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The Dynamic Allocated Bees Algorithms for Multi-objective Problem

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Abstract : The aim of this research is to develop the Bees Algorithm named 'the dynamic allocated Bees Algorithm' for multi-objective problem, especially in order to be suit for Pareto optimality. In addition two new neighbourhood search methods have been developed to produce enhanced solutions for a multi-objective problem named 'random selection neighbourhood search' and 'weighted sum neighbourhood search' and they were compared with the basic neighbourhood search in the dynamic allocated Bees Algorithm. They were successfully applied to an Environmental/Economic (electric power) dispatch (EED) problem and simulation results presented for the standard IEEE 30-bus system and they were compared to those obtained using other approaches. The comparison shows the superiority of the proposed dynamic allocated Bees Algorithms and confirms its suitability for solving the multi-objective EED problem.

Key words : Bees Algorithm, Neighbourhood search, Multi-objective, Pareto optimality, 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.

Abido has pioneered this research by applying Non-dominated Sorting Genetic Algorithm (NSGA)[1], Niched Pareto Genetic Algorithm (NPGA)[2], Strength Pareto Evolutionary Algorithm (SPEA)[3] and NSGA-Ⅱ[4] to the standard IEEE 30-bus system.

This paper discusses the Bees Algorithm with Pareto optimality to the EED problem to minimize fuel costs and nitrogen oxides (NOx) emission simultaneously.

2. The Bees Algorithm

The Bees Algorithm is inspired by honey bees' foraging behaviors in nature and it was developed by Pham et al. [5]

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However, they only adopted scout bees' behaviour among the all foraging behaviors. In order to apply the Bees Algorithm for multi-objective problem, especially for Pareto set, whole foraging behaviors 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 [6] 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 is called 'random search' in Fig. 1.

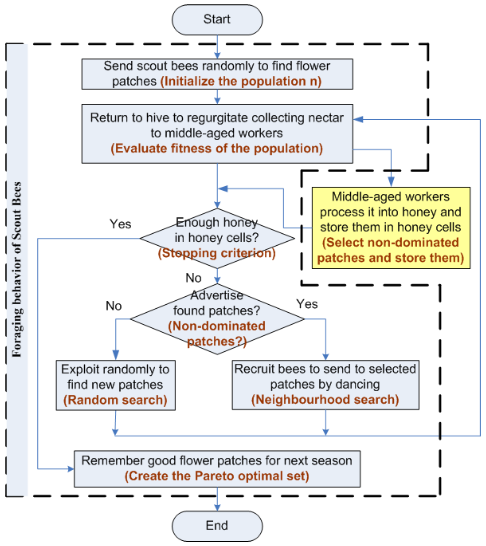

Fig. 1 Flowchart of the proposed dynamic allocated Bees Algorithm for a multi-objective

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. In the latter, after middle-aged workers received 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 basic Bees Algorithm[5] only takes the former part. However, in order to achieve Pareto optimality the latter concept as well is adopted to solve multi-objective problem (MOP) and it is called the 'dynamic allocated Bees Algorithm' and Fig. 1 illustrates its flowchart. The flowchart within the area bounded by the dotted line in Fig. 1 represents the foraging behaviour from scout bees and the section of the flowchart outside a dotted line in Fig. 1 represents the procedure from middle-aged workers. While the basic Bees Algorithm uses 6 parameters[7], the proposed dynamic allocated Bees Algorithm requires only 3 parameters to be set, namely: 1) The number of scout bees (n), 2) The number of recruited bees ($n1$), 3) Initial patches size (ngh). The algorithm starts with n scout bees which are randomly sent to the search space. After fitness evaluation, those patches with non-dominated scout bees are designated 'selected patches' for further neighbourhood search to be conducted on them. In the basic Bees Algorithm, the number of selected patches *m* and their locations are always static within an initial neighbourhood area in each iteration. However, the proposed dynamic allocated Bees Algorithm is totally dynamic both the number of selected patches and their locations in each iteration. After this neighbourhood search, only the bee with the highest fitness is elected in each of the selected patches for the next bee population. The remaining bees in the population are randomly assigned in the search space to scout for new potential solutions. The random search is also dynamic because the number of remaining bees totally depends on the number of non-dominated sites. These steps are repeated until a stopping criterion is met. The Pareto optimal set is created from all the non-dominated bees in each iteration. Moreover, although basic neighbourhood search[7] can work satisfactorily for a MOP, new types of neighbourhood search could produce enhanced solutions.

In the basic neighbourhood search, a recruited bee is sent to a selected patch and its fitness is evaluated. The recruited bee is then compared with the scout bee in the patch and, if the recruit is fitter than the old scout bee, the latter is replaced by the new bee. Otherwise, the old scout bee is retained. However, instead of posting recruited bees to a selected patch one at a time, the random selection and the weighted sum neighbourhood search involve sending all the *n1* recruited bees to the selected patch simultaneously and then evaluating their fitnesses. Non-dominated bees are then chosen from among the recruited bees. If there are no non-dominated bees, then the old scout bee will be retained for this patch. If there is only one non-dominated bee, it will replace the old scout bee. However, if there are two or more non-dominated bees in random selection neighbourhood search, one of them will be chosen at random to replace the old scout bee for this patch. If there are two or more non-dominated bees in weighted sum neighbourhood search, the weighted sum method involves using a linear combination of the objective functions to decide which non-dominated bee is to be selected to replace the old scout in this patch. Fig. 3 shows the flowchart for the weighted sum neighbourhood search.

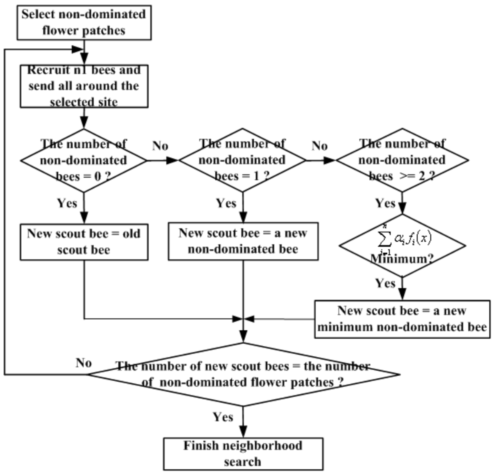

Fig. 2 Flowchart for the weighted sum neighbourhood search.

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 (P_{Gi}) 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.)[4]. Fuel cost and NOx emission coefficients for this system are given in[8].

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	$E_{NOx}=\sum_{i=1}^{n}(a_{iN}+b_{iN}\times P_{Gi}+c_{iN}\times P_{Gi}^2+d_{iN}\times\exp(e_{iN}\times P_{Gi})$ E_{NOx} : total Nox emission(ton/hr) a_{iN}, b_{iN}, c_{iN}, d_{iN}, e_{iN}: NOx emission characteristics coefficients of the i^{th} 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

To obtain the average performance of the algorithm, 10 runs were carried out for each of the neighborhood searches. This gave statistics showing how the percentage of relative deviation ($\triangle$) differs 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). $\triangle_{avg}$ was computed as follows:

$$\Delta_{avg}=\sum_{i=1}^{R}\left(\frac{(F_{BA}-F_{ref})}{F_{ref}}\times 100\right)\Big/R \tag{1}$$

where F_{BA} is the fitness function values generated by the dynamic allocated Bees Algorithm in each run, F_{ref} is the reference fitness function value generated by previous approaches, and R is the total number of runs. $\triangle_{min}$ and $\triangle_{max}$ denote the minimum and maximum values of the percentage of relative deviation in fitness function value over R runs, respectively. Tables 2 shows the parameter values used for this experiment. The basic neighbourhood search and the random neighbourhood search only require the parameters given in top table in Table 3 but the weighted sum neighbourhood search needs extra weights parameters for weighted sum method as shown in down table in Table 3. The total power generated must be satisfying the total demand as power balance constraint. Here the accuracy for power balance constraint is 0.00001.

Table 2 Parameters for the Bees Algorithm and Weights

Parameters	Value
n : Number of scout bees	50
ngh : Initial patch size	0.05
n1: recruited bees for selected sites	5

Weights	Value
w_1: fuel cost	1
w_2: NOx emission	1, 1,000, 100,000

Tables 3 to 5 present the simulation results. It should be noted the better results when compared to the previous approaches are reported in negative percentage relative deviations in all Tables given in this paper. Tables 3 and 4 show the average, minimum and maximum percentage relative deviations ($\triangle_{avg}$, $\triangle_{min}$ and $\triangle_{max}$) of the best Fuel cost and the best NOx emission between the proposed Bees Algorithms and previous approaches. In Table 3, $\triangle_{min}$ of all approaches by the Bees Algorithms are negative, which means they outperform all previous approaches. In particular, $\triangle_{avg}$ of weighed sum neighbourhood search in Table 3 (d), when w2 is 1, is superior to all previous approaches. In addition, corresponding Emission at that time for most of them also outperforms previous approaches.

Table 3 Best Fuel cost regarding neighbourhood search (WS = weighted sum neighbourhood)

(a) Basic	Best Fuel Cost			Corresp. Emission		
	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$
LP	-0.98	-1.02	-0.92	-2.33	-3.58	-1.03
MOSST	-0.91	-0.95	-0.85	-1.85	-3.11	-0.54
NSGA	-0.03	-0.07	0.03	-2.12	-3.37	-0.82
NPGA	0.02	-0.02	0.08	-1.38	-2.65	-0.07
SPEA	0.04	-0.00	0.10	-1.53	-2.80	-0.23
NSGA	0.04	-0.00	0.10	-1.70	-2.97	-0.40

(b) Random	Best Fuel Cost			Corresp. Emission		
	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$
LP	-1.00	-1.02	-0.98	-0.61	-2.19	0.90
MOSST	-0.93	-0.95	-0.91	-0.12	-1.71	1.40
NSGA	-0.06	-0.07	-0.03	-0.39	-1.98	1.11
NPGA	-0.00	-0.02	0.02	0.35	-1.25	1.87
SPEA	0.01	-0.00	0.04	0.20	-1.40	1.72
NSGA	0.01	-0.00	0.04	0.03	-1.57	1.54

(c) WS (w2=100,000)	Best Fuel Cost			Corresp. Emission		
	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$
LP	-1.00	-1.02	-0.97	-0.64	-1.39	0.40
MOSST	-0.93	-0.95	-0.90	-0.15	-0.90	0.90
NSGA	-0.06	-0.08	-0.02	-0.43	-1.18	0.62
NPGA	-0.00	-0.02	0.03	0.32	-0.43	1.37
SPEA	0.01	-0.00	0.05	0.17	-0.59	1.22
NSGA	0.01	-0.01	0.05	-0.00	-0.76	1.05

(d) WS (w2=1)	Best Fuel Cost			Corresp. Emission		
	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$
LP	-1.02	-1.02	-1.02	-0.51	-1.12	0.04
MOSST	-0.95	-0.95	-0.95	-0.02	-0.63	0.54
NSGA	-0.07	-0.07	-0.07	-0.30	-0.91	0.26
NPGA	-0.02	-0.02	-0.02	0.45	-0.16	1.01
SPEA	-0.00	-0.00	0.00	0.30	-0.32	0.86
NSGA	-0.00	-0.01	0.00	0.13	-0.49	0.69

Emission values shown in Table 4 (c), $\triangle_{min}$, are slightly better than or the same as for previous approaches with the exception of MOSST as the average standard deviation is virtually zero. In Tables 4 (a)-(d), the $\triangle_{avg}$ and $\triangle_{min}$ of corresponding fuel costs obtained by the Bees Algorithms are much better than those for all previous approaches. Although the gains per hour are relatively small, cost savings and emission reductions become much more significant on an annual basis.

Table 4 Best Emission regarding neighbourhood search (WS = weighted sum neighbourhood)

(a) Basic	Best Emission			Corresp. Fuel Cost		
	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$	$\triangle_{avg}$	$\triangle_{min}$	$\triangle_{max}$
LP	0.09	-0.02	0.34	-1.01	-1.94	-0.61
MOSST	0.12	0.01	0.37	-1.71	-2.63	-1.31
NSGA	0.03	-0.08	0.28	-0.96	-1.88	-0.56
NPGA	0.04	-0.07	0.29	-0.95	-1.88	-0.55
SPEA	0.11	0.00	0.36	-0.84	-1.77	-0.44
NSGA	0.11	0.00	0.36	-0.81	-1.74	-0.41

(b) Random	Best Emission △avg	△min	△max	Corresp. Fuel Cost △avg	△min	△max
LP	0.04	0.03	0.08	-0.47	-1.13	0.10
MOSST	0.07	0.06	0.11	-1.16	-1.82	-0.61
NSGA	-0.03	-0.03	0.02	-0.41	-1.07	0.15
NPGA	-0.01	-0.02	0.04	-0.40	-1.07	0.16
SPEA	0.06	0.05	0.10	-0.30	-0.96	0.27
NSGA	0.06	0.05	0.10	-0.26	-0.92	0.30

(c) WS (w2=100,000)	Best Emission △avg	△min	△max	Corresp. Fuel Cost △avg	△min	△max
LP	0.02	-0.02	0.03	-0.49	-0.91	-0.02
MOSST	0.05	0.01	0.06	-1.18	-1.60	-0.72
NSGA	-0.04	-0.08	-0.03	-0.43	-0.85	0.04
NPGA	-0.03	-0.07	-0.02	-0.42	-0.84	0.05
SPEA	0.04	0.00	0.05	-0.32	-0.74	0.16
NSGA	0.04	0.00	0.05	-0.28	-0.70	0.19

(d) WS (w2=1)	Best Emission △avg	△min	△max	Corresp. Fuel Cost △avg	△min	△max
LP	0.12	0.03	0.24	-0.08	-1.19	0.95
MOSST	0.15	0.06	0.27	-0.78	-1.88	0.24
NSGA	0.06	-0.03	0.17	-0.02	-1.13	1.01
NPGA	0.08	-0.02	0.19	-0.02	-1.12	1.02
SPEA	0.14	0.05	0.26	0.09	-1.02	1.12
NSGA	0.14	0.05	0.26	0.13	-0.98	1.16

Table 5 shows the average number of Pareto solutions. The number of Pareto solutions can be determined by tailoring the neighbourhood size and the number of iterations according to the characteristics of the Bees Algorithm. It was found that using a small neighbourhood with a large number of iterations leads to an increase in the number of Pareto solutions. Moreover the standard deviation in Table 5 is virtually zero showing that the proposed Bees Algorithms are stable and robust.

Table 5 Standard deviation and average number of solutions

	Standard deviation In Table 3	In Table 4	Avg. no. of solutions
(a)	0.17	0.00	21.50
(b)	0.07	0.00	107.20
(c)	0.08	0.00	108.80
(d)	0.01	0.00	95.70
Avg. STD	0.08	0.00	

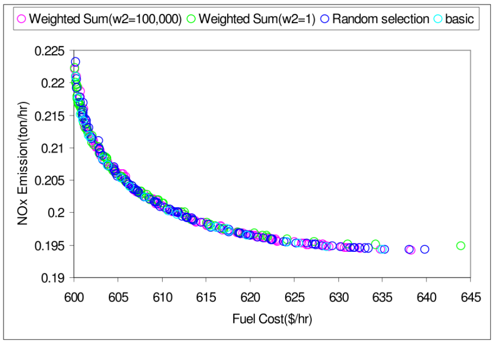

Fig. 3 Pareto frontier from the proposed neighbourhood searches

Ten runs of the proposed Bees Algorithms consisting of 200 iterations each were conducted and the results of one run are shown in Fig. 3 demonstrating a good diversity in Pareto optimality. Compared to the basic neighbourhood search, the random selection and weighted sum neighbourhood search provide far greater diversity with big number of Pareto solutions.

5. Conclusion

This paper has described the application of the dynamic allocated Bees Algorithms to the multi-objective Environmental/Economic Dispatch problem with a view to achieving Pareto optimality. The number of parameters utilized was half of that in the basic Bees Algorithm through the use of the 'dynamic allocated' concept. Three different methods of conducting neighbourhood search were adopted and they were tested on the standard IEEE 30-bus system. From the results obtained, all three neighbourhood search approaches delivered good outcomes. In particular, the minimum fuel cost and minimum emission obtained using the weighted sum neighbourhood search method were lower than those for all existing approaches. Moreover, the Bees Algorithm also gave a Pareto frontier with an excellent diversity for Pareto optimality while proving stable and robust with a virtually zero standard deviation. 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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