Parameter Analysis for Differential Evolution on Loop Flow Problem in Power System

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***Abstract*—In electrical power systems preventing and regulating the loop flow phenomena is very important issue especially after the de-regulation. The problem should be solved very efficiently. We have formulated the loop flow problem in fuzzy environment, as a multi-objective optimization problem using fuzzy set theory and fuzzy decision making rules. Then the resulted single objected optimization problem is solved using differential evolution (DE). Then a sets of simulations are done to figure out the most efficient parameter values of DE to fit our problem. DE is one of the evolutionary search methods. The parameter settings play an important role on reducing the required time and getting better solution to the problem. We applied our loop flow method to IEEE 30 bus test system and presented the results.**

***Index Terms*—Differential evolution, fuzzy set, fuzzy decision-making, interconnected power systems, loop flows, unscheduled flows.**

I. Introduction

The high power losses, low efficiencies, or the long path power travelling through (occupying transmission lines) before arriving to the loads have not been problem in government controlled power systems. Since rising costs of electrical energy were directly adjusted to the customers' bill or were partly subsidized by the governments the loop flows inherited in interconnected power systems (or the heat loses due to loop flows) was not seen as a serious problem [1]. After the privatization (de-regulation) the issues such as; how much power flows on which transmission lines, which company uses the other's transmission lines and/or the amount and the time of the transmission line usage have become important. If a system runs into a problem due to a heavy transmission line usage it is important to identify the responsible parties (systems causing unscheduled power flows). The path electrical power takes depends on the physical laws. That is, Kirchhoff's current and resistance laws determine the path for the electrical power to flow. It takes the shortest path (in terms of resistivity) instead of a contracted path.In this case a third party between a buyer and a seller of electrical energy may come into the picture. In such a case the question becomes who is to pay for the transmission line usage between a seller and a buyer [2], [3].

Unscheduled flows that refer to the deviation of actual electric power flows in transmission circuits from the scheduled (expected) power flows, may result in blackouts and affect cross border trading in the electricity markets. Therefore, unscheduled flows which are also termed inadvertent interchange or loop flows, should be managed/controlled to improve both the operation conditions of the electric network and the market. The effects of parallel paths in system network topology and a survey to explore the present state of practices used to determine transfer capability issues are well studied in [4], [5]. Suryanarayanan et al, proposes an approach based on Lp-norms to estimate the unscheduled flows occurring in a wide area interconnected system [6], [7].

In recent years, there have been a lot of applications of fuzzy set theory to various power system problems [8], [9], [10], [11]. In the past power system optimization problems were dealt with using non-linear and linear programming methods. The optimization problems under an uncertain environment can be reformulated using fuzzy sets. Many interesting applications of fuzzy sets in the optimization of the power system operating and planning stages have been reported.

Differential evolution method was introduced by Price and Storn [16] in 1995. It has gained popularity by years, and has been applied to various scientific problems. Some examples of power systems applications are reactive power optimization [19], power systems planning [20], power system transfer capability assessment [21], and power plant control [22], etc.

In this study, a multi-objective optimization approach based on fuzzy decision making and differential evolution is proposed to manage unscheduled flows. We handle the problem in a fuzzy environment since in practice, the small variations of power systems variables (bus voltages, line currents etc.,) from their limit values can be tolerated, and this can help to obtain one of the best solutions to the problem.

In the next section, a summary regarding unscheduled flows is given. In Section III and IV, the basic principles of fuzzy decision making and differential evolution are introduced briefly. In Section V, the implementation of the proposed approach is described in detail. The simulation results are provided and discussed in the subsequent section. Finally conclusions are provided.

II. Loop Flows(Unscheduled flows)

In an interconnected transmission network, when some amount of the scheduled power flows through an adjacently connected system, a loop flow phenomenon occurs. That is, the loop flow is the difference in between the actual flow and the scheduled flow in a particular path. It is also referred to as the parallel path flow, unscheduled flow or circulating flow. The main reason of this phenomenon is that the Kirchhoff's laws that determine the path for the electrical power to flow. Loop flow could exist in an interconnected power transmission network depending on the system topology and operating conditions.

It has been known that, without exceeding power transfer limits of lines (not overloaded) and disturbing system reliability, for the sake of efficient operation, neighbouring systems can buy and sell power to and from each other through the transmission system that exists between them. But unscheduled flows affect the operation of the electric power system and the market.

Unscheduled flows can play an important role in causing blackouts and creating the cross-border bottlenecks, they need to be managed.

III. Fuzzy Decision Making

This section summarizes the basic concepts of fuzzy sets used for the fuzzy model, and offers brief information about the multi-objective fuzzy model and the essentials of the techniques for solving the multi-objective fuzzy model.

Fuzzy set theory is a generalization of traditional crisp set theory. The idea is to replace the concept that each variable has a precise value by the fuzzy concept that each variable is assigned a degree of membership for each possible value of the variable. A fuzzy set in the universal set U, is a generalization of a classical set, and it can be characterized by a membership function, $\mu(x)$, that takes real values in the continuous interval [0,1]. A fuzzy set A, in U can be represented by an ordered pair composed by a generic element x and its membership value, that is,

$$A = \{(x, \mu_A(x)), x \in U\} \tag{1}$$

A fuzzy set can be characterized by a membership function to map a parameter to membership grade between the scaled intervals. For modelling the objectives and the constraints in fuzzy environment, initial step is the fuzzification process, are assigned membership values using fuzzy membership functions. The closer the membership is to one the better the solution is for that objective or constraint. Fuzzy sets representing the objectives and constrains may vary considerably. The membership functions may be similar in the sense that numbers outside the interval are excluded from the associated fuzzy sets. Generally a triangular membership function is selected for representing fuzzy sets. The other most common shapes are trapezoidal, exponential, and Gaussian.

In fuzzy decision making fuzzy objective functions and constraints can be characterized by the membership function of the fuzzy objectives, $\mu_g(x)$ and the membership function of the fuzzy constraints, $\mu_c(x)$, respectively. The optimal solution, which is the fuzzy decision μ_D, is given as an intersection of the fuzzy sets describing the constraints and the objectives. Using the membership functions, the overall membership function value is obtained as

$$\mu_D = \min\lfloor \mu_g(x), \mu_c(x) \rfloor \tag{2}$$

The optimal solution is defined to be the one with the highest degree of membership, and thus the optimization problem becomes that of maximizing the satisfaction with the solution, subject to the crisp and fuzzy constraints [12].

IV. Differential Evolution

Differential evolution (DE) is a population based, inherently parallel, heuristic search method. It is powerful to handle non linear and non differentiable functions.

DE procedure is similar to other evolutionary algorithms, such as genetic algorithms, particle swarm optimization, tabu search, simulated annealing, etc. Main parts of the algorithm is shown below.

Algorithm 1 Main Parts of DE Algorithm

```
Initialization
Evaluation
repeat
   Mutation
   Crossover (Recombination)
   Evaluation
   Selection
until Stopping criterion is satisfied
```

Since, DE is a population based method, at every iteration, it operates on a population of Np candidate solution vectors. The first step of the algorithm generates a random solution vector. A population can be represented as shown below.

$$P^i = [X_1^i, \cdots, X_{N_p}^i] \tag{3}$$

where i represents the iteration number, and X is a candidate solution vector. Each solution candidate vector consists of n objective function parameters, where n is the number of unknowns in the function to be optimized. The solution candidates must be initialized within the lower and upper bounds of the unknowns.

The second step of the algorithm creates mutant vectors, by adding a weighted difference vector of two randomly indexed vectors to the third one. There are several versions for this process [18]. Famous scheme DE/rand/1 process can be mathematically represented as shown below.

$$x_j^{'i} = x_{r3}^i + F(x_{r1}^i - x_{r2}^i) \tag{4}$$

where r_1, r_2, and r_3 are randomly selected integers from 1 to N_p and $j \neq r_1 \neq r_2 \neq r_3$. The mutant vector is represented by $x_j^{'i}$. F is the scaling factor, which has effect on the difference vector, within the range of [0,2].

The third step creates trial vectors by mixing the parent vectors, and the mutant vectors. Mathematical representation for this process is given below.

$$x_j^{\text{trial}(G)} = \begin{cases} x_{kj}^{'(i)} & \text{if rand}(0,1) \leq (CR) \text{ or } k = q, \\ x_{kj}^{(i)} & \text{otherwise.} \end{cases} \tag{5}$$

where, q is a random parameter chosen for each j, CR represents crossover constant, within the range of [0,1], and rand is a randomly generated number between 0 to 1.

Decision of inclusion of the trial vector in the next generation is made in the selection step, by comparing the fitness values of the trial vectors with the associated target vectors. This process can be represented as shown below.

$$x_j^{(i+1)} = \begin{cases} x_j^{\text{trial}(i)} & \text{if} f(x_j^{\text{trial}(i)}) \leq f(x_j^{(i)}), \\ x_j^{(i)} & \text{otherwise.} \end{cases} \quad (6)$$

Finally if the stopping criterion is met the algorithm stops otherwise it goes to the second step.

V. Problem Formulation

A classical general optimization problem formulation is given below.
Minimize

$$f(x, u)$$

Such that

$$g(x, u) = 0$$
$$h(x, u) \leq 0$$

where x represents system variables, u represents control variables for the objective function $f(x, u)$ with the equality constraints $g(x, u) = 0$ and the inequality constraints $h(x, u) \leq 0$.

In our formulation, the objective function is the minimization of fitness function

$$fitness = \frac{1}{1 + \mu_D} \quad (7)$$

which is the maximization of the minimum satisfaction value of fuzzy memberships . In the fuzzy environment both the objective functions (minimization of both total active losses and total reactive losses and the scheduled line flow on a contracted path) and the constraints (voltages remaining within the limits, line flows remaining within the limits etc.,) are modelled as fuzzy sets. The intersection of both membership sets, μ_c and μ_g, is the overall satisfaction, μ_D needs to be maximized.

We use control variables such as tap changing transformers tap ratios, generation bus voltages, active power generations, and if available reactance of series compensation with their upper and lower limits to create candidate solutions to established the initial population for DE. Each candidate solution in the population is evaluated by load flow program. The results of load flow (voltages, line flows, loses, etc.) are passed to fuzzy decision making process, where a membership value is assigned for all constraints and objectives. The minimum of those membership values is then tried to be maximized by DE. The process continues until all population is exhausted or a pre-set number of iterations is reached.

The exponential membership function, see 2, has been selected for the fuzzification of the unscheduled flows since our earlier study showed that more satisfying results can be obtained using this kind of membership function [13], [14], [15]. A trapezoidal membership function could have also been used.

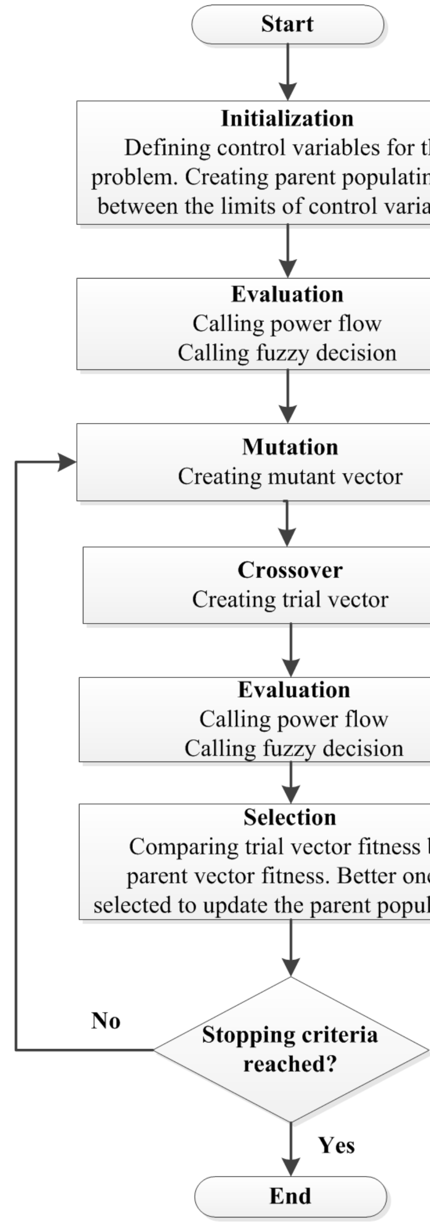

Fig. 1. Flow chart of the problem.

The function in 2 can be described by four parameters (a, b, c, d) with four breakpoints of the shape. The membership function $\mu_{g,ij}(P_{ij})$ belongs to the MW flow (line flow) through the line between bus i and bus j. The system operators taking into account the amount of the scheduled power flowing through the contracted paths can determine the four parameters of the function. The membership function $\mu_{g,ij}(P_{ij})$ is defined as

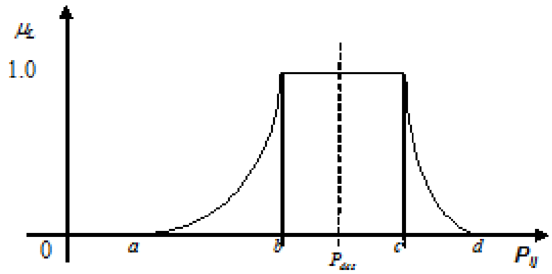

Fig. 2. The fuzzy memberships function for the loop MW flows (the exponential form).

$$\mu_{g,ij}(P_{ij}) = \begin{cases} \frac{P_{ij}-a_{ij}}{b_{ij}-a_{ij}} & a_{ij} < P_{ij} < b_{ij} \\ 1 & b_{ij} < P_{ij} < c_{ij} \\ 1 + \frac{d_{ij}-P_{ij}}{d_{ij}-c_{ij}} & c_{ij} < P_{ij} < d_{ij} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where, $a_{ij} < b_{ij} < c_{ij} < d_{ij}$ must hold.

VI. Simulation Results

The chosen values of the parameters of DE is as follows.
F will be vary in between [0.0,1.0]
CR will be vary in between [0.0,1.0]
$n = 14$
$Np = 100$
$ub = [1.1, 1.1, 1.1, 1.1, 1.06, 1.06, 1.06, 1.06, 1.06, 140, 100, 100, 100, 100];$
$lb = [0.9, 0.9, 0.9, 0.9, 0.94, 0.94, 0.94, 0.94, 0.94, 0.0, 0.0, 0.0, 0.0, 0.0];$
ub is the upper bound of the unknowns (power system parameters).
lb is the lower bound of the unknowns (power system parameters).

The paths chosen to control power flows are given below:

- Path 1, branch between buses 2 and 6,
- Path 2, branch between buses 2 and 5,
- Path 3, branch between buses 6 and 7.

The fuzzy membership function parameters (a,b,c,d) are chosen as 50,59,61,70 respectively for the path 1.
The fuzzy membership function parameters (a,b,c,d) are chosen as 55,59,61,65 respectively for the path 2.
The fuzzy membership function parameters (a,b,c,d) are chosen as 15,21,23,29 respectively for the path 3.

The averaged values are the results of twenty runs.
According to the table I and II we see that the solutions reached from the 0.4 value of F is better. But the deviations from the targeted values are high.
According to the table III and IV we see that the solutions reached from the 0.4 value of F is the best one.
According to the table V and VI we see that the solutions reached from the 0.2, 0.4 and 0.6 values of F are not really different than each other. The iteration number for the case 0.4 of F is the lowest.
According to the table VII and VIII we see that the solutions reached from the 0.2, 0.4 and 0.6 values of F are not really different than each other. The iteration number for the case 0.6 of F is the lowest.
According to the table IX and X we see that the solutions reached from the 0.4 and 0.6 values of F are fairly good. Iteration number is lower for the 0.4 of F then the 0.6 of F. The 0.4 value of F provides better fuzzy membership values for the paths as well.
Overall conclusion is that we have obtained a value as 0.4 for the parameter F and two values as 0.6 and 1.0 for the parameter CR. When the value of CR is high DE might converge fast and arrive at a local minimum. That is why we concluded the parameter settings for DE as 0.4 for the F and 0.6 for the CR.

After parameter analysis of DE our problem is solved using the best case parameter to compare to base case solution of the system. The results are given from the tables XI and XII.

TABLE I
AVERAGED OBJECTIVE VALUES.

CR=0.2	fitness	generation	path 1 (MW)	path 2 (MW)	path 3 (MW)
F=0.2	0.7099	344.2857	47.2075	51.2710	22.3625
F=0.4	0.7026	288.4286	53.6023	57.0964	22.0552
F=0.6	0.7437	224	44.5404	54.6725	27.1232
F=0.8	0.7679	203.7143	35.9105	43.1106	21.5093
F=1.0	0.7918	213.5714	12.7435	25.7443	25.3571

TABLE II
AVERAGED FUZZY MEMBERSHIP VALUES FOR OBJECTIVES AND CONSTRAINTS.

CR=0.2	min fitness	path 1	path 2	path 3	P_{loss}	Q_{loss}
F=0.2	0.3122	0.3357	0.6508	0.6055	0.5152	0.4315
F=0.4	0.3528	0.4928	0.6643	0.6934	0.4450	0.3978
F=0.6	0.1040	0.3655	0.2415	0.1946	0.2663	0.2550
F=0.8	0.0022	0.0109	0.0252	0.0459	0.3156	0.2761
F=1.0	0	0	0	0.0664	0.3447	0.2429

TABLE III
AVERAGED OBJECTIVE VALUES.

CR=0.4	fitness	generation	path 1 (MW)	path 2 (MW)	path 3 (MW)
F=0.2	0.7372	299.2857	52.7136	54.1790	19.4998
F=0.4	0.6919	335.2857	58.2337	59.7074	20.3662
F=0.6	0.7315	230.4286	52.3205	53.2260	21.1080
F=0.8	0.8504	209	38.4646	44.9840	23.0930
F=1.0	0.8213	201.7143	20.1798	51.5315	48.4237

VII. Conclusion

Regulating or controlling loop flow is formulated as a multi-objective problem subject to operational and electrical

TABLE IV
AVERAGED FUZZY MEMBERSHIP VALUES FOR OBJECTIVES AND CONSTRAINTS.

CR=0.4	min fitness	path 1	path 2	path 3	P_{loss}	Q_{loss}
F=0.2	0.3779	0.3837	0.6998	0.4184	0.3780	0.3791
F=0.4	0.4420	0.4649	1.0000	0.5307	0.4426	0.4426
F=0.6	0.1540	0.2419	0.5065	0.4138	0.2603	0.2643
F=0.8	0.0133	0.0237	0.0970	0.1774	0.2110	0.1834
F=1.0	0	0	0	0.0870	0.1569	0.1306

TABLE V
AVERAGED OBJECTIVE VALUES.

CR=0.6	fitness	generation	path 1 (MW)	path 2 (MW)	path 3 (MW)
F=0.2	0.6963	367.4286	58.1737	58.9501	20.1867
F=0.4	0.6915	252	58.2259	59.3840	20.3931
F=0.6	0.6994	296.8571	58.3525	60.3773	21.3662
F=0.8	0.8072	231	47.6865	57.5251	28.1167
F=1.0	0.8375	201	36.3017	45.1145	28.8744

TABLE VI
AVERAGED FUZZY MEMBERSHIP VALUES FOR OBJECTIVES AND CONSTRAINTS.

CR=0.6	min fitness	path 1	path 2	path 3	P_{loss}	Q_{loss}
F=0.2	0.4361	0.4377	0.9052	0.4411	0.4362	0.4363
F=0.4	0.4437	0.4611	1.0000	0.5553	0.4437	0.4451
F=0.6	0.4144	0.5245	0.9782	0.8188	0.4204	0.4150
F=0.8	0.1309	0.2873	0.3836	0.5651	0.2354	0.2366
F=1.0	0.0110	0.1313	0.3214	0.2840	0.2910	0.1686

TABLE VII
AVERAGES OBJECTIVE VALUES.

CR=0.8	fitness	generation	path 1 (MW)	path 2 (MW)	path 3 (MW)
F=0.2	0.6954	341.1429	58.1755	58.8678	20.2524
F=0.4	0.6904	314.2857	58.2037	59.116	20.2139
F=0.6	0.6996	260.2857	58.4694	60.2493	20.9606
F=0.8	0.7453	219.1429	55.7606	65.9365	27.9187
F=1.0	0.9104	203.8571	50.5513	51.8493	18.6307

TABLE VIII
AVERAGED FUZZY MEMBERSHIP VALUES FOR OBJECTIVES AND CONSTRAINTS.

CR=0.8	min fitness	path 1	path 2	path 3	P_{loss}	Q_{loss}
F=0.2	0.4381	0.4384	0.7539	0.4776	0.4383	0.4382
F=0.4	0.4481	0.4509	0.9925	0.4532	0.4482	0.4483
F=0.6	0.4174	0.5795	0.9548	0.7241	0.4223	0.4179
F=0.8	0.1810	0.2343	0.5679	0.8239	0.2868	0.2607
F=1.0	0	0.1325	0.0692	0.1429	0.1927	0.0938

constraints in fuzzy environment. After fuzzy decision resulted single objective optimization problem is solved by using differential evolution. The primary goal of our problem is to obtain the highest satisfaction level(maximizing the fuzzy membership value) to reach the targeted flow levels. The problem is tested for the many different cases of the parameters of DE to obtained the best solution to our problem.

TABLE IX
AVERAGED OBJECTIVE VALUES.

CR=1.0	fitness	generation	path 1 (MW)	path 2 (MW)	path 3 (MW)
F=0.2	0.8440	211.1429	52.5332	57.8209	23.1920
F=0.4	0.7062	213.8571	58.2072	59.9108	20.6898
F=0.6	0.6904	362.2857	58.2042	59.1771	20.2409
F=0.8	0.7117	238.7143	58.4986	60.0911	21.5948
F=1.0	0.8257	218.4285	53.6428	63.4230	30.1184

TABLE X
AVERAGED FUZZY MEMBERSHIP VALUES FOR OBJECTIVES AND CONSTRAINTS.

CR=1.0	min fitness	path 1	path 2	path 3	P_{loss}	Q_{loss}
F=0.2	0.1967	0.2104	0.4583	0.3823	0.3296	0.3036
F=0.4	0.4163	0.4537	1.000	0.7096	0.4208	0.4163
F=0.6	0.4479	0.4511	0.9860	0.4665	0.4480	0.4482
F=0.8	0.3568	0.6278	0.8173	0.9171	0.3899	0.3684
F=1.0	0.0773	0.2650	0.3486	0.4782	0.1585	0.1294

TABLE XI
AVERAGED OBJECTIVES AND CONSTRAINTS, (BEST FITNESS = 0.6915).

	path 1 (MW)	path 2 (MW)	path 3 (MW)	P_{loss} (MW)	Q_{loss} (MVAr)
test	58.2259	59.3840	20.3931	8.0104	35.0194
target	60.00	60.00	20.00	1.8x7.999	1.8x35.06
base case	52.68	37.80	5.05	7.999	35.06

TABLE XII
AVERAGED FUZZY MEMBERSHIP VALUES FOR OBJECTIVES AND CONSTRAINTS, 3 PATHS.

	min fitness	path 1	path 2	path 3	P_{loss}	Q_{loss}
test	0.4437	0.4611	1.0000	0.5553	0.4437	0.4451
base case	0.00	0.0016	0.00	0.00	0.4444	0.4444

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