1518
DS	0.6926	0.7595

IV. CONCLUSION

Interesting coding of control variables for conventional PSO and TVAC-PSO is assigned to our computational code.

An efficient TVAC-PSO algorithm of Multi-Objective Optimal Power Flow using Fuzzy set theory, with robustness and proficiency over the conventional PSO.

TVAC-PSO is applied on IEEE 30 bus test system describing accurate results to deal with different types of objective functions, uncertainties about constraints, ambiguities about practical data description language and interactive Algorithm with decision Maker.

A best security constraint of voltage limitation is developed for the test system for Multi-Objective Optimization using fuzzy logic. The proposed approach creates a platform of relationship analysis between objective functions denoted by the trade-off.

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