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The Bees Algorithm with Weighted Sum Using Memorized Zones for Multi-objective Problem

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Abstract : This paper presents the newly developed Pareto-based multi-objective Bees Algorithm with weighted sum technique for solving a power system multi-objective nonlinear optimization problem. Specifically, the Pareto-based Bees Algorithm with memorized zone has been developed to alleviate both difficulties from classical techniques and intelligent techniques for multi-objective problems (MOP) and successfully applied to an Environmental/Economic (electric power) dispatch (EED) problem. This multi-objective Bees Algorithm has been examined and applied to the standard IEEE 30-bus six-generator test system. Simulation results have been compared to those obtained using other approaches. The comparison shows the potential and effectiveness of the proposed Bees Algorithm for solving the multi-objective EED problem.

Key words : The Bees Algorithm, Weighted sum, Multi-objective, Environmental/Economic dispatch

1. Introduction

The aim of the classical economic dispatch problem has only been to minimize the total fuel cost. However, this objective can no longer be considered singly due to rising concerns about the environment from the emissions produced by fossil-fuelled electric power plants. As a result, the economic dispatch problem can be handled as a multi-objective optimization problem with non-commensurable and conflicting objectives.

Solving this problem has traditionally consisted of converting two objectives into a single objective (SO) function and the goal is to find the solution that minimizes this single objective while maintaining the physical constraints of the system. Although this technique is relatively simple to implement, it is no longer acceptable for systems with multiple conflicting objectives because system engineers may desire to know all possible optimization solutions of all objectives simultaneously, which is a set of acceptable trade-off optimal solutions called Pareto front introduced by Francis Ysidro and generalized by Vilfredo Pareto[1].

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In contrast to the classical techniques, some intelligent techniques like population-based algorithms are geared towards direct generation of the Pareto front by simultaneously optimizing the individual objectives because they can evaluate multiple potential solutions in a single iteration. Recently, multi- objective evolutionary algorithms, which include genetic algorithm (GA), evolutionary algorithm (EA) and evolutionary strategies (ES), have been applied to EED problem. Abido has pioneered this research by applying Non-dominated Sorting Genetic Algorithm (NSGA)[2], Niched Pareto Genetic Algorithm (NPGA)[3], Strength Pareto Evolutionary Algorithm (SPEA)[4] and NSGA-II[5] to the standard IEEE 30-bus system. However, their main drawback is performance degradation as the number of objectives increases since there does not exist computationally efficient methods to perform Pareto ranking. Furthermore, they require additional parameters such as sharing factor or the number of Pareto samples which need to be tweaked[6].

In this paper, the newly developed Pareto-based multi-objective Bees Algorithm with weighted sum technique for solving a power system multi-objective nonlinear optimization problem. The weighted sum technique, which is one of classical techniques, basically has been chosen because the proofs of convergence to the Pareto-optimal set are the main strong advantage of classical technique, in addition it is simple and easy to implement on a computer. Moreover the Bees Algorithm has been combined with it in order to alleviate both difficulties from classical techniques and intelligent techniques.

2. The Bees Algorithm

The Bees Algorithm is inspired by honey bees′ foraging behaviors in nature and it was developed by Pham et al[7]. However, they only adopted scout bees′ behaviour among the all foraging behaviors in the colony. Fig. 1 illustrates all foraging behaviour of honey bees in nature. The flowchart within the area bounded by the dotted line in Fig. 1 represents foraging behaviors of scout bees which the basic Bees Algorithm adopted. In order to apply the Bees Algorithm for multi-objective problem, especially for Pareto set, whole foraging behaviors of honey bees in the colony should be accounted. The foraging behaviors in the colony consist of two parts; one is by foraging bees outside the hive and the other by middle-aged workers inside the hive. In the former, the foraging process conducted by scout bees which are sent to flower patches to search for a food source. When they return to the hive, they regurgitate the nectar to middle-aged workers inside the hive and then split into three roles[8] such as foraging without dancing, foraging with dancing or abandon nectar source to exploit new sources. The basic Bees Algorithm only adopts last two roles, and among them the first role is called ′neighbourhood search′ and the second role is called 'random search' in Fig. 3. A Bee's dance called the 'waggle dance' contains important information regarding a flower patch which they have found and it helps unemployed foragers to go precisely to the found flower patches. Unemployed foragers are more attracted by more promising patches therefore more bees are sent to more fruitful sites. As a result, the colony gathers food much quicker and more efficiently.

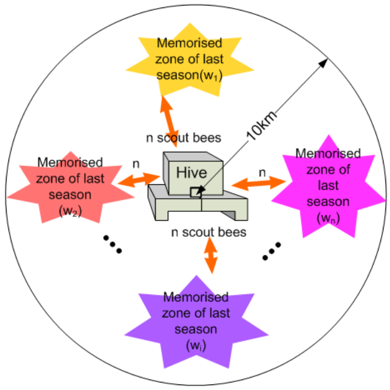

Fig. 2 Illustration of the concept for the proposed Bees Algorithm with memorized zone

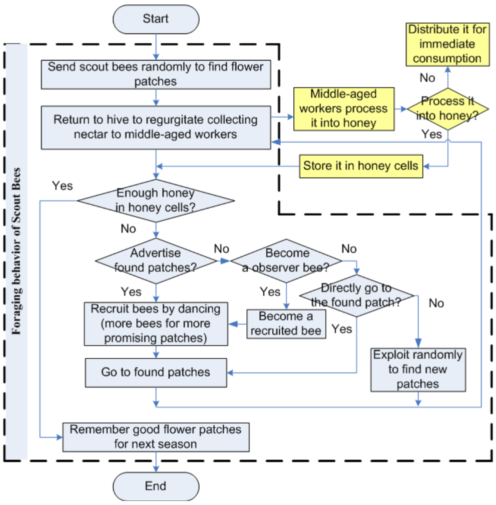

Fig. 1 Flowchart for all foraging behaviour of honey bees in nature for one season

In the latter, after middle-aged workers receive the nectar from foragers, they either distribute the nectar for immediate consumption or process it into honey and store it in special honey cells. The section of the flowchart outside a dotted lined in Fig. 1 represents this middle-aged workers' procedure. The basic Bees Algorithm[7] only takes the former part. However, in order to achieve Pareto optimality, the latter concept as well is adopted to solve MOP.

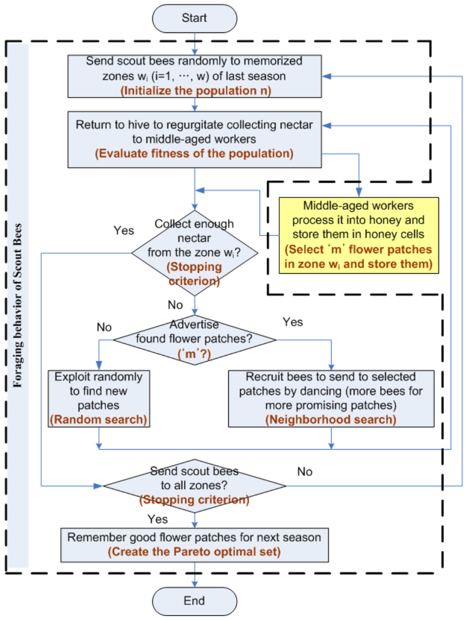

Fig. 3 Flowchart of the proposed Pareto-based Bees Algorithm for a multi-objective problem

Lee[9] applied the basic Bees Algorithm with weighted sum to solve multi-objective problem by repeating the solution process after modifying weights to approximate the Pareto front but it did not overcome many difficulties of classical methods, although its results were better than existed approaches. In order to alleviate the difficulty of classical method which is the generation of one solution by one solution process, this paper introduces a new parameter called 'memorized zone from the last season' which totally depends on Decision Maker (DM)/engineer's desire and it equals to the number of selected weights for weighted sum. If they desire to know many solutions, they should increase the number of memorized zones. The diagram in Fig. 2 represents this concept. The memorized zone corresponds to the search area in the objective space. The same number of scout bees is randomly sent to each zone and they conduct foraging which follows the basic Bees Algorithm. Fig. 3 shows its flowchart and the section of the flowchart outside a dotted line represents middle-aged workers' procedure to create the Pareto optimal set. After evaluation, middle-aged workers select 'm' number of fruitful flower patches and store them to create Pareto solutions.

3. EED Problem

The economic dispatch problem in power generation is to simultaneously minimize the total fuel cost and total NOx emission while satisfying a number of constrains. The total power generated must supply the total load demand and the transmission losses and the power generated by each generator is constrained between its minimum and maximum limits. Table 1 shows all equations for EED problem. Simulations were performed on the standard IEEE 30-bus 6-generator test system. The power system is interconnected by 41 transmission lines and the total system demand for the 21 load buses is 2.834(p.u.)[5]. Fuel cost and NOx emission coefficients for this system are given in Lee[9].

Table 1 Equations for EED problem

Objective functions	
Fuel cost	$C=\sum_{i=1}^{n}(a_i+b_i\times P_{Gi}+c_i\times P_{Gi}^2)$ c : total fuel cost (\$/hr) a_i, b_i, c_i: fuel cost coefficients of generator i P_{Gi} : power output by generator i n : number of generators.
NOx emission	$E_{NOx}=\sum_{i=1}^{n}\left(a_{iN}+b_{iN}\times P_{Gi}+c_{iN}\times P_{Gi}^2+d_{iN}\times \exp(e_{iN}\times P_{Gi})\right)$ E_{NOx} : total Nox emission(ton/hr) a_{iN}, b_{iN}, c_{iN}, d_{iN}, e_{iN}: NOx emission characteristics coefficients of the ith generator
Constraints	
Power balance	$\sum_{i=1}^{n}P_{Gi}-P_D-P_L=0$ P_D : total load demand P_L : transmission losses was taken as 0 in this work
Limits of power	$P_{Gi\min}\le P_{Gi}\le P_{Gi\max}$ $P_{Gi\min}$: minimum power generated $P_{Gi\max}$: maximum power generated

4. Results

Table 2 Parameters for the Bees Algorithm and weighted sum

Parameters	Value
n : Number of scout bees	20
ngh : Initial patch size	0.02
e: Number of elite sites	3
m: Number of selected sites	8
n2: recruited bees for elite sites	10
n1: recruited bees for selected sites	5
itr : Number of iterations	10, 15, 20, 25

Weights	Value
w_1: fuel cost	1
w_2: NOx emission (11)	1, 50, 100, 500, 900, 1400, 3000, 5000, 10000, 30000, 70000
w_2: NOx emission (22)	1, 25, 50, 75, 100, 300, 500, 700, 900, 1100, 1400, 2000, 3000, 4000, 5000, 7000, 10000, 15000, 30000, 50000, 70000, 100000

Tables 2 show the parameter values used for this experiment and the accuracy is 0.00001. Three tests were carried out such as Test 1 was applied without middle-aged workers′ procedure and Test 2 and 3 were applied with middle-aged workers' procedure to create the Pareto optimal set. The difference between Test 2 and 3 is using the number of memorized zones such as Test 2 using 22 and Test 3 using 11. From Test 1 to 3 is process by a single run in order to compare results accurately. The result of Test 1 is obtained by taking the fittest solution from each memorized zone but the results of Test 2 and 3 are obtained by involving ′*m*′ selected sites. To obtain the average performance of the algorithm, 20 runs were carried out. This gave statistics showing how minimum total fuel cost and total NOx emission differ from those for previous approaches such as Linear Programming (LP), Multi-Objective Stochastic Search Technique (MOSST), Non-dominated Sorting Genetic Algorithm (NSGA), Niched Pareto Genetic Algorithm (NPGA), Strength Pareto Evolutionary Algorithm (SPEA) and Non-dominated Sorting Genetic Algorithm-Ⅱ (NSGA-Ⅱ). Four different iteration were applied such as 10, 15, 20 and 25 and among them the number of iteration, the number of evaluation and the number of solutions were calculated when both minimum total fuel cost and NOx emission are lower than or equal to NSGA-Ⅱ which obtained the minimum values found so far among existing approaches. The total minimum NOx emissions from all tests are the similar to NSGA-Ⅱ as 0.1942 *ton/hr*, therefore only total minimum fuel cost was compared and analyzed.

Table 3 One-Sample t-test from Test 1, 2 and 3

One-Sample Statistics (BestFuelCost)

	N	Mean	Std. Deviation	Std. Error Mean
Test1	20	600.12906	.010603	.002370
Test2	20	600.12714	.007932	.001773
Test3	20	600.12924	.009331	.002086

One-Sample Test (BestFuelCost)

Test Value = 600.155 (NSGA-Ⅱ)

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Test1	-10.941	19	**.000**	-.02594	-.030902	-.020978
Test2	-15.708	19	**.000**	-.02786	-.031572	-.024148
Test3	-12.345	19	**.000**	-.02576	-.030127	-.021393

One-Sample t-test by SPSS program was used to analyze significant difference regarding minimum total fuel cost between existing approach (NSGA-Ⅱ) and the proposed Bees Algorithms. Table 3 shows its results and all tests′ p-value 0.000 is less than significance level 0.05, which is concluded that the relationship is strong enough. As a result, there is significant difference in the means of Test 1, 2 and 3 compared to NSGA-Ⅱ, which means the all proposed algorithms outperform because even mean values from the Test 1, 2 and 3 are much smaller than NSGA-Ⅱ. Table 4 shows the minimum total fuel cost and total NOx emission between the proposed Bees Algorithm and the other existing approaches and it proves that the proposed Bees Algorithm superiors to the other existing algorithms.

Table 4 Minimum total fuel cost and minimum total NOx emission

	LP	MOSST	NSGA	NPGA	SPEA	NSGA-II	BA
PG1	0.1500	0.1125	0.1567	0.1080	0.1062	0.1059	0.1037
PG2	0.3000	0.3020	0.2870	0.3284	0.2897	0.3177	0.2969
PG3	0.5500	0.5311	0.4671	0.5386	0.5289	0.5216	0.5245
PG4	1.0500	1.0208	1.0467	1.0067	1.0025	1.0146	1.0189
PG5	0.4600	0.5311	0.5037	0.4949	0.5402	0.5159	0.5257
PG6	0.3500	0.3625	0.3729	0.3574	0.3664	0.3583	0.3642
Best cost (\$/hr)	**606.314**	**605.889**	**600.572**	**600.259**	**600.15**	**600.155**	**600.096**
Corresp. NOx (ton/hr)	0.2233	0.2222	0.2228	0.2211	0.2215	0.2218	0.2225
	LP	MOSST	NSGA	NPGA	SPEA	NSGA-II	BA
PG1	0.4000	0.4095	0.4394	0.4002	0.4116	0.4074	0.4015
PG2	0.4500	0.4626	0.4511	0.4474	0.4532	0.4577	0.4503
PG3	0.5500	0.5426	0.5105	0.5166	0.5329	0.5389	0.5465
PG4	0.4000	0.3884	0.3871	0.3688	0.3832	0.3837	0.3906
PG5	0.5500	0.5427	0.5553	0.5751	0.5383	0.5352	0.5361
PG6	0.5000	0.5142	0.4905	0.5259	0.5148	0.5110	0.5091
Best NOx (ton/hr)	**0.19424**	**0.19418**	**0.19436**	**0.19433**	**0.1942**	**0.19420**	**0.1942**
Corresp. Cost (\$/hr)	639.600	644.112	639.231	639.182	638.51	638.269	637.105

One data set from Test 1 to 3 has been arbitrarily selected among 20 runs and it has been shown in Fig. 4. Although the number of evaluation of Test 1 and 2 are same, the number of solution of Test 2 is almost five times bigger than Test 1. Some of solutions from Test 3 are worse than Test 1 and 2 but it has the only half number evaluations and its solution number is almost three times bigger than Test 1.

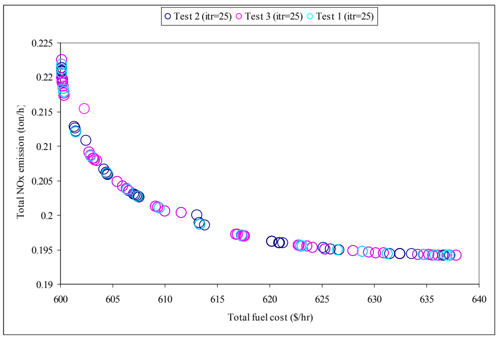

Fig. 4 Pareto frontier from Test 1, 2 & 3

In summary, although the Bees Algorithm using memorized zones (Test 1) solved the main difficulty of classical techniques, which generates only one solution by one solution process, it could not improve the other difficulties. However, the Pareto-based Bees Algorithm (Test 2 and 3) achieved to solve the problems of classical techniques and its results are globally non-dominated Pareto front. Moreover, it can be faster than the Test 1 because using only half number of evaluation (Test 3) can find the best solution. Compared to other swarm-based intelligent techniques, this proposed Bees Algorithm is quite simple to implement and it is quite user friendly. A DM/engineer can control the range covered by solutions along each of the objectives using memorized zones and they also can focus on their interesting search areas because memorized zones depend on the importance of each objective in the context of the problem and a scaling factor. Furthermore the Pareto-base Bees Algorithm can prevent premature convergence compared to intelligent techniques because even if there is premature convergence in one memorized zone the global non-dominated Pareto front is consisted of only globally non-dominated solutions among all zones.

5. Conclusion

The aim of this research is to alleviate both difficulties from classical techniques and intelligent techniques for MOP by using the Bees Algorithm. The paper has described the Bees Algorithm with weighted sum to the multi-objective

Environmental/Economic dispatch problem and it was tested on the standard IEEE 30-bus system. From the results obtained, the proposed Bees Algorithm delivered a good Pareto frontier with an excellent diversity while proving stable and robust. Therefore, this work has confirmed the suitability of the Bees Algorithm for solving the multi-objective EED problem, simultaneously achieving financial savings and reducing the emission of greenhouse gases into the atmosphere.

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