

## Heuristics in Labor Management: An Application of Modified Camel Algorithm<sup>1</sup>

### İşgücü Yönetiminde Sezgiseller: Geliştirilmiş Deve Algoritmasının Bir Uygulaması

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**Article Info:** Research Article  
**Date Submitted:** 10.06.2024  
**Date Accepted:** 27.06.2024

**Makale Bilgisi:** Araştırma Makalesi  
**Geliş Tarihi:** 10.06.2024  
**Kabul Tarihi:** 27.06.2024

#### Abstract

*Modified Camel Algorithm (MCA) is a challenging algorithm applied to engineering problems in 2016, 2019, and 2021. MCA can be implemented to the field of business, economics, labor management, and science compared to the other techniques. The pure MCA solves optimization problems effectively and quite fast in literature. To develop and apply the mathematical model in labor management using the modified camel algorithm, it was combined with popular heuristics, such as constructive heuristic (MC), and then improved with local searches, for instance 2-opt, 3-opt, and k-opt. The suggested hybrid algorithms are tested under proper parameters. In the experimental study, random model datasets, and suitable parameters are used via uniform distribution. The experimental outcomes are given as best, average, std. deviation and CPU time for sample datasets with proper parameters. In short, the suggested hybrid metaheuristics find reasonable solutions of labor management in acceptable CPU time for all random datasets.*

**Keywords:** Assignment problem, Heuristics, Labor Management, Metaheuristics, Modified Camel algorithm

**JEL codes:** C610, M12, M210, M54

#### Öz

*Geliştirilmiş Deve Algoritması (MCA), 2016, 2019 ve 2021 yıllarında mühendislik problemlerine uygulanan zorlu bir algoritmadır. MCA, diğer tekniklere kıyasla işletme, ekonomi, işgücü yönetimi ve bilim alanlarına uygulanabilir. Saf MCA, literatürdeki optimizasyon problemlerini etkili ve oldukça hızlı çözer. Geliştirilmiş deve algoritmasını kullanarak iş gücü yönetiminde matematiksel modeli geliştirmek ve uygulamak için bu algoritma, tur oluşturma yöntemi (MC) gibi popüler buluşsal yöntemle birleştirildi ve daha sonra örneğin 2-opt, 3-opt ve k-opt gibi yerel aramalarla iyileştirildi. Önerilen hibrit algoritmalar uygun parametreler altında test edilmiştir. Deneysel çalışmada düzgün dağılım sağlanarak rastgele model veri setleri ve uygun parametreler kullanılmıştır. Deneysel sonuçlar örnek verisetleri ve uygun parametreler için en iyi, ortalama, standart sapma ve CPU zamanı olarak verilmiştir. Özet olarak, önerilen hibrit meta-sezgiseller, örnek rastgele veri kümeleri için kabul edilebilir CPU zamanında makul iş gücü yönetimi çözümleri bulmaktadır.*

**Anahtar Kelimeler:** Atama problemi, Geliştirilmiş Deve Algoritması, İşgücü Yönetimi, Metasezgiseller, Sezgiseller

**JEL kodları:** C610, M12, M210, M54

<sup>1</sup> The findings of this study are evaluated with the findings in the Demiral (2024) source. Bu çalışmanın bulguları Demiral (2024) kaynağındaki bulgularla değerlendirilmektedir.

## INTRODUCTION

There exist many exact methods for solving combinatorial problems such as branch-and-bound method, cutting plane method, column generation method, cutting plane method, dynamic programming, lagrangian-based approaches, integer programming, and cplex programming algorithms. Heuristics are problem-based approaches, which are useful to solve optimization problems. Metaheuristics are nature-inspired algorithms and are very effective for solving business, economics, engineering, global optimization, various mathematical problems, symmetric and asymmetric TSPs, traveling purchaser problem, knapsack problems, timetabling, assembly-line balancing, and production problems. The advantageous of those methods is that the near-optimal and acceptable solutions can be obtained to provide flexibility, time-saving, and particular solutions. Metaheuristic algorithms are general-based techniques and frequently used in optimization problems. Classical metaheuristics are counted as single solution-based methods, for instance simulated annealing (Geng, Chen, Yang, Shi, & Zhao, 2011), tabu search (Lin, Bian, & Liu, 2016), and multi solution-based methods, for instance genetic algorithm and its varieties, ant colony system and population algorithms (Mian, Muhammad, & Riaz, 2012).

Popular algorithms are counted as suggested artificial bee colony algorithm (Szeto, Yongzhong & Ho, 2011), black-hole algorithm applications for clustering and traveling salesman problem (Hatamlou, 2013, 2018), firefly algorithm (Yang, 2010a), cuckoo search optimization (Rajabioun, 2011), whale optimization (Bozorgi & Yazdani, 2019; Mirjalili & Lewis, 2016), a discrete sine cosine algorithm (Tawhid & Savsani, 2019), bat algorithm (Yang, 2010b), grasshopper optimization algorithm (Saremi, Mirjalili & Lewis, 2017), artificial atom algorithm (Yıldırım & Karçı, 2018) and bio-inspired optimization (Feng, Liu, Yu, & Luo, 2019; Liu, Song, Zhang, Huadong, & Vasilakos, 2015).

The rest part of the full-text is structured as follows: In Section 1, the literature research with the applied mathematical model is expressed. In Section 2, the material and method discussed on the modified camel algorithm is given. The experimental analysis is presented in Section 3. At final, the conclusion and future suggestions are given in Section 4.

### 1. MATHEMATICAL PROBLEM AND ITS VARIETIES

Although most of the two-dimensional mathematical problems can be solved optimally, large scale problems are solved near-optimal. Those mathematical models are solved by integer programming methods. High-dimensional mathematical problems can be solved approximately by heuristics and metaheuristics. There exist popular types of mathematical models, such as classical mathematical problems with its varieties (Caron, Hansen & Jaumard, 1999; Nowak, Epelman & Pollock, 2006), k-cardinality mathematical problem, balanced mathematical problem, minimum deviation mathematical problem, multi-criteria mathematical problem, additional constrained mathematical problem, quadratic mathematical problem, and multidimensional mathematical problems (Gilbert & Hofstra, 1988) that are useful in discrete optimization. Hungarian Method could solve the lower dimensional labor mathematical problems optimally. Metaheuristics are general-purpose methods searching for optimal/near-optimal solutions to combinatorial problems (Bouajaja & Dridi, 2017; Pentico, 2007).

In the literature, the classic assignment problem and its varieties (Bouajaja & Dridi, 2017) aim to find optimal matchings between  $m$  jobs and  $n$  employees while minimizing the objective, maximizing sales, or maximizing revenues of all matchings. The goal of the  $k$ -cardinality mathematical problem is that to find optimal  $k$ -subset while minimizing the objective function between jobs and employees. There exists an additional constraint ( $k$ -matching subset) with classical optimization constraints. The balanced mathematical problem defines that the objective minimizes the difference between the maximum and minimum goals. The constraints of the balanced AP are the same as the classical mathematical constraints. Generalized mathematical problem (GAP), the problem finds the optimal matchings between an employee and more than one job while the employee has a limited capacity to do assigned jobs. The three-dimensional mathematical problem calculates the optimal matchings between the  $m$  jobs,  $n$  employees, and  $r$  machines, and the total model cost. Many objective functions could be minimized and maximized with multi-dimensional mathematical problems. Multi-dimensional mathematical models require heuristics/metaheuristics and more CPU time than the lower dimensional mathematical models. When the hybrid metaheuristics are implemented to the high-dimensional mathematical models to search for optimal solutions, it could be obtained remarkable solutions in the literature.

## 2. MATERIAL AND METHOD

### 2.1. Hybrid Modified Camel Algorithm

The metaheuristic (MCA) is a popular nature-inspired metaheuristic since it was applied to combinatorial and engineering problems in science and technology. The modified camel algorithm (MCA) acts as the traveling behavior of a modified camel population with scarce endurance in the hot deserts (Hassan, Abdulmuttalib, & Jasim, 2021; Ibrahim & Ali, 2016). The discrete modified camel algorithm is a base searching for the best objective when looking for sufficient endurance to survive in the hot deserts (Ali, Alnahwi & Abdullah, 2019; Utama, Safitri, & Garside, 2022). The temperature in the current step ( $T_{now}^{i,iter}$ ) is updated using Eq. 1.

$$T_{now}^{i,iter} = (T_{max} - T_{min}) * rand + T_{min} \quad (1)$$

The endurance in the current step ( $E_{now}^{i,iter}$ ) is updated with the temperature in the current step and number of steps using Eq. 2.

$$E_{now}^{i,iter} = \left(1 - \frac{T_{now}^{i,iter} - T_{min}}{T_{max} - T_{min}}\right) \quad (2)$$

In combinatorial optimization, the initial heuristic (MC) and some improvement algorithms, for instance 2-opt, 3-opt, and  $k$ -opt hybridize with the algorithm during the computation. In this work, the modified camel algorithm initializes with a constructive heuristic (MC), and it is hybridized with an improvement heuristic (2-opt, 3-opt, or  $k$ -opt). Then, the hybrid modified algorithms are experimented with the random datasets.

In the MCA, each camel's endurance is scarce and randomly diminishes with the number of steps. It is also noted that the supply factor is no longer used during the camel caravan's desert journey.

The discrete updating position equation by using the objective values of functions such as combinatorial problems, engineering problems, and other optimization problems, etc. is applied randomly in two ways for searching optimal solutions by using Eq. 3.

$$Obj_{now}^{i,j} = Obj_{old}^{i,j} + E_{now}^{i,iter} * (BObj - Obj_{old}^{i,j}) \quad (3)$$

Otherwise, the updating equation is applied in the following way.

$$Obj_{now}^{i,j} = (\max(Obj) - \min(Obj)) * rand + \min(Obj)$$

In this work, minimum selection of multiple operators (heuristics) finds acceptable solutions in longer iterations and CPU time in combinatorial problems, such as assignment problems, and traveling salesman problems. Though the solutions from the assignment problem are acceptable, the traveling salesman problem solutions are more acceptable. The candidate solutions are defined by the minimum of the heuristics using Eq. 4.

$$\begin{aligned} NeighObj_{now}^{i,iter}(x) \\ = \text{Minimum of the heuristics (swap, insert, reverse, swap - reverse)} \end{aligned} \quad (4)$$

The improved solutions (2-opt, 3-opt, and k-opt) are evaluated with the objectives found via Eq. 3 in Eq. 5.

$$\begin{aligned} NeighObj_{now}^{i,iter} < Obj_{now}^{i,iter} \\ Obj_{new}^{i,iter} = NeighObj_{now}^{i,iter} \end{aligned} \quad (5)$$

The new solution is updated via Eq. 5. When the new solution (candidate) has better value in the solution space, then the previous endurance of each candidate is updated (oasis condition) by using the traveling factors in Eq. 6.

$$fitness_{now}^{i,iter} > fitness_{old}^{i,iter} \quad (6)$$

$$E_{past}^{i,iter} = E_{initial}^{i,iter}$$

In this work, the solution space dimension is given as 10 for all the computations and used to determine the taking advantage of the candidate solutions (j-loop). The pseudocode of the suggested discrete metaheuristic is presented in Figure 1 (Demiral, 2022, 2024).

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Modified Camel Algorithm (MCA)
Initialize the Camel Caravan with initial (MC) heuristic
Initialize Modified Camel Algorithm parameters (End, Temp)
Calculate Modified Camel Algorithm goal values and find the best
goal
While (Iteration <=MaxIteration)
For i =1: Camel Caravan
For j=1: Solution Space Dimension
 $T_{now}^{i,iter}, E_{now}^{i,iter}$  using Eqs. 1-2.
Update camels' locations using Eq. 4.
Improve the metaheuristic with heuristic (2-opt swap, 3-opt swap, k-opt
swap)
End For j
End For i
Decide the acceptance of new solutions using Eq. 5.
If (oasis condition occurs)
Replenish Endurance using Eq. 6
End If
Rank Caravan individuals and find the best solution in the population
End While
State the final results (Final Statistics)

```

**Figure 1.** Pseudocode of the Suggested Hybrid MCA (DHMCA)

### 3. EXPERIMENTAL RESULTS

A sample medium-scale random datasets were randomly generated in scale from 30 to 150 in the application. In the mathematical problems, the required data is taken from  $x$  and  $y$  coordinates for the optimal matchings between employees and jobs as a uniform number between  $[1,100]$ . The considered costs were computed as Euclidean cost using  $x$ - $y$  plane. All the varieties of metaheuristics were run 5 times and 3000 iterations independently using Matlab. The suggested hybrid algorithm, MCA+MC+3-opt is compared to demonstrate the performance of other metaheuristics, which are MCA, MCA+2-opt, MCA+3-opt, MCA+MC+2-opt. In MCA, the population size (Pop\_size=100), the base dimension of space (dim=10), the other camel algorithm parameters are taken as basis for MCA and its derived forms.

**Table 1** Experimental solutions of hybrid metaheuristics for AssignR50

Problem	Algorithm	Best Solution	Average Solution	Standard Deviation	CPU Time
AssignR50 (488)	MCA	537.23	557.05	11.6	51.84
	MCA+2-opt	518.34	530.05	9.23	48.03
	MCA+3-opt	507.4	526.94	11.81	78.24
	MCA+MC+2-opt	507.85	520.37	13.29	45.38
	MCA+MC+3-opt	505.94	519.33	10.51	88.63

**Table 2** Experimental solutions of hybrid metaheuristics for AssignR80

Problem	Algorithm	Best Solution	Average Solution	Standard Deviation	CPU Time
AssignR80 (586)	MCA	840.3	876.57	22.36	69.05
	MCA+2-opt	766.33	794.94	23.78	73.68
	MCA+3-opt	743	784.87	41.32	119.6
	MCA+MC+2-opt	621.36	648.43	16.36	71.03
	MCA+MC+3-opt	615.55	638.82	13.71	128.03

**Table 3** Experimental solutions of hybrid metaheuristics for AssignR100

Problem	Algorithm	Best Solution	Average Solution	Standard Deviation	CPU Time
AssignR100 (616)	MCA	1085.93	1197.54	64.23	79.52
	MCA+2-opt	971.74	1020.98	31	105.71
	MCA+3-opt	941.38	959.9	15.92	154.44
	MCA+MC+2-opt	735.76	741.12	4.6	107.91
	MCA+MC+3-opt	727.72	737.09	11.84	175.17

**Table 4** Experimental solutions of hybrid metaheuristics for AssignR130

Problem	Algorithm	Best Solution	Average Solution	Standard Deviation	CPU Time
AssignR130 (712)	MCA	1573.05	1644.25	61.14	107.58
	MCA+2-opt	1472.5	1493.05	22.5	131.87
	MCA+3-opt	1326.65	1413.01	63.73	218.27
	MCA+MC+2-opt	919.68	939.62	16.49	136.32
	MCA+MC+3-opt	909.61	926.41	14.28	247.49

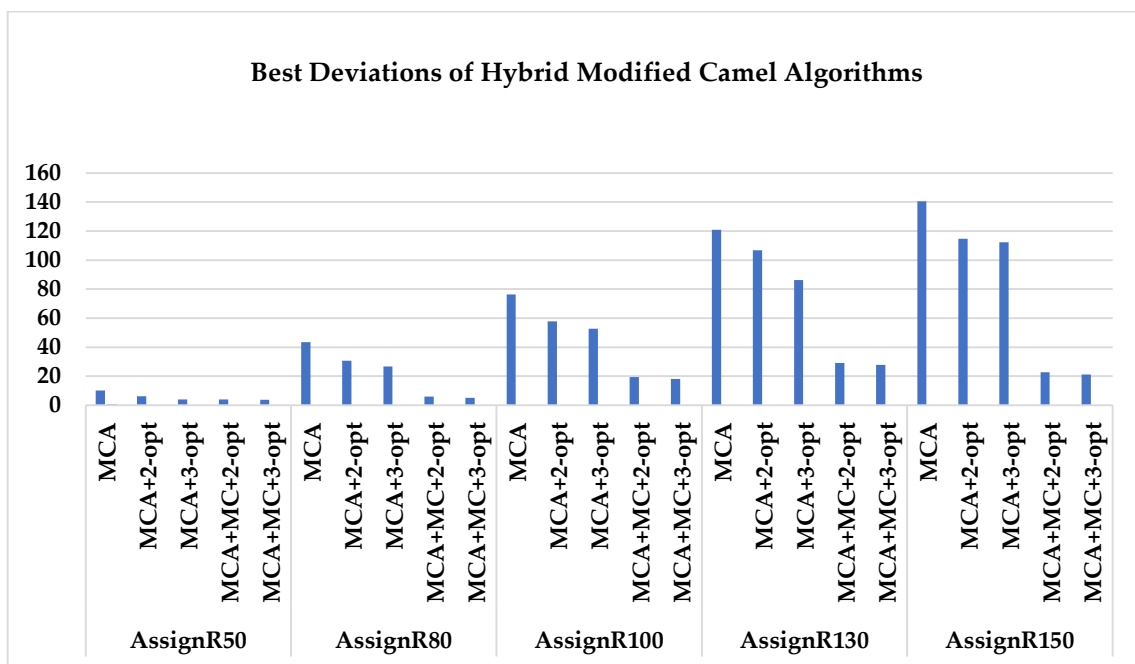
**Table 5** Experimental solutions of hybrid metaheuristics for AssignR150

Problem	Algorithm	Best Solution	Average Solution	Standard Deviation	CPU Time
AssignR150 (805)	MCA	1936.16	2039.65	80.4	140.58
	MCA+2-opt	1728.89	1806.88	52.8	138.59
	MCA+3-opt	1709.23	1767.97	41.69	262.08
	MCA+MC+2-opt	987.25	1037.61	51.86	208.13
	MCA+MC+3-opt	974.96	1018.97	38.91	302.64

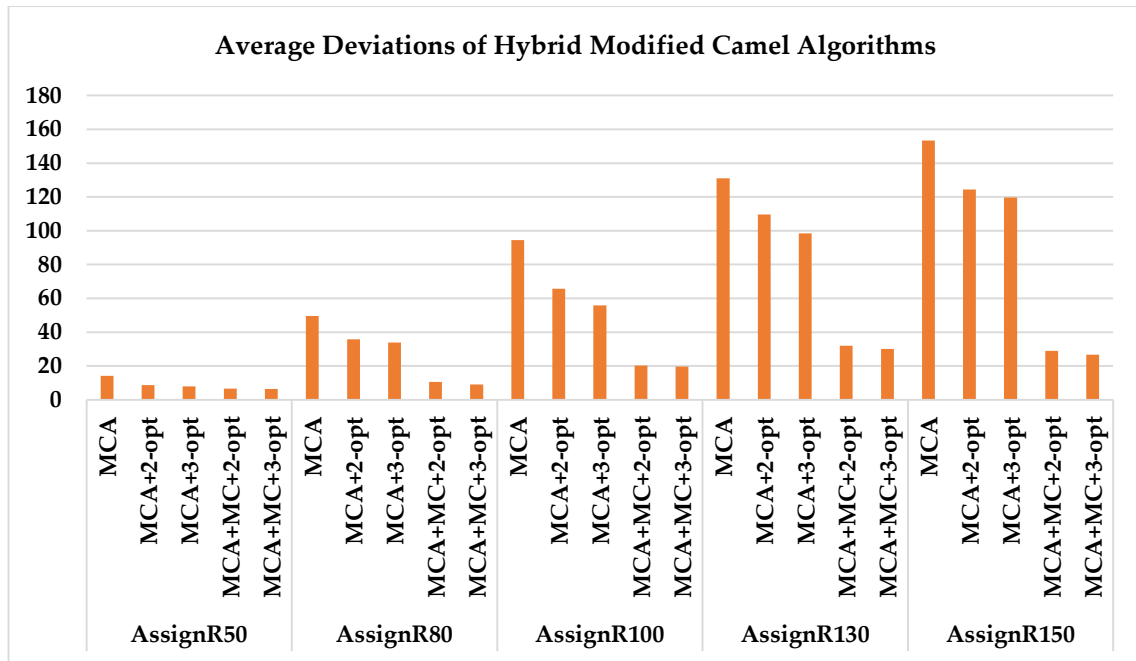
Table 1-5 shows the experimental results of the hybrid algorithm, MCA+MC+3-opt, and other algorithms. In Table 5, AssignR150 expresses the number of equal assignments for the random dataset (AssignR). Though Matlab calculates the optimal solution in AssignR30, AssignR50, AssignR130, and AssignR150 datasets, the program reaches the near-optimal solution in AssignR80 and AssignR100 datasets (586-616). The total minimum model cost (AssignR150: 805) denotes the best-known model cost for the instance dataset. The analysis results of the

hybrid algorithms, MCA+MC+3-opt, and MCA+MC+2-opt show better performance than the base MCA+3-opt, MCA+2-opt, and MCA algorithms. To conclude Table 1-5, MCA with 2-opt, and 3-opt heuristics solve the problem in a more efficient way than the modified camel algorithm, MCA while the data size increases. Moreover, the quality of solutions using the minimum cost heuristic with the modified camel algorithm, (MCA+MC+2-opt, and MCA+MC+3-opt) is quite better. On the other hand, MCA+2-opt, and MCA+MC+2-opt require less computational time than MCA+3-opt and MCA+MC+3-opt metaheuristic.

The first conclusion drawn is that the MCA and its hybrids require more time and max. iteration number to solve the random mathematical problems to reach different acceptable solutions when compared to the traveling salesman problem.



**Figure 2.** Best deviations of hybrid metaheuristics on labor model datasets



**Figure 3.** Average deviations of hybrid metaheuristics on labor model datasets

The second conclusion drawn is that the hybridized modified camel metaheuristics contribute differently to mathematical problems when compared to the pure camel algorithm, and its hybrids.

The third conclusion drawn from statistics is that clear differences are observed between the best and average deviations of the hybrid metaheuristics (MCA and its derived forms).

Figure 2 and Figure 3 demonstrate the best and average deviations of hybrid metaheuristics (MCA and its derived forms) on random mathematical datasets.

**Table 6** Experimental solutions of MCA+MC+3-opt for the sample random datasets (AssignR30-AssignR150)

Problem	Scale	Optimal Solution	Best Solution	Average Solution	CPU Time
AssignR30	30	369	369	369	58.66
AssignR50	50	488	505.94	519.33	88.63
AssignR80	80	586	615.55	638.82	128.03
AssignR100	100	616	727.72	737.09	175.17
AssignR130	130	712	909.61	926.41	247.49
AssignR150	150	805	974.96	1018.97	302.64

The performance analysis of the suggested algorithm is demonstrated in Table 6. The computational time of the hybrid algorithm for the datasets is higher than the pure camel algorithm with heuristic (CA+MC+3-opt) when the size of the combinatorial problem increases. The total labor costs are slightly better than the pure camel algorithm and more reasonable when compared to the other hybrid camel algorithms (Demiral, 2024).



## CONCLUSION

An applied metaheuristic algorithm named MCA (Modified Camel Algorithm) and its hybrid varieties were implemented for workforce and labor management (AssignR30-150). MCA is a quite applicable nature-inspired algorithm based on the behavior of candidates with scarce endurance during the long horizon. To reproduce new candidates, the program operates multiple heuristics called swapping, insertion, 2-opt heuristic, and swap-reversing heuristic/one type of 3-opt heuristic. It is noted that the 3-opt heuristic shows better performance than the swap-reversing heuristic. After that, the minimum operator of multiple heuristics has been applied. The frequently used parameters are taken as the basis for all the hybrid metaheuristics. Conversely, the length of the interchanging part contributes differently to the scale of the dataset. The problem related to labor management belongs to the class of NP-hard, various methods of heuristics (k-opt, and MC+ k-opt types) were operated. The experimental results were shown as best, average, standard deviation and CPU time by various methods of metaheuristics (MCA, MCA+ k-opt, and MCA+MC+ k-opt types). As a result, those methods contribute differently to the metaheuristic algorithm, and the corresponding combinatorial problem.

Euclidian cost is calculated by each assignment between the jobs and the employees. Matlab calculates optimal/near-optimal cost from optimal assignment of the jobs and employees. The best, average, and CPU time are calculated when the program operates 5 times and 3000 iterations. The best and average statistics of MCA+MC+3-opt are dominant to the other test metaheuristics. The suggested hybrid algorithm, MCA+MC+3-opt (Ave. CPU time= 166.77 secs.) has found reasonable solutions later than CA+MC+3-opt. It can be also obtained reasonable solutions by the suggested hybrid algorithm, MCA+MC+2-opt (Ave. CPU time= 113.75 secs.) later than CA+MC+2-opt when the best and average statistics are taken into account. On the other hand, the other camel algorithms demonstrate poor performance against suggested metaheuristics with constructive heuristic.

In conclusion, the suggested algorithms with various constructive and improvement methods can be applied to more datasets, such as large-scale instances, instances from OR-library, and real-world data. The computational analysis of the algorithm can be developed in further studies. Moreover, a job-shop scheduling or timetabling problem will be solved using MCA and its hybrid algorithms, to improve or develop the performance of the suggested algorithms.

**Disclosure Statements (Beyan ve Açıklamalar)****Researchers' Contribution Rate Statement / Araştırmacıların Katkı Oranı Beyanı**

The author declared that he has contributed to this article alone. Yazar bu çalışmaya tek başına katkı sağladığını beyan etmiştir.

**Researchers' Conflict of Interest Statement / Araştırmacıların Çatışma Beyanı**

The author declares that there is no conflict of interest. Yazar ya da herhangi bir kurum kurum/kuruluş arasında çıkar çatışması yoktur.

**Ethical Statement of Researchers / Etik Beyanı**

The author(s) declared that the ethical rules are followed in all preparation processes of this study. In the event of a contrary situation, Pamukkale Journal of Eurasian Socioeconomic Studies has no responsibility, and all responsibility belongs to the author of the study. Bu çalışmanın tüm hazırlanma süreçlerinde etik kurallara uyulduğunu yazar beyan eder. Aksi bir durumun tespiti halinde Pamukkale Avrasya Sosyoekonomik Çalışmalar Dergisi hiçbir sorumluluğu olmayıp, tüm sorumluluk çalışmanın yazarına aittir.

**REFERENCES**

- Ali, R.S., Alnahwi, F.M., & Abdullah, A.S. (2019). A modified camel travelling behavior algorithm for engineering applications. *Australian Journal of Electrical and Electronics Engineering*, 16(3), 176-186. doi: 10.1080/1448837X.2-019.1640010
- Bouajaja, S., & Dridi, N. (2017). A survey on human resource allocation problem and its applications. *Operational Research*, 17(2), 339-369.
- Bozorgi, S.M., & Yazdani, S. (2019). IWOA: An improved whale optimization algorithm for optimization problems. *Journal of Computational Design and Engineering*, 6(3), 243-259.
- Caron, G., Hansen, P. & Jaumard, D. (1999). The assignment problem with seniority and job priority constraints. *Operations Research*, 47(3), 449-454.
- Demiral, M. F. (2022). Application of a Hybrid Camel Traveling Behavior Algorithm for Travelling Salesman Problem. *Dokuz Eylul University Journal of Science and Engineering*, 24(72), 725-735. doi: 10.21205/deufmd.2022247204
- Demiral, M. F. (2024). Perspective Chapter: Computational Analysis of Camel Algorithm with Heuristics in Assignment Problem. In: M.S. Cengiz (Ed.) *New Studies in Engineering* (pp. 4-18). Duvar Yayınları, Izmir
- Feng, X., Liu, Y., Yu, H., & Luo, F. (2019). Physarum-energy optimization algorithm. *Soft Computing*, 23, 871-888. doi: 10.1007/s00500-017-2796-z.
- Geng, X., Chen, Z., Yang, W., Shi, D., & Zhao, K. (2011) Solving the travelling salesman problem based on an adaptive simulated annealing algorithm with greedy search. *Applied Soft Computing*, 11(4), 3680-3689.
- Gilbert, K.C., & Hofstra, R.B. (1988). Multidimensional assignment problems. *Decision Sciences*, 19(2), 306-321.
- Hassan, K.H., Abdulmuttalib, T.R., & Jasim, B.H. (2021). Parameters estimation of solar Photo-

- voltaic module using camel behavior search algorithm. *International Journal of Electrical Computer Engineering (IJECE)*, 11(1), 788-793.
- Hatamlou, A. (2013). Black hole: a new heuristic optimization approach for data clustering. *Information Sciences*, 222, 175–184
- Hatamlou, A. (2018). Solving travelling salesman problem using black hole algorithm. *Soft Computing*, 22(24), 8167-8175. doi: 10.1007/s00500-017-2760-y
- Ibrahim, M.K., & Ali, R.S. (2016). Novel optimization algorithm inspired by camel traveling behavior. *Iraqi Journal for Electrical and Electronic Engineering*, 12(2), 167-177.
- Lin, Y., Bian, Z., & Liu, X. (2016). Developing a dynamic neighborhood structure for an adaptive hybrid simulated annealing-tabu search algorithm to solve the symmetrical traveling salesman problem. *Applied Soft Computing*, 49, 937-952.
- Liu, L., Song, Y., Zhang, H., Huadong, M., & Vasilakos, A.V. (2015). Physarum optimization: a biology-inspired algorithm for the steiner tree problem in networks. *IEEE Transactions on Computers*, 64(3), 818–831.
- Mian, T.A., Muhammad, U., & Riaz, A. (2012). Jobs scheduling and worker assignment problem to minimize makespan using ant colony optimization metaheuristic. *World Academy of Science, Engineering and Technology*, 6(12), 2823-2826.
- Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in Engineering Systems Software*, 95, 51-67.
- Nowak, M., Epelman, M. & Pollock, S.M. (2006). Assignment of swimmers to dual meet events. *Computers & Operations Research*, 33, 1951-1962.
- Pentico, D.W. (2007). Assignment problems: a golden anniversary survey. *European Journal of Operational Research*, 176(2), 774-793.
- Rajabioun, R. (2011) Cuckoo optimization algorithm. *Applied Soft Computing*, 11(8), 5508–5518
- Saremi, S., Mirjalili, S., & Lewis, A. (2017). Grasshopper optimization algorithm: theory and application. *Advances in Engineering Software*, 105, 30-47.
- Szeto, W.Y., Yongzhong, W., & Ho, S.C. (2011). An artificial bee colony algorithm for the capacitated vehicle routing problem. *European Journal of Operational Research*, 215(1): 126-135.
- Tawhid, M.A., & Savsani P. (2019) Discrete sine-cosine algorithm (DSCA) with local search for solving traveling salesman problem. *Arabian Journal for Science and Engineering*, 44, 3669-3679. <https://doi.org/10.1007/s13369-018-3617-0>
- Utama, D.M., Safitri, W. O. N., & Garside, A. K. (2022). A Modified Camel Algorithm for Optimizing Green Vehicle Routing Problem with Time Windows. *Jurnal Teknik Industri: Jurnal Keilmuan dan Aplikasi Teknik Industri*, 24(1), 23-36.
- Yang, XS (2010a). Firefly algorithm, lévy flights and global optimization. In: M. Bramer, R. Ellis & M. Petridis (Eds.) *Research and Development in Intelligent Systems XXVI* (pp.209-218). Springer, London

- Yang, XS (2010b). A new metaheuristic bat-inspired algorithm. In: J.R. González, D.A. Pelta, C. Cruz, G. Terrazas & N. Krasnogor (Eds.) *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)* (pp. 65-74). Studies in Computational Intelligence 284. Springer, Heidelberg.
- Yildirim, A.E., & Karci, A. (2018). Applications of artificial atom algorithm to small-scale traveling salesman problems. *Soft Computing*, 22(22), 7619-7631. <https://doi.org/10.1007/s00500-017-2735-z>