An Enhanced Donkey and Smuggler Optimization Algorithm for Choosing the Precise Job Applicant

Nazir M. Hasan
University of Kurdistan Hewler
Tarik A. Rashid (tarik.ahmed@ukh.edu.krd)
University of Kurdistan Hewler
Abeer Alsadoon
Charles Sturt University
Ahmed S. Qosaeri
University of Kurdistan Hewler
Laith Abualigah
Amman Arab University, Amman, Jordan

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Abstract

Throughout the last few decades, Nature-Inspired Algorithms (NIA) have become very popular in solving real-world problems by getting inspiration from nature and animals' and insects' social behavior. This work suggests the Modified Donkey and Smuggler Optimization (MDSO) algorithm for solving the selection problem to choose the suitable job applicants for a specific position. The original Donkey and Smuggler Optimization algorithm (DSO) has two modes: smuggler and donkey mode (non-adaptive and adaptive, respectively). In the smuggler mode, the algorithm tries to find the best solutions, which is the path to send the donkey to the destination; once the best path is found, the smuggler will send the donkey through the selected path. The donkey's actions will start when the smuggler mode's best solution is no longer the best one. Certain modifications have been made in the smuggler mode, including replacing the original fitness with a new fitness equation since that method can work more accurately. The Human Resource (HR) department in Korek-telecom has been used as a resource to achieve real-world data to test the original and Modified DSO. By using MDSO, not only will organizations be able to choose suitable job applicants more accurately but will manage to do so at a faster pace as well.

Introduction

NIAs are widely used in solving real-world problems by getting inspiration from nature. Most of them are based on swarm intelligence, such as Ant Colony Optimization and Particle Swarm Intelligence(Yang, 2014). Swarm intelligence (SI) is a cooperative behavior of individuals to find the best solution (Chakraborty and Kar, 2017). Various researchers have used it in different areas to solve optimization problems. These cooperative behaviors play a critical role in the survival of these animals and insects (Blum, National, and Li, 2008). NIA could be either heuristic or meta-heuristic algorithms (Bozorg-Haddad, Solgi, and Loáiciga, 2017). Heuristic algorithms are designed to solve only one specific problem, whereas meta-heuristic algorithms can be used to solve different problems in different areas (Gandomi et al., 2013).

Examples of the most widely used meta-heuristic algorithms that can serve in solving various problems include ACO, PSO, Artificial Bee Colony (ABC), and Cuckoo Search (CS) (Abdullah and Ahmed, 2019). There is no global algorithm that can be applied and solve every problem in the real world. To put it another way, an algorithm can be used for some problems, but no algorithm can work for all types of problem that exists in the real world (Wolpert and Macready, 1997). This research suggests the MDSO algorithm, which originated from the DSO. In the MDSO algorithm, the fitness functions have been modified to deliver solutions that are more reliable and expand the range of applications in which the algorithm can be used. To test the viability of MDSO, it has been implemented to solve a real-life obstacle, which is the employee selection problem that the human resources division continuously carries on. HR management's key domains are recruitment and selection, which play a critical role in promoting the organization in different sectors(Gusdorf, 2008). Having a positive perspective is important in the recruitment process since it involves attracting as many candidates for a specific job vacancy as possible (Lievens and Chapman, 2019). Selection is the process of choosing the most suitable candidate for a

particular position by interviewing the applicants and assessing whether their qualities meet the requirements needed for the job (Collins and Kehoe, 2008). The motivations related to this paper are as follows. 1) The recruitment and selection processes are time-consuming, highly costly, and require considerable effort. Besides, the organizations are always at the risk of losing prized job applicants to another organization; therefore, the organizations must have an accurate way of recruiting and selecting to find the right person for the right position (Chalidabhongse, Jirapokakul, and Chutivisarn, 2006). 2) The DSO requires some enhancement in finding the fitness of the solutions since the procedure of calculating the parameters is neither accurate nor suitable for these types of applications, such as selection problems. In case there is no reversely proportional parameter in DSO, the result of the fitness will be unrealistic. Besides, there is no weight for the parameters in the DSO's fitness equation, indicating that all of the parameters have the same priority, so when the summation of parameters of two different solutions is the same, then both of them will have the same value.

This paper's main objectives are to reduce the probability of selecting the wrong people for a specific position by introducing the MDSO algorithm. We have also developed software that can perform a selection process using the MDSO algorithm. This work aims to modify the original DSO algorithm and test both versions of the algorithm on the selection problem, then compare the original and modified algorithms' performance to find out the differences.

The main contributions of this paper can be summarised as follows:

1. The original algorithm has been modified to make the DSO more accurate and easier to use. The modification has been done in the first part of the DSO algorithm, referred to as the non-adaptive part.
2. In this work, the MDSO algorithm has been adapted to eliminate the complexity of the selection problem that the human resources staff face when recruiting new employees. For our application, Korek-telecom has been used as a real-life example.
3. The unique software has been developed according to the MDSO algorithm to solve a selection problem. Another software has been produced according to the DSO algorithm.

The remaining structure of this paper is organized as follows. Section 2 presents the more related works to the job applicant based-optimization technique. Section 3 shows the proposed Donkey Smuggler Optimization Algorithm for solving the job applicant problem. Experiments and results are presented in Section 4. Finally, the conclusion and future works are given in Section 5.

Literature Review

The DSO algorithm has two modes: the donkey and smuggler modes or adaptive and non-adaptive modes. In the first mode, the algorithm finds the best solution. When the best solution has been found, then the second mode will start. The second mode, which has three phases (run, face, and support, face, and suicide), will either maintain the best solution or return to the best solution after the conditions are found (Shamsaldin et al., 2019). In this work, we mainly focus on the earlier works on swarm intelligence

as they mimic groups of animals' social behaviors. Doringo developed ACO in 1992, which is an algorithm that imitates the social behaviors of ants. Ants are working perfectly in finding the best path between their nest and food source. Ants achieve this by using a pheromone to mark the path and attract other ants to follow the same path to reach the food source (Dorigo et al., 2004).

In 1995, Kennedy and Eberhart developed PSO, which is the most famous nature-inspired algorithm. The algorithm has been developed by getting inspiration from flying birds and fish behaviors (Poli, Kennedy, and Blackwell, 2007). PSO is a population-based algorithm, and so far, it has gone through many modifications by researchers. Furthermore, the PSO algorithm has been adapted to a huge number of applications (Poli, Kennedy, and Blackwell, 2007).

In 2006 Xin-She Yang developed the Firefly Algorithm (FA) at Cambridge University, which originated from the behaviors of fireflies (Sergio, Desta, and Jao, 2017). Fireflies have flashing activities, and they use this behavior to communicate, attract each other, and risk warning predators (Yang et al., 2014). Fireflies are unisexual, and they attract their partners through brightness. The attractiveness is directly proportional to individuals' brightness level (Yang and Papa, 2016).

In 2009, Xin-she Yang and Suash Deb suggested an optimization algorithm, which was a CS algorithm, and has been inspired by the social behaviour of some cuckoo classes. One of the behaviours of this type of cuckoo bird was leaving their eggs in other host bird’s nests and they also removing existing eggs that belong to host birds (Yang and Deb, 2009).

ABC is one of the most famous SI algorithms and is derived from the natural life of bees when they try to find an essential resource of food. The bees are categorized into three groups which are scouts, employees, and onlookers. The scout's mission is to explore the best-searching area to find a source of food. The mission of employees and onlookers is to exploit promising solutions (Karaboga et al., 2014).

Another nature-inspired algorithm is the Bat Algorithm (BA), which has been developed by Xin-She Yang in 2010. BA is inspired by the social behaviour of bats. The two most crucial behaviours of bats are prey and navigation. Bats use echolocation to find out the distance between themselves and their prey (Yang and Gandomi, 2012).

Grey Wolf Optimization (GWO) is a SI algorithm inspired by the social life of the grey wolf. GWO was developed by Mirjalili in 2014 and imitates the leadership style of wolves for their group hunting. In the GWO algorithm, a group of wolves is classified into four categories which are (Alpha, Beta, Omega, and Delta). The leader known as Alpha is responsible for decision-making in different situations. The betas behave as assistance for alpha wolves. The omega and Delta have a lower ranking compared to previous ones and are responsible to obey the commitments (Mirjalili, Mirjalili, and Lewis, 2014).

Another algorithm, which imitates the social life of cats, is called Cat Swarm Optimization (CSO) and was suggested by Bouzidi and Riffi in 2013. It has two modes (seeking mode and tracing mode) and they are the major behaviours of cats in their social life (Chu and Tsai, 2007). The first mode is the seeking mode

and is used to model the status of the cat. The second mode is the tracing mode, which represents the cat's behaviour when they trace the target (Bouzidi, Riffi, and Barkatou, 2019).

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The Proposed Method

This section consists of two subsections. The first section describes the data obtained and how it was managed to be used in MDSO. The second section describes MDSO in terms of the modifications that were implemented to the DSO.

3.1 dataset

The data has been obtained by interviewing with the HR department of Korek-telecom. According to the interview, the selection process in Korek-telecom has three resources: external, internal, and hybrid resources. The first resource, which is an external resource, is about getting employees outside of the organization. This resource comes in three stages, the first being the phone screening. In this stage, two questions are asked. First, where the job applicant’s current location is? And second, how much do they expect to be paid?. The second stage, which is the pre-employment test, includes an IQ test and an English test. Job applicants who passed this stage will be an input for the third and the last stage. The third stage is the interview, which has five parameters: experience, education qualification, motivation,

communication skills, and organizational and cultural fit. All of the above parameters have their scores, and the applicants will be assessed according to how high they have scored. For scoring, they are using a range, which is from 1 to 5. Furthermore, it is essential to mention that in Korek-telecom, each parameter from each stage has its weight.

In MDSO, we have defined the weight for each parameter. In each stage, the summation of all weights of the parameters is equal to one. The second resource is the internal resource, where the applicant is already an employee in the organization. In this case, the assessment has much fewer stages because most of the parameters are known before. The interview stage parameters are motivation, qualification and education, experience, communication skills, and organization and cultural fit. The third resource is a hybrid resource; it is used when the organization decides to have employees for a specific job in internal and external resources. The weight of each parameter has been assigned according to the importance of each parameter to Korek-telecom. During the interview, we defined numerator and denominator parameters to adapt DSO to the selected application. Lastly, we had a restriction in obtaining the job applicants' information, such as their CVs and testing results. Tables (1,2,3 and 4), show the dataset which has been obtained from Korek-telecom and used to compare DSO and MDSO.

Table (1): the dataset of the Internal resource applicants

parameter/ Candidate name	Motivation	Qualification & education	experience	Organizational fit	Communication skills
Candidate A-In	Neutral	Bad	Neutral	Good	Neutral
Candidate B-In	Good	Neutral	Good	Good	Good
Candidate C-In	Neutral	Good	Very bad	Good	Good
Candidate D-In	Good	Good	Good	Neutral	Good
Candidate E-In	Good	Neutral	Good	Good	Good
Candidate F-In	Neutral	Good	Bad	Good	Good
Candidate G-In	Good	Good	Bad	Good	Good
Candidate H-In	Good	Good	Very bad	Good	Good
Candidate I-In	Neutral	Good	Bad	Good	Neutral
Candidate J-In	Good	Very good	Good	Neutral	Neutral

Table (2): Dataset of the external resource applicants (First Stage)

parameter/ Candidate name	Location	Salary	Speaking skills
Candidate A-EX	Neutral	Good	Neutral
Candidate B-EX	Good	Neutral	Very Good
Candidate C-EX	Neutral	Good	Good
Candidate D-EX	Neutral	Good	Very Good
Candidate E-EX	Good	Good	Bad
Candidate F-EX	Very Good	Bad	Bad
Candidate G-EX	Good	Very good	Bad
Candidate H-EX	Good	Good	Good
Candidate I-EX	Good	Neutral	Neutral
Candidate J-EX	Good	Bad	Neutral
Candidate K-EX	Good	Very bad	Neutral
Candidate L-EX	Good	Bad	Very bad

Table (3): Dataset of the external resource applicants (Second Stage)

parameter/ Candidate name	IQ test	Spelling & grammar test
Candidate A-EX	Good	Bad
Candidate B-EX	Neutral	Good
Candidate C-EX	Very bad	Bad
Candidate D-EX	Good	Neutral
Candidate E-EX	Neutral	Bad
Candidate G-EX	Bad	Bad
Candidate H-EX	Neutral	Good

Table (4): Dataset of the external resource applicants (Third Stage)

parameter/ Candidate name	Motivation	Qualification & education	experience	Organizational fit	Communication skills
Candidate A-EX	Neutral	Good	Bad	Good	Neutral
Candidate B-EX	Good	Good	Good	Good	Neutral
Candidate D-EX	Good	Good	Bad	Good	Good
Candidate H-EX	Good	Good	Neutral	Good	Good

Modified Donkey And Smuggler Optimization Algorithm

As mentioned in the previous sections, the DSO algorithm's modification has been done in the smuggler (non-adaptive) mode of the algorithm, which is used to find the fitness of the solutions. The original equation for finding the fitness for solutions is shown below:

$$f\left(x_i\right) = \frac{\sum_{j=0}^{J}\left(x_{ij}\right)^2 + \prod_{j=0}^{J} x_{ij}}{\sum_{z=0}^{Z}\left(x_{iz}\right)^2 + \prod_{z=0}^{Z} x_{iz}} (1)$$

When x_i is the solution number *i*, *i* is a number of a solution, *j* is several directly proportional parameters of each solution, *z* is of reversely proportional parameters of each solution, x_{ij} is the directly proportional parameter of solution *i*, and x_{iz} is the reversely proportional parameter of solution *i*. In MDSO, the fitness equation has been changed completely, as shown below:

$$f\left(x_i\right) = \sum_{i=1}^{i=n}\sum_{j=1}^{j=n}\left(x_{ij}\right)^2 * w_j (2)$$

When x_i is the solution, x_{ij} is the parameter of solution *i*, *i* is the number of the solutions, *j* is the number of the parameters and *w* is the weight of the parameters. In MDSO each parameter is squared first and then multiplied by its weight. The last step is the addition of the parameters.

Equation (3) is used to choose the second-best solution as the best solution. When *i* is the number of possible solutions. The equation will subtract the fitness of the best solution from the fitness of the possible solutions and the one that gives the least difference is considered the new best solution.

$$secondbest_{Solution} = x_i if\left(f\left(best_{Solution}\right) - f\left(x_i\right)\right) isMIN (3)$$

- The first and second best solutions are joined by using Equation (4). When $best_{Solution}$ is the current best solution and $second - best_{Solution}$ is the second-best solution which has been chosen by Equation(3).

$$best_{SupportSolution} = \left(best_{Solution}\right) + \left(second - best_{Solution}\right) (4)$$

4. Experiments and results

This section describes the data obtained and how it was managed to be used in the proposed MDSO, and how MDSO and DSO have been adapted to the selection problem using real data, which have been obtained from Korek-telecom.

4.1 Non-adaptive Mode

The non-adaptive part of the algorithm is used to find the job applicants' fitness by using Eq. (2) for MDSO and Eq. (1) for DSO. Three stages of the external resource will process in this mode; these are explained as follows:

4.1.1 External Resource

This resource has three stages; the first stage's output will become the input for the next stage. When the data pass to the next stage, there is a shortlisting for the job applicants. This happens by adding all job applicants' fitness and dividing by the number of applicants, as shown in Eq. (5).

$$\mathrm{Theoutputofshortlist} = \frac{\sum_{f=1}^{n} f\left(x_n\right)}{\mathrm{totalnumberofapplicants}} \quad (5)$$

When f is the fitness of the job applicants, $f_{(Xn)}$ is the summation of the fitness of all job applicants and the *total number of applicants* is the number of job applicants.

1. Phone Screening

The first stage in the external resource is phone screening. Table (5) shows the results of adapting MDSO in the first stage of the problem.

Table (5): The Job applicants are sorted according to their fitness in MDSO (phone screening).

Weight	0.25	0.5	0.25	
Parameter/Name	Location	Salary	Speaking Skills	Fitness
G	4	5	2	17.5
D	3	4	5	16.5
H	4	4	4	16
B	4	3	5	14.75
C	3	4	4	14.25
E	4	4	2	13
A	3	4	3	12.5
I	4	3	3	10.75
F	5	2	2	9.25
J	4	2	3	8.25
K	4	1	3	6.75
L	4	2	1	6.25

DSO algorithm has been adapted to the same stage with the same data, as shown in Table (6). Since the salary and location in DSO are denominator parameters, then filling the data for these parameters will be vice versa for the same parameters in MDSO, the procedure described in Table (7). Whereas for numerator parameters, the data are the same in DSO and MDSO.

Table (6): The Job applicants are sorted according to their fitness in DSO (phone screening).

Name	Location	Salary	Speaking Skills	Fitness
H	2	2	4	1
D	3	2	5	0.967
B	2	3	5	0.967
C	3	2	4	0.64
G	2	1	2	0.54
A	3	2	3	0.387
I	2	3	3	0.38
E	2	2	2	0.3
J	2	4	3	0.27
K	2	5	3	0.203
F	1	4	2	0.2
L	2	4	1	0.04

Table (7): Fill in the data for the numerator and denominator parameters in DSO and MDSO.

Data in MDSO	Data for numeratorparameter in DSO	Data for Denominator parameter in DSO	Range
1	1	5	Very bad
2	2	4	Bad
3	3	3	Medium
4	4	2	Good
5	5	1	Very good

As shown in Figure 2, there is a huge difference between DSO and MDSO in choosing the right person in the first stage.

If we consider Korek-telecom's point of view, we can see how MDSO outperforms DSO in finding the best job applicants by checking the scores of the first best solutions of DSO and MDSO. Both applicants have the same score in their locations because, for the denominator parameter in DSO, number 2 is in the range of Good, as shown in Table (7). Furthermore, job applicant H asked for a salary which is in the range of Good. But job applicant G asked for an ideal salary, which is in the Very Good range. Suppose

we judge both job applicants without considering their weight. In that case, we may choose job applicant H because if we add all parameters' scores, then job applicant H has a higher fitness, regarding Table (7). Still, when we are MDS, applicant G is preferred because the salary parameter has 50% of all parameters' total weight. Location and speaking skills together have 50% of the total weight. Even job applicant H has a higher English speaking skills score, but it is not as effective as the salary parameter.

2. Pre-employment test

MDSO is more accurate than DSO. In DSO there are three first-best solutions, which are job applicants B, D, and H. On the other hand, in MDSO there is only one first-best solution, which is job applicant D, as shown in Fig. 3.

3. Interview

Figure 4 illustrates the difference between DSO and MDSO in choosing the right person for a specific position in the external resource's last stage. The issue of using DSO is presenting the same fitness for more than one job applicant. For example, applicants H and D have the same fitness. In MDSO, however, the fitness of all the applicants is different. Furthermore, according to the data which have been achieved from the HR department in Korek-telecom. Job applicant B has been accepted as an employee there.

4.1.2 Internal Resource

The second resource is the internal resource. Table (8) shows the filled data for 10 job applicants to be adapted by the MDSO and DSO algorithm.

Table (8): the Job applicants are sorted according to their fitness in MDSO and MDSO (Internal).

weight	0.15	0.30	0.25	0.15	0.15	Fitness	
P/N	Motivation	Quali&edu	Experience	Org&cul	Com. Skills	DSO	MDSO
J	4	5	4	3	3	1081	16.6
D	4	4	4	3	4	1129	14.95
E	4	3	4	4	4	1129	13.9
B	4	3	4	4	4	1129	13.6
G	4	4	2	4	4	836	13
H	4	4	1	4	4	545	12.25
F	3	4	2	4	4	673	11.95
C	3	4	1	4	4	448	11.2
I	3	4	2	4	3	544	10.9
A	3	2	3	4	3	441	8.55

Figure 5 shows the results of applying DSO and MDSO to the internal resource. In DSO, there are three first-best solutions which are job applicants B, D, and E. However, in MDSO, there is only one first-best solution, which is job applicant J. MDSO outperforms DSO in choosing the right job applicant because MDSO has chosen applicant J as the first-best solution. Also, the HR department in Korek-telecom determines the same job applicant as an employee.

4.1.3 Hybrid Resource

The best solutions for both internal and external resources have to be obtained first to use this resource. After having the best solutions for both resources, the first-best solution of both resources will be the first-best solution. Once the best solutions are obtained, the second part of the algorithm is performed in the donkey's mode.

4.2 Adaptive Mode

The adaptive part of the algorithm has the same options and processes in all choices (external, internal, and hybrid). Thus, we just mentioned the external resource only. So, in MDSO, if the first-best solution leaves the job permanently, the algorithm will replace (employee B) with (employee H). The second option is a provisional change employee. The algorithm uses this option when the first-best solution leaves its job temporarily; then, the algorithm will replace employee B with employee H by using Eq. (3). The third option is the support employee which will be taken when there is an overload (employee B). In such cases, the algorithm will join the (employee B) with the (job applicant H) simultaneously. This is done by using two equations, which are Equations (3) and (4).DSO algorithm is failed in the second (adaptive) mode because there are two first-best solutions, and the organization can not decide which job applicant

is the first and second-best solution. Otherwise, the adaptive part of the algorithm has the same process for both DSO and MDSO.

4.3 Evaluation of Both DSO and MDSO

This section gives information about the evaluation of both DSO and MDSO when they have been adapted to the selection problem, as shown in Table (9).

Table (9): Final table to compare the performance of both DSO and MDSO

Algorithm/Resource	DSO	MDSO
External Resource	● Gives fewer solutions ● Less accurate in choosing the best solutions. ● Most of the time more than one job applicant has the same fitness.	● Gives more solutions ● More accurate in choosing the best solutions ● Rarely have repetition in the job applicant's fitness.
Internal Resource	● Less accurate in choosing the best solutions. ● Most of the time it has repetition in fitness solutions.	● More accurate in choosing the best solutions. ● No repetition in fitness.
Hybrid Resource	● The same results as mentioned in internal and external resource	● The same results as mentioned in internal and external resource

Conclusion

This paper suggests the MDSO algorithm, which originated from the DSO algorithm. The DSO algorithm requires some enhancements in terms of finding the best solution. Furthermore, the DSO algorithm has been adapted to a few numbers of real-world applications. Thus, it should be adapted to different real-world problems. Besides, without modification, the original DSO could not be adapted to the selected application. By using MDSO, all the above restrictions have been overcome. In MDSO, we have modified the DSO algorithm, and the modification has been done in the first part of the algorithm, which is a non-adaptive mode. The modification aims to make the algorithm more accurate to reduce the risk of choosing inappropriate job applicants in organizations.

The results show that MDSO is more accurate than DSO in finding the best solution. This has been proved by applying both DSO and MDSO into the same application with the same data. The results show the superiority of the MDSO over DSO in finding the best solutions. To find the best equation for finding the solutions' fitness, three equations have been tested, the best equation, which had the best results in Eq. 2, which is used in MDSO.To reduce the probability of selecting the wrong people in the organizations, we have developed software that can perform a selection process using the MDSO algorithm.

In future work, we would like to adapt MDSO to different applications, such as traveling salesman problems, ambulance routing, and packet routing, to ensure that it can be applied to other applications.

Moreover, it can be planned to assess the MDSO algorithm with more test functions such as CEC 2019 test functions. Furthermore, The MDSO algorithm can be hybridized with the FDO algorithm because both algorithms are meta-heuristic and swarm intelligence. Besides, both algorithms are flexible and can be modified easily. This algorithm should also be evaluated against newer algorithms such as FOX, ANA, CDDO, etc. (Mohammed and Rashid, 2022; Hama Rashid and Rashid, 2021; Abdulhameed and Rashid, 2021).

Declarations

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Compliance with Ethical Standards

Conflict of Interest: The authors declare that they have no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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Figures

First mode: The Smuggler's mode (non-adaptive mode)
Begin

1) *Define the parameters of each solution.*
2) *Define the weights of each parameter*
3) *Calculating the fitness of each possible solution using Equation (2).*
4) *Choose the best solution and send the donkey*

End
Second mode: The Donkey's mode (adaptive mode)
Begin

1) *chosing the solution, which has been defined by the suggler's mode.*
2) *evaluate the fitness of the current best solution, if for any reason the current solution is no more the best solution*
3) *If the current best solution is no more the best solution, then:*

   1- Run: *updating the first best solution by evaluating the fitness of each solution.*

   2. Face and Suicide: *choosing the second-best solution as a best solution when the first-best solution is no more the best one, by using Equation (3).*

   3. Face and Support: *this action will take place when there is overload on the first best solution.using the second-best solution to support current best solution to reduce the overload, and when the overload reduced then the second-best solution will return to its original location.*
   Both Equations (3 and 4) represent the face and support action in adaptive mode. In Equation (3) the algorithm finds the second-best solution, and in Equation (4) the algorithm will join both first-best solution and second-best solution to reduce the overload on the first-best solution.

End

Figure 1

Pseudocode of the MDSO algorithm

Figure 2

The name and the fitness of each job applicant in DSO and MDSO (phone screening).

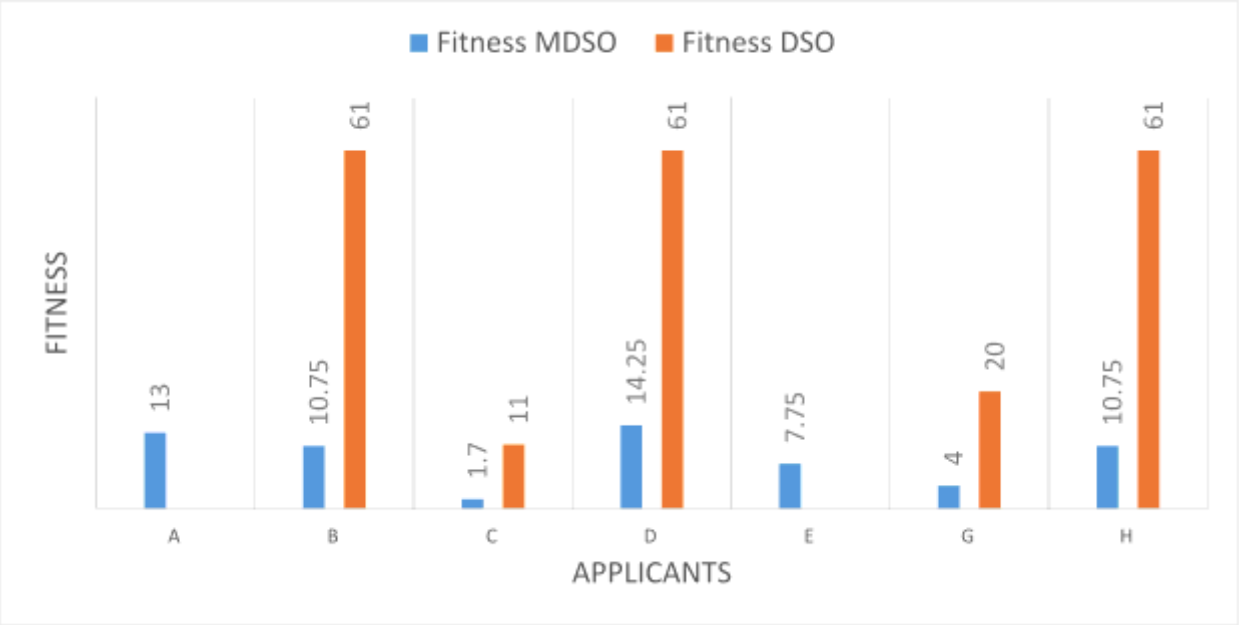

Figure 3

the best solutions in both DSO and MDSO (pre-employment).

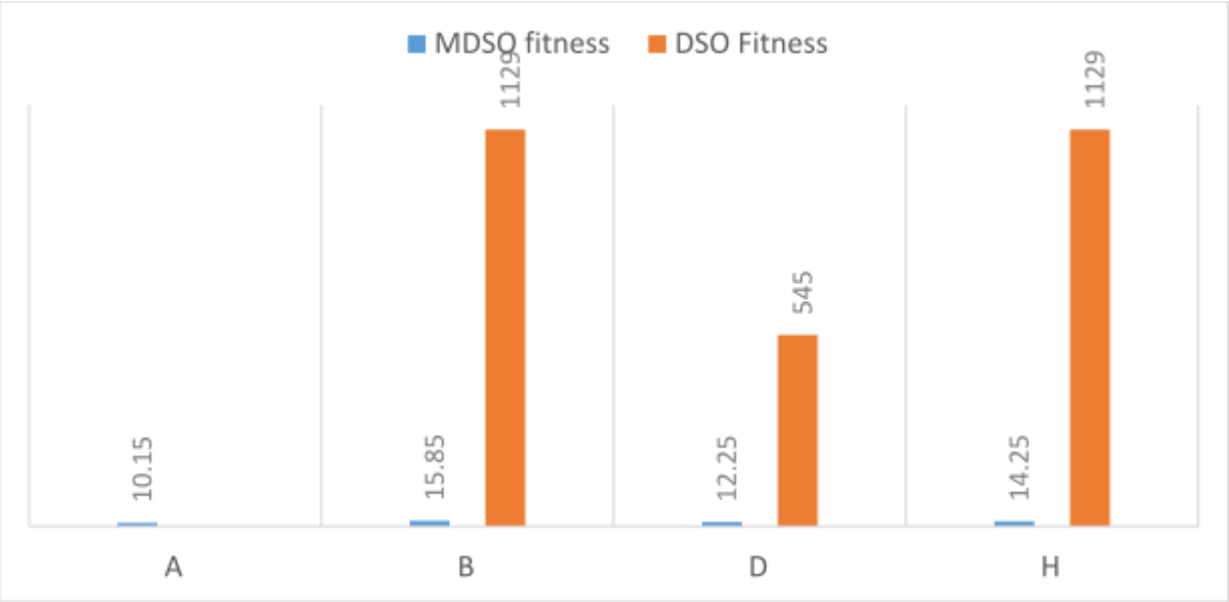

Figure 4

the best solutions in both DSO and MDSO (interview).

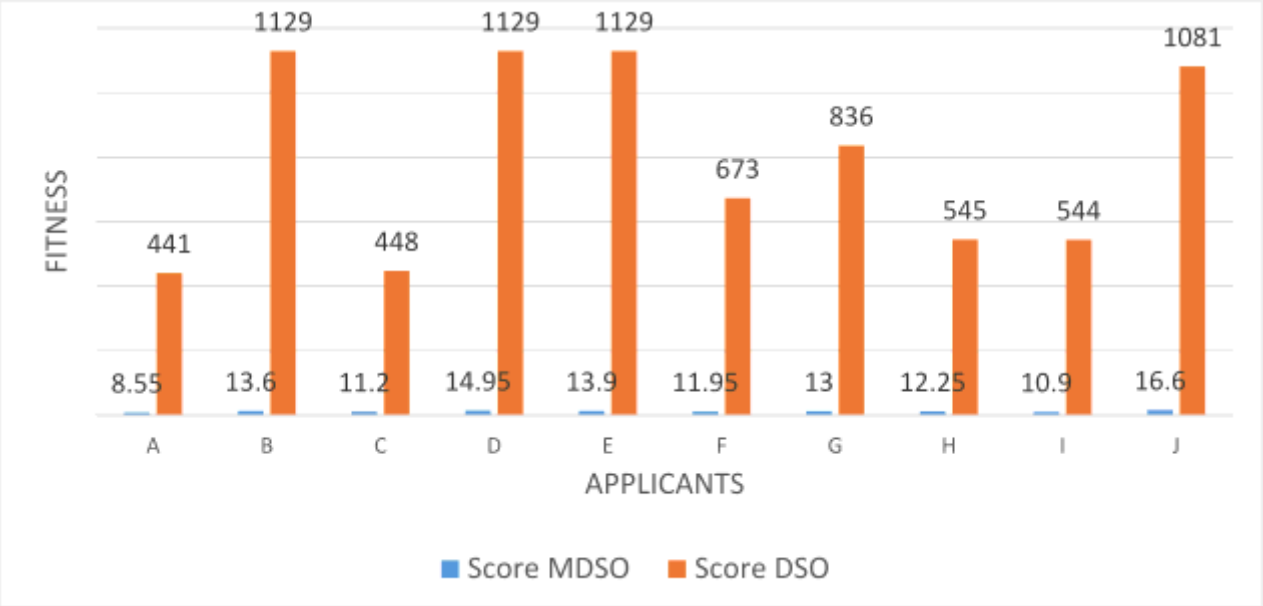

Figure 5

The name and the fitness of each job applicant in DSO and MDSO (internal)