Migrating Birds Optimization: A New Meta-heuristic Approach

http://mbo.dogus.edu.tr

Ekrem Duman
Industrial Engineering Department
Ozyegin University

Mitat Uysal
Computer Engineering Department
Dogus University

Ali Fuat Alkaya
Computer Engineering Department
Marmara University

Introduction

In this study we propose a new nature inspired meta-heuristic approach based on the V flight formation of the migrating birds which is proven to be an effective formation in energy minimization. Its performance is tested on quadratic assignment problem instances arising from a real life problem and very good results are obtained. The quality of the solutions turned out to be better than simulated annealing, tabu search and guided evolutionary simulated annealing approaches.

V Formation in Bird Migration

The V formation is the most famous formation that the migrating birds use to fly long distances. It gets this name because of the similarity of the shape the birds make to the letter "V" (Figures 1 and 2). Here there is a bird leading the flock and two lines of other birds following it.

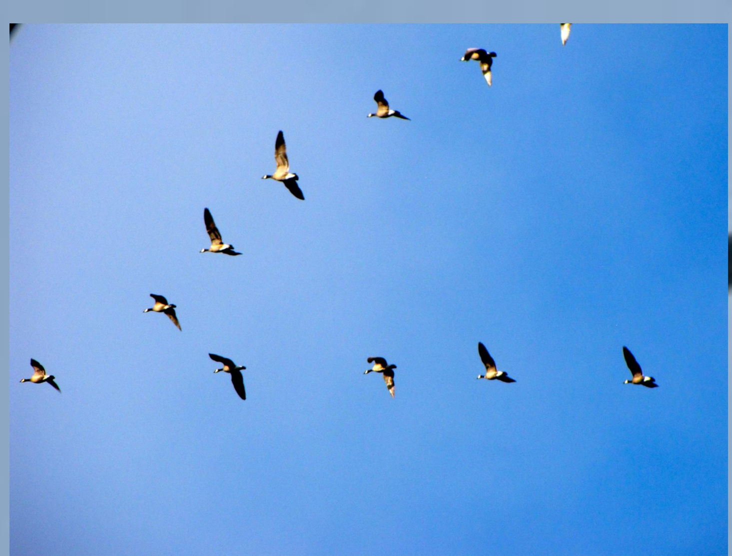

Figure 1. The V formation.

Figure 1b. The V formation.

The main drive of the formation is proved to be saving in the energy.

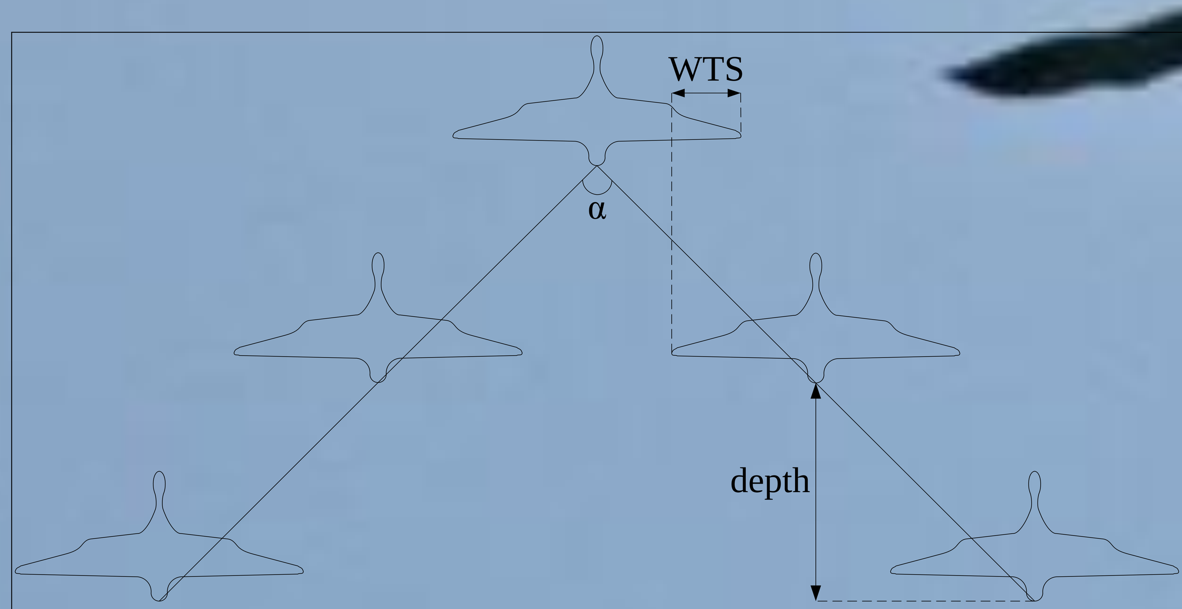

Figure 2. The V formation.

In the V formation the leader bird is the one spending most energy. The birds in the other positions gets benefit from the birds in their front. It sounds reasonable that the energy saving is higher as we go back in the line but we could not find a study in the literature to support this idea. However it was stated that, the savings of the birds other than the leader bird are either the same or the saving is a bit more for the birds in the middle part.

The Migrating Birds Optimization Algorithm

The MBO algorithm is a neighborhood search technique. It starts with a number of initial solutions corresponding to birds in a V formation. Starting with the first solution (corresponding to the leader bird) and progressing on the lines towards the tales, each solution is tried to be improved by its neighbor solutions (in our study, for the QAP implementation a neighbor solution is obtained by pairwise exchange of two locations).

Parameters of the MBO

n = the number of initial solutions (birds)
k = the number of neighbor solutions to be considered
x = the number of neighbor solutions to be shared with the next solution
m = number of tours
K = iteration limit

The properties of the MBO which distinguishes it from the other meta-heuristic approaches are

- **a number of solutions running in parallel and**
- **the benefit mechanism between the solutions.**

Parallel processing can somehow be regarded as inherited to genetic algorithms and scatter search but the benefit mechanism is totally unique to the MBO.

The MBO Algorithm

1. Generate *n* initial solutions in a random manner and place them on a V formation randomly.
2. Try to improve the leading solution by generating and evaluating *k* neighbors of it.
3. Try to improve the other solutions by evaluating (*k*-*x*) neighbors of them and *x* unused best neighbors from the solution in the front.
4. Repeat steps 2 and 3 *m* times.
5. Move the first solution to the end and forward one of the solutions following it to the leader position. If the total number of neighbors considered so far has not exceeded *K* yet repeat steps 2, 3 and 4.

Application

After the implementation of the MBO algorithm, we conducted an extended set of experiments to find the best values of the four parameters of the MBO. For this we have determined a number of possible and reasonable values for the parameters. This makes a total of 5670 (10x9x7x9) different combinations. Another parameter that needs to be decided on is the iteration limit (*K*) where better solutions could be expected with higher values of *K*. In our experiments we kept the value of *K* constant at N^3.

Results and Conclusion

The performance of the algorithm is tested on solving quadratic assignment problems arising from printed circuit board assembly workshops. A previous study on this problem where three different metaheuristic (simulated annealing, tabu search and guided evolutionary simulated annealing) approaches are implemented and compared is taken as the benchmark. The MBO algorithm outperformed the best performing heuristic reported therein (the simulated annealing) by about three per cent on the average (Table 1).

Table 1. Results of QAP instances obtained from real PCB data.

		Simulated Annealing			MBO			Improvement		
Board	**N**	**avg**	**min**	**max**	**avg**	**min**	**max**	**avg**	**min**	**max**
B1	58	**1165**	1076	1206	**1124**	1074	1174	**3,67%**	0,19%	2,73%
B2	54	**842**	800	912	**803**	764	824	**4,83%**	4,71%	10,68%
B3	52	**820**	740	882	**784**	762	840	**4,62%**	-2,89%	5,00%
B5	50	**1543**	1474	1680	**1496**	1462	1546	**3,17%**	0,82%	8,67%
B6	48	**807**	756	896	**786**	758	816	**2,65%**	-0,26%	9,80%
B7	49	**1461**	1392	1536	**1416**	1398	1456	**3,18%**	-0,43%	5,49%
B8	47	**1396**	1370	1460	**1378**	1358	1402	**1,34%**	0,88%	4,14%
B9	40	**752**	718	768	**729**	722	736	**3,16%**	-0,55%	4,35%
Average								**3,32%**	**0,31%**	**6,36%**

We also wanted to see the ability of MBO in obtaining optimum solutions for widely known QAP instances found in QAPLIB web page.
The results obtained when these problems are solved with the parameter values settled in the previous section (n=51, k=3, m=10, x=1, $K=N^3$) are tabulated in Table 2. Performance of other two meta-heuristics are also presented on the same table.
We observe that MBO was able to find best known solutions (BKS) for all sparse problems and it was very close to BKS for dense problems except lipa40b. Besides, MBO outperforms GA and Scatter Search for all problems.

Table 2. Results of QAP instances from QAPLIB.

Problem		**N**	**Density**	**BKS**	MBO		GA		Scatter Search	
					Result	**Deviation**	**Result**	**Deviation**	**Result**	**Deviation**
sparse	esc32e	32	1,17	2	2	**0,00%**	2	0,00%	2	0,00%
	esc32f	32	1,17	2	2	**0,00%**	2	0,00%	2	0,00%
	esc32g	32	1,76	6	6	**0,00%**	6	0,00%	6	0,00%
	esc32h	32	27,54	438	438	**0,00%**	442	0,91%	458	4,57%
	esc64a	64	3,17	116	116	**0,00%**	122	5,17%	130	12,07%
	tai64c	64	4,13	1855928	1855928	**0,00%**	1888914	1,78%	1946740	4,89%
dense	lipa40b	40	94,81	476581	501794	**5,29%**	580179	21,74%	578185	21,32%
	sko49	49	97,96	23386	23684	**1,27%**	24776	5,94%	25266	8,04%
	wil50	50	98	48816	49096	**0,57%**	50516	3,48%	50484	3,42%
	tai60b	60	98,33	608215054	609244543	**0,17%**	647247321	6,42%	701274200	15,30%
	lipa70a	70	97,16	169755	171138	**0,81%**	172102	1,38%	172276	1,49%
	lipa80a	80	97,52	253195	255063	**0,74%**	256525	1,32%	256471	1,29%
Average						**0,74%**		**4,01%**		**6,03%**

For the details see:
E. Duman, M. Uysal and A.F. Alkaya, Migrating Birds Optimization: A New Metaheuristic Approach and its Performance on Quadratic Assignment Problem, Information Sciences, http://dx.doi.org/10.1016/j.ins.2012.06.032