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A Novel Elite-Oriented Meta-Heuristic Algorithm: Qashqai Optimization Algorithm (QOA)

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Abstract

Optimization problems are becoming more complicated, and their resource requirements are rising. Real-life optimization problems are often NP-hard and time or memory consuming. Nature has always been an excellent pattern for humans to pull out the best mechanisms and the best engineering to solve their problems. The concept of optimization seen in several natural processes, such as species evolution, swarm intelligence, social group behavior, the immune system, mating strategies, reproduction and foraging, and animals' cooperative hunting behavior.

This paper proposes a new Meta-Heuristic algorithm for solving NP-hard nonlinear optimization problems inspired by the intelligence, socially, and collaborative behavior of the Qashqai nomad's migration who have adjusted for many years. In the design of this algorithm uses population-based features, experts' opinions, and more to improve its performance in achieving the optimal global solution. The performance of this algorithm tested using the well-known optimization test functions and factory facility layout problems. It found that in many cases, the performance of the proposed algorithm was better than other known meta-heuristic algorithms in terms of convergence speed and quality of solutions.

The name of this algorithm chooses in honor of the Qashqai nomads, the famous tribes of southwest Iran, the Qashqai algorithm.

Keywords: Optimization; Meta-Heuristic algorithms; Qashqai Optimization Algorithm (QOA); Complexity; NP-hard problems; Swarm algorithms

1- Introduction

The concept of optimization has expanded from engineering design to financial markets, stock markets, hospitality, tourism, and from our day-to-day activities to vacation planning and from computer science to industrial applications. An organization strives to maximize profits, minimize costs, and maximize its efficiency. Even when planning our vacation plans, we want to maximize utilization at the least cost (ideally free). [1]

Optimization problems categorize in terms of complexity into P problems, NP problems, NP-complete problems, and NP-hard problems. [2] The concept of problem complexity derived from computational complexity theory. Many of the critical issues are NP-hard, meaning that the time required to solve a sample in the worst-case grows exponentially with the size of the problem, so it isn't possible to solve such problems using exact methods in logical time. Many of our real-world problems are NP-hard, which means that a thorough and effective search is unlikely to meet our computational demand. [3] NP-hard problems include complex transportation network planning, data and computer network planning, human resources allocation, workshops, and machinery scheduling.

The approximate algorithms are dividing into three categories: heuristic, meta-heuristic, and hyper-heuristic. The basic principles of approximation algorithms are constructive heuristics and local search methods. [4]

The two main problems of the heuristic algorithms are their trapping at optimal local points and their early convergence. Heuristic algorithms presented to solve these problems. The main advantage of using meta-heuristic methods is the existence of limited assumptions in model formulation and no need for accurate search space information. At the same time, this is not the case in mathematical programming. Most nature-inspired or bio-

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inspired algorithms have been developed based on the successful evolutionary behavior of natural systems, learning from nature. Nature has solved complex problems for millions or even billions of years. In the environment, only the best and most sustainable solutions remain. [1]
The steps in this article are shown in Fig 1, respectively.

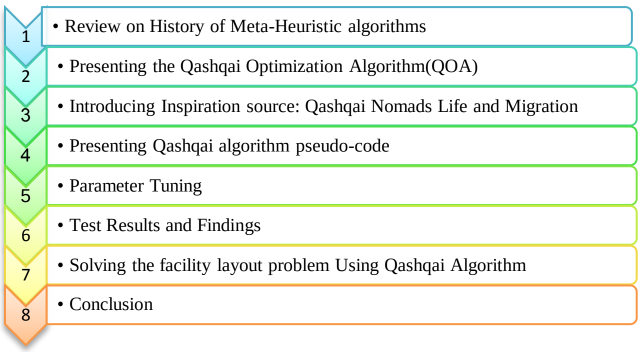

Fig. 1. Steps in this article

Eventually, the innovation of this research and the main objective is as follows:

- Presenting a novel Meta-heuristic algorithm with inspiration from Nomads' behavior, life, and Migration
- Ability to search the answer space extensively.
- It does not require gradient information.
- Requires few parameters to adjust.
- Find the optimal global answer or the near-optimal solution.
- It is elite-oriented and concatenates particular importance to swarm intelligence.

2- History of Meta-Heuristic Algorithms

A meta-heuristic optimization algorithm is a higher-level heuristic method that can be applied, especially with little information and with few modifications to search and find the optimal solution to various optimization problems. The use of meta-heuristic algorithms substantially increases the ability to find high-quality solutions to solve severe optimization problems. The characteristic of these algorithms is the use of exit from optimal local mechanisms. [5] The characteristic feature of meta-heuristic algorithms is to inspire biological and natural systems to solve complex optimization problems. The capabilities of these algorithms include the ability to search for vast spaces in low time efficiently, no need for the derivative of the objective function, the ability to evade from the local optimal points, low computational cost, and easy mathematics. These features have made these algorithms very attractive today. The development of meta-heuristic algorithms began in 1960. In recent decades, due to the ability and capability of nature-inspired algorithms
To solve various problems, the number of these algorithms has grown significantly and is growing. Fig 2 shows the cumulative number of meta-heuristic algorithms. [14]

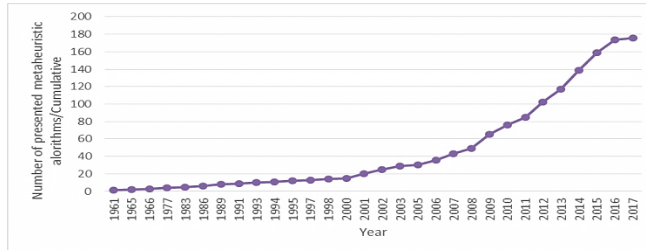

Fig. 2. The cumulative trend of presented Meta-Heuristic algorithms

Meta-Heuristic algorithms used in many areas of engineering design including structural optimization in electronics, aerodynamics, fluid dynamics, telecommunications, automotive, machine learning, data mining, computational biology, chemistry, and physics detection, signal and image processing, routing, scheduling, logistics and transportation, and supply chain management. Meta-heuristic algorithms are a subset of computational intelligence or soft computing, which is itself a subset of artificial intelligence. Fig 3 shows the place of meta-heuristic algorithms in artificial intelligence. [15]

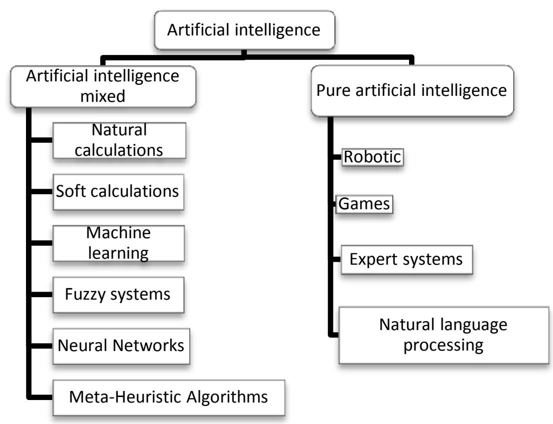

Fig. 3. The place of Meta-Heuristic algorithms in artificial intelligence

Fig 4 shows the general process of meta-heuristic algorithms to achieve the optimal solution.

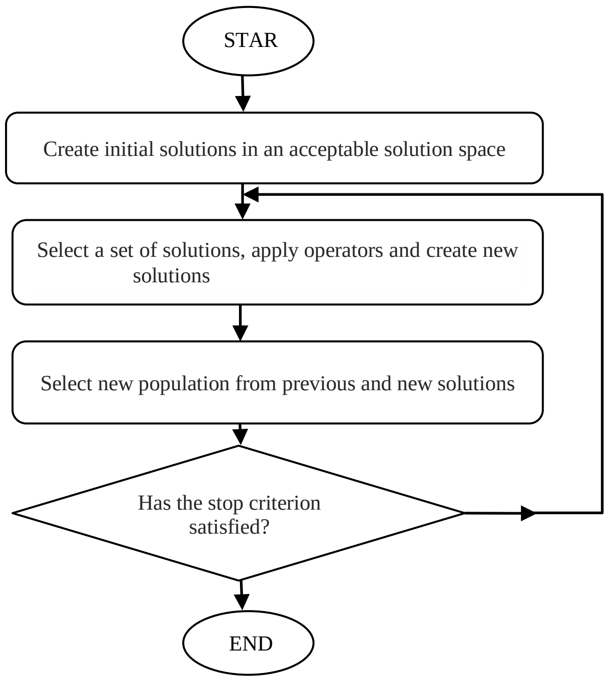

Fig. 4. General process of meta-heuristic algorithms

- **Research Gap**

The classification of the literature is addressed in Table 1. [14] Table 1. List of meta-heuristic algorithms with their specifications Table 1 shows that no metaheuristic algorithm inspired by nomadic life and migration has been proposed so far.

Therefore, the innovations of this research are:

- Study of nomadic life and migration and cooperative way of life and the role of nomadic elites in guiding migration.
- Presenting a novel meta-heuristic algorithm with high execution speed and achieving near-optimal solutions

Presenting an algorithm with low parameters that require low parameter tuning.

Table 1: List of meta-heuristic algorithms with their specifications

Row	Algorithm	Authors	Year	Brief Description	Ref
1	Red deer algorithm (RDA)	A. M. Fathollahi-Fard, M. Hajiaghaei-Keshteli, R. Tavakkoli-Moghaddam	2020	A new optimization algorithm inspired by red deer mating is developed. The Scottish red deer (Cervus Elaphus Scoticus) is a sub-species of red deer, which lives in the British Isles	[17]
2	Find-Fix-Finish-Exploit-Analyze (F3EA) meta-heuristic algorithm	A. H. Kashan, R. Tavakkoli-Moghaddam	2019	The F3EA algorithm is classified into the population based algorithm which simulates battleground and mimics the F3EA targeting process of object or installations selection for destruction in the warfare.	[18]
3	Tree Growth Algorithm (TGA)	A. Cheraghalipour, M. Hajiaghaei-Keshteli, M. M. Paydar	2018	The proposed algorithm is inspired by trees competition for acquiring light and foods	[19]
4	Whale Optimization Algorithm	Mirjalili, Seyedali Lewis, Andrew	2016	This algorithm imitates the hunting habits of whales.	[20]
5	Dragonfly Algorithm	Mirjalili, Seyedali	2016	Mimics from dragonflies behavior such as foraging and avoiding dangers.	[21]
6	African Buffalo Optimization	Odili, Julius Beneoluchi Kahar, Mohd Nizam Mohmad Anwar, Shahid	2015	Mimics foraging and organizational skills of African buffalos.	[22]
7	Ant Lion	Mirjalili, Seyedali	2015	Inspired by ant lions hunting behavior.	[23]
8	Ions Motion Algorithm	Javidy, Behzad Hatamlou, Mirjalili, Seyedali	2015	This algorithm imitates the movement of ions.	[24]
9	Monarch Butterfly Optimization	Wang, Gai-Ge Zhao, Xinchao Deb, Suash	2015	Monarch butterflies' massive journey from North America to California and Mexico inspire it.	[25]
10	Artificial Ecosystem Algorithm	Adham, Manal T Bentley, Peter J	2014	Inspired by characteristics of the ecosystem.	[26]
11	Grey Wolf Optimizer	Mirjalili, Seyedali	2014	Mimics the hierarchical leadership and hunting	[27]

Row	Algorithm	Authors	Year	Brief Description	Ref
		Mirjalili, Seyed Mohammad Lewis, Andrew		behavior of grey wolves.	
12	Keshtel Algorithm	Hajiaghaei-Keshteli, Aminnayeri, MJASC	2014	Based on the food searching strategy of a bird called a keshtel	[28]
13	Black Holes Algorithm	Hatamlou, Abdolreza	2013	Imitates the black hole's features.	[29]
14	Electro-magnetism Optimization	Cuevas, Erik Oliva, Diego Zaldivar, Daniel Pérez-Cisneros, Sossa, Humberto	2012	Electromagnetic problems inspire it.	[۳۰]
15	Flower Pollination Algorithm	Yang, Xin-She	2012	The pollination process of flowers inspires it.	[31]
16	Krill Herd	Gandomi, Amir Hossein Alavi, Amir Hossein	2012	Emulates the krills behavior in herding and searching food.	[32]
17	Bat Algorithm	Xin-She Yang	2010	Imitates the echolocation behavior of bats.	[33]
18	Cuckoo Search Algorithm	Yang, Xin-She and Deb, Suash	2009	Mimics the behavior of cuckoo in brood parasitic and levy flight.	[34]
19	Firefly Algorithm	Yang, Xin-She	2009	Fireflies flashing light behavior inspired it.	[35]
20	Imperialist Competitive Algorithm	Atashpaz-Gargari, Esmaeil Lucas, Caro	2007	Mimics the behavior of the imperialists in expanding their colonies.	[36]
21	Gravitational Search Algorithm	Webster, Barry Bernhard, Philip J	2003	The gravitational force inspires it.	[37]
22	Shuffled Frog Leaping Algorithm	Eusuff, Muzaffar M Lansey, Kevin E	2003	The collaborative behavior of frogs inspires it in search of food.	[38]
23	Honey-bees Mating Optimization Algorithm	Abbass, HA	2001	Honey bee's mating behavior inspires it.	[39]
24	Differential Evolution	Storn, Rainer Price, Kenneth	1997	It is inspired by the information exchange feature of chromosomes to generate better offspring.	[40]
25	Particle Swarm Optimization	Eberhart, Russell Kennedy, James	1995	The intelligent movements of bird swarms inspire it.	[41]
26	Cultural Algorithms	Reynolds, Robert G	1994	It is a Kind of evolutionary computation that has a knowledge component in addition to the population component.	[42]
27	Genetic Algorithm	Goldberg, David E	1989	The Darwinian evolution theory inspires it.	[43]
28	Tabu Search	Glover, Fred	1986	Enhancement of local search by essential rules modifications.	[44]

Dhiman and Kumar algorithms classify meta-heuristics into five categories of evolutionary algorithms, physics-based algorithms, swarm-based algorithms, biology-based algorithms, and nature-inspired algorithms. [6] Dalwani and Agrawal have inspired nature-based meta-heuristic algorithms into five categories of evolutionary algorithms, swarm-based algorithms, physics-based algorithms, biology-based algorithms, and other nature-inspired algorithms. [7] Memari and Ahmad classified the meta-heuristic algorithms into three categories of single-solution algorithms, population-based algorithms, and hybrid algorithms. [8] Birattari and Pokotti classify meta-heuristics algorithms into four continuous and discontinuous, population-based and single- solutions, memory-based and memory-free, single-neighbor, and multiple-neighbor, static and dynamic objective function, inspired by nature, and without inspiration. They were divided by nature. [9] Rajporehit, Sharma, and colleagues classified the meta-heuristic algorithms into three categories: evolutionary, logical search, and other nature-inspired algorithms. [10]

Most meta-heuristic algorithms inspired by natural species problem-solving strategies.

Features of algorithms inspired by species of insects, mammals, birds, and fishes include movement, routing, feeding, mating, reproduction, mass hunting, territorial protection, and risk aversion. The lifestyles of many species such as bacteria, frogs, dragonflies, fireflies, shrimp bunch, have also been inspired. Algorithms inspired by plant roots, photosynthesis, and pollination presented. Some of the natural Events, such as galaxies, river formation, chemical reactions, cloud formation, and crystals, gravitational forces, have also inspired to design the meta-heuristic algorithms. Algorithms inspired by sports competitions, training, learning, and imperialist competition also introduced as the smartest species inspired by the processes of human societies. Fig 5 shows most of the articles presented in the field of meta-heuristic algorithms based on the source. [14]

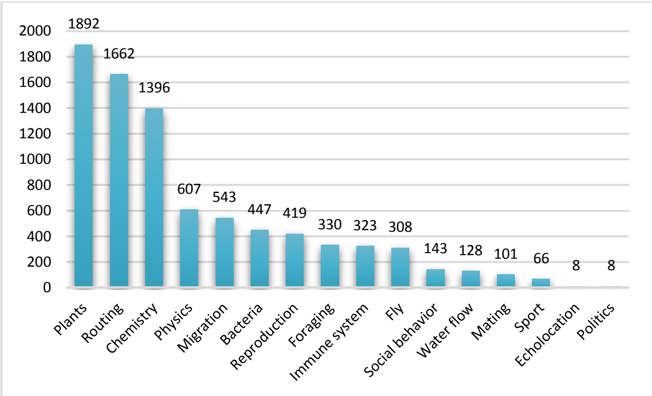

Fig. 5. Most of the papers in the field of Meta-Heuristic algorithms based on inspiration source (WOS source)

Due to the complexity of problems and the changing real world from 2000 onwards, we see the introduction of new Meta-Heuristic algorithms to solve various problems. Also, according to the NFL[1] theory proposed by Wolpert and McReady in 1997, there is no meta-heuristic algorithm suitable for solving all problems. For this reason, in this article, we have developed a new meta-heuristic algorithm inspired by the intelligent, cooperative, and social behavior of Qashqai nomads in their life and migration.

3- Presenting the Novel Qashqai Optimization Algorithm (QOA)

Organizing, designing, and testing the Qashqai Nomads' meta-heuristic algorithm was implemented in seven steps as follows:

3-1- Introducing Inspiration Source: Qashqai Nomads Life and Migration

The history of the nomads' life in Iran goes back about 8,000 years. Since the nomadic livelihoods depend on livestock, they have to migrate between the areas of Qeshlaq (winter quarters) and Yilagh (Summer quarters) to avoid the overwhelming heat and cold needed to provide forage.
Livestock, pasture, and migration are the three main pillars of immigrant human life. The nomad's immigration based on a timing plan for the tribal power structure. It is subject to the opinions of the tribal elders and Experts as well as the climatic and weather conditions, thus making it the best time for nomadic families and livestock to move from Qeshlaq to Yilagh areas. It is determined based on local experience and knowledge gained over many years.

[1] No Free Lunch

Concerning the components and delicacies of the nomads' lives and migration and to the swarm intelligence of the nomads' movement over the many years that have resulted from the collective experience, perseverance, and collaboration of the tribe members, these experiences are transmitted from generation to generation intuitively and systematically. The name of this algorithm chosen in honor of the Qashqai tribe from the famous tribes of the southwest of Iran. [45-48, 55-57]

Fig. 6. Qashqai Nomads

3-2- The Basics of Algorithm Design

An algorithm is a problem-solving procedure involving a finite set of commands that must define as step-by-step and carefully. Each algorithm has a specific starting point and stop point and must consider all possible scenarios in solving different problem scenarios. An algorithm to solve the problem requires two sources of time and memory space. The behavioral analysis indices of the algorithm are the rate of efficiency, robustness in computing, rate of convergence, intelligence, Self-Adaptiveness, and error bound.
The time complexity function of the algorithm is a function such as f (n) that determines the time required to execute an algorithm based on n. The Big-O symbol is one of the universal symbols in the complexity analysis of algorithms. This symbol uses to calculate the complexity of an algorithm's time or memory space. [11]
The process of designing and implementing meta-heuristic algorithms has three successive stages. The first step is preparation, in which we need to get a detailed understanding of the problem we want to solve. The next step is called construction, the most important of which is to choose a solution strategy, to define performance metrics, and to design an algorithm for the solution strategy. The last step is implementation, in which utilization of the algorithm developed in the previous step, including parameter adjustment, performance analysis, and finally reporting of results, should be performed.

3-3- Method of Designing the Qashqai Optimization Algorithm (QOA)

3-3-1- Creating an Initial Population (Initialization)

Suppose tribe has n members, each having a starting point (from Yilagh to Qeshlaq and vice versa). The starting point of each tribe member is random in the problem space.

3-3-2- Elite Selection (Elitism)

A practical variant of the general process of constructing a new population is to allow the best organism(s) from the current generation to carry over to the next, unaltered. This strategy is known as elitist selection and guarantees that the solution quality obtained by the Meta-heuristic algorithm will not decrease from one generation to the next. [49]
Usually, the tribes have their territory and are governed by Ilkhan or Il Big, under their leadership and management. Clan elders have rich experience of the best and the least risky paths to their memory and rely more on it in choosing paths. However, younger members of the tribe have a shorter experience and mind, so they are less likely to refer to their memory and rely more on their previous position. In contrast, the elders of the tribe are less likely to take their next place as their next move. This item has inspired us to update the algorithm's new locations of movement.

3-3-3- How to Update New Locations (Positions)

In this algorithm, the best cost function selects as Ilkhan (The head of the clan), and Formula one is used to updating a new place.

$$x_i^{t+1} = C_1 * \frac{fitness(pop(i))-m_1}{m_2-m_1} * x_i{}^t + C_2 * \frac{m_2-fitness(pop(i))}{m_2-m_1} * rand[varmin, varmax]$$

Formula One

The rest of the population update according to Formula two. m_1 is the best solution in each iteration, and m_2 is the worst solution.

$$x_i^{t+1} = C_1 * \frac{m_2-fitness(pop(i))}{m_2-m_1} * x_i{}^t + C_2 * \frac{fitness(pop(i))-m_1}{m_2-m_1} * rand[varmin, varmax]$$

Formula Two

Table 2 represents the parameters of the Qashqai optimization algorithm (QOA).

Table 2: Parameters of the Qashqai optimization algorithm (QOA)

Parameter	***Description***
Varmax	Maximum number of tribe members
x_i^t	The position of the ith member in iteration of t
x_i^{t+1}	The position of the ith member in the iteration of t+1
Pop(i)	The ith member of the tribe population
$fitness(pop(i))$	The fitnes function of a member of the i population of the tribe
Varmin	Minimum number of tribe members
C1, C2	Algorithm parameters
m_1	The best solution to each iteration
m_2	The worst solution (answer) of each iteration

3-3-4- Migration Route

A set of best-traversed points that equivalent to the best solutions in the algorithm for the general path of the migration.

3-3-5- Strategy to Prevent the Optimal Solution from Worsening

In this algorithm, an approach adopted to prevent the optimal solution from getting worse, so that if the optimal solution of the algorithm in one iteration were worse than the previous iteration of the algorithm, the worst of the current iteration would be replaced by the optimal point of the previous iteration. It will prevent the answer from getting worse.

3-3-6- Diversification and Intensification Strategy

The critical components of any meta-heuristic algorithm are intensification and diversification, or exploitation, and exploration. In the proposed algorithm, whatever greater focus on the previous position, have more exploitation. The less attention to the previous situation, result in more exploration.

3-3-7- Algorithm Stopping Conditions

Different conditions can consider for terminating the algorithm, such as specified execution time, a specified number of iteration, no response improvement.

3-4- Qashqai Optimization Algorithm (QOA) Pseudo-code

Table 3 shows the pseudo-code of the Qashqai optimization algorithm (QOA).

Table 3: Qashqai optimization algorithm (QOA) pseudo-code

Qashqai Optimization Algorithm (QOA) Pseudo Code
Result: Find The best solution Objective min or max $f(x), X = (x_1, x_2, \ldots, x_d)^T$ Generate initial population, of n members of tribes(or nomads) Find the best solution g_* in the population in each iteration While(t<Max Iteration) or (stop criterion) do For i=١:n (all n members of each tribe's) $m_1 \leftarrow$ The best solution(it) $m_2 \leftarrow$ Worst solution(it) Update Position if pop(i) is the best solution of each Iteration then

$$x_i^{t+1} = C_1 * \frac{\text{fitness}(\text{pop}(i)) - m_1}{m_2 - m_1} * x_i{}^t + C_2 * \frac{m_2 - \text{fitness}(\text{pop}(i))}{m_2 - m_1} * \text{rand}[\text{varmin}, \text{varmax}]$$

else

$$x_i^{t+1} = C_1 * \frac{m_2 - \text{fitness}(\text{pop}(i))}{m_2 - m_1} * x_i{}^t + C_2 * \frac{\text{fitness}(\text{pop}(i)) - m_1}{m_2 - m_1} * \text{rand}[\text{varmin}, \text{varmax}]$$

end if
Evaluate new solutions
If new solutions are better, update them in the population
end for
Find the current best solution g_*
end while

3-5- Flowchart of the Qashqai optimization Algorithm (QOA).

Fig 7 shows a diagram of the Qashqai optimization algorithm (QOA).

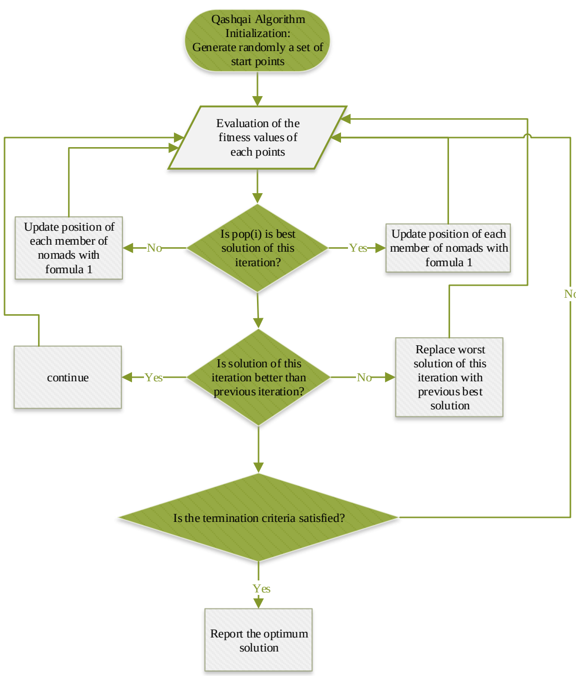

Fig. 7. Flowchart of Qashqai Optimization Algorithm (QOA)

3-6- Qashqai Optimization Algorithm (QOA) Parameter Tuning

Because input parameters influence the output of meta-heuristic algorithms, in order to adjust the parameters, the Taguchi method and Minitab software have been used. For example, according to Table 4, in five levels for the parameters of MaxIt, Npop, C1, and C2, the parameter adjustment of the Qashqai meta-heuristic algorithm has been made.

Table 4: Tuning the parameters of the Qashqai optimization algorithm (QOA)

Row	Parameter	Level 1	Level 2	Level 3	Level 4	Level 5
1	MaxIt	50	100	150	200	250
2	Npop	50	100	150	200	250
3	C1	0.1	0.5	1	2	3
4	C2	0.1	0.5	1	2	3

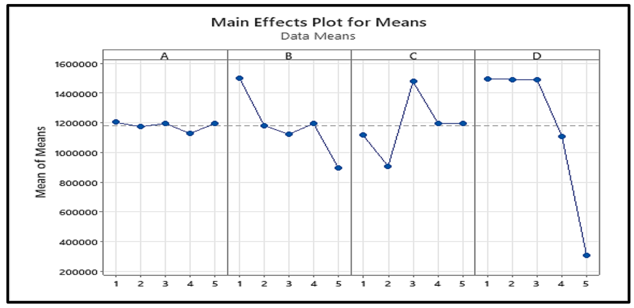

Fig. 8. Average diagram of means for each level of Qashqai optimization algorithm parameters.

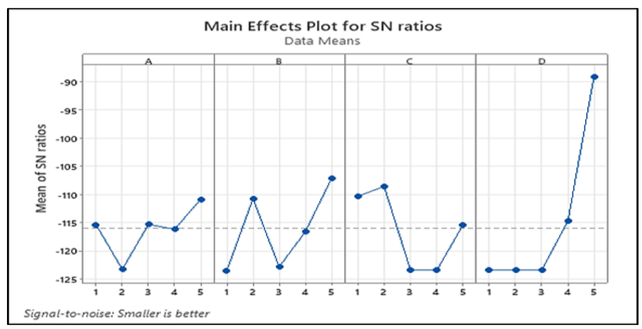

Fig. 9. Graph of the average S/N for each level of Qashqai optimization algorithm parameters.

Fig 8 and 9 show the analysis of the results of the parameter setting Taguchi method using Minitab software, according to which MaxIt = 200 or 250, Npop = 250, C1 = 0.5 and C2 = 3 have the best performance.

3-7- Test Results and Findings

After coding and implementing the proposed meta-heuristic algorithm using the eleven well-known optimization problems listed in Table 5, the algorithm runs with specific repetitions, and the responses and computational times of the proposed algorithm are recorded and compared with genetic algorithms, particle swarm, and differential evolution.

Table 5: Famous Optimization Test Functions [16]

Function name	**Function formula**	**Function domain**	**Optimal point (Minimum Function)**	**The value of the function at the minimum point**
Sphere	$f(x) = \sum_{i=1}^{d} x_i^2$	$x_i \in [-5.12,5.12]$	$x_i^* = (0,0,\ldots,0)$	$f(x^*) = 0$
Rastrigin	$f(x) = 10d + \sum_{i=1}^{d} [x_i^2 - 10\cos(2\pi x_i)]$	$x_i \in [-5.12,5.12]$	$x_i^* = (0,0,\ldots,0)$	$f(x^*) = 0$
Rosenbrock	$f(x) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 - (x_i - 1)^2]$	$x_i \in [-2.048,2.048]$	$x_i^* = (1,1,\ldots,1)$	$f(x^*) = 0$
Griewank	$f(x) = \sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod_{i=1}^{d} \cos(\frac{x_i}{\sqrt{i}}) + 1$	$x_i \in [-600,600]$	$x_i^* = (0,0,\ldots,0)$	$f(x^*) = 0$
Ackley	$f(x) = -a\exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sqrt{\sum_{i=1}^{d} \cos(cx_i)}\right) + a$	$x_i \in [-32.768,32.768]$	$x_i^* = (0,0,\ldots,0)$	$f(x^*) = 0$
EggHolder	$f(x) = -(x_2 + 47)\sin\left(\sqrt{\left\lvert x_2 + \frac{x_1}{2} + 47\right\rvert}\right) - x_1\sin(\sqrt{\lvert x_1 - (x_2 + 47)\rvert}$	$x_i \in [-5.12,5.12]$	$x_i^* = (512,404.2319)$	$f(x^*) = -959.6407$
Michalewicz	$f(x) = -\sum_{i=1}^{d} \sin(x_i)\sin^{2m}(\frac{ix_i^2}{\pi})$	$x_i \in [0,\pi]$	$d = 2; x_i^* = (2.20,1.57)$	$f(x^*) = -1.8013$
Six-Hump Camel	$f(x) = \left(4 - 2.1x_1^2 + \frac{x_1^4}{3}\right)x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2$	$-5 \le xi \le 5, i = 1, 2.$	$x_1^* = (0.0898,-0.7126), x_2^* = (0.0898,-0.7126)$	$f(x^*) = 0$
Levy	$f(x) = \sin^2(\pi w_1) + \sum_{i=1}^{d-1} (w_i - 1)^2[1 + 10\sin^2(\pi w_i + 1)] + (w_d - 1)^2[1 + \sin^2(2\pi w_d)], where\ w_i = 1 + (x_i - 1)/4$	$x_i \in [-10,10]$	$x_i^* = (1,1,\ldots,1)$	$f(x^*) = 0$
Rotated Hyper-Ellipsoid	$f(x) = \sum_{i=1}^{d}\sum_{j=1}^{i} x_j^2$	$x_i \in [-65.536,65.536]$	$x_i^* = (0,0,\ldots,0)$	$f(x^*) = 0$
Shubert	$f(x) = \prod_{i=1}^{n}(\sum_{j=1}^{5} \cos(j+1)x_i + j))$	$x_i = [-10,10]$	18 global minima	$f(x) = -186.7309$

Fig 10 shows the shapes of these famous optimization test functions.

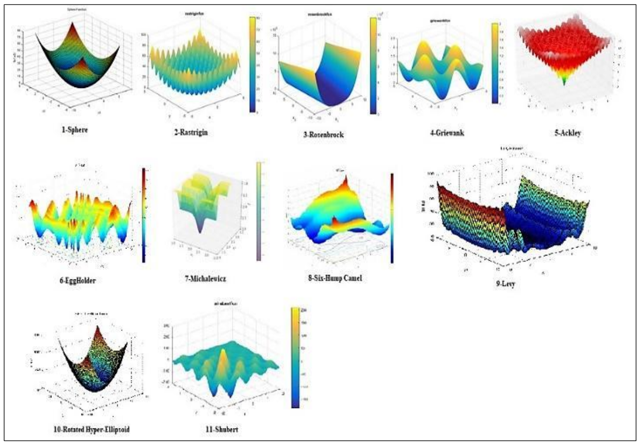

Fig. 10. Shapes of test functions

After recording the results of 30 consecutive runs of the Qashqai optimization algorithm (QOA) and genetic algorithm (GA), particle swarm optimization (PSO), and differential evolution (DE), the hypothesis test, according to Table 6, was performed to compare the cost function and speed of the algorithm.

Table 6: Testing the assumptions

TEST ASSUMPTIONS OF COST FUNCTION AND COMPUTATIONAL TIME	H_0 :THE GENETIC ALGORITHM(GA) OVERCOMES THE QASHQAI OPTIMIZATION ALGORITHM(QOA).	$H_0: \mu > \mu_0$
	H_1 :The genetic algorithm(GA) does not overcome the Qashqai optimization algorithm(QOA).	$H_1: \mu \leq \mu_0$
	H_0 :The particle swarm optimization (PSO) algorithm overcomes the Qashqai optimization algorithm(QOA).	$H_0: \mu > \mu_0$
	H_1 :The particle swarm optimization algorithm(PSO) does not overcome the Qashqai optimization algorithm(QOA).	$H_1: \mu \leq \mu_0$
	H_0 :The Differential evolution(DE) algorithm overcomes the Qashqai optimization algorithm(QOA).	$H_0: \mu > \mu_0$
	H_1 :The Differential evolution(DE) algorithm does not overcome the Qashqai optimization algorithm(QOA).	$H_1: \mu \leq \mu_0$

The Mann-Whitney test use to compare the two independent samples. Table 7 shows the results of the comparison of the two genetic and Qashqai algorithms for the Sphere function. Genetic algorithms, particle swarm, and differential evolution use to compare the results of the cost function and computational time of the proposed algorithm. A computer with the specifications of Table 8 uses to perform the calculations. The average results of 30 consecutive runs of the Qashqai optimization algorithm and the genetic algorithm and the cost function and computation time of the algorithm present in Table 9 and Table 10. It should be explained that nPop = 10, nVar = 5 and MaxIt = 100 are taken into account.

Table 7: Comparison of two genetic and Qashqai optimization algorithms (Sphere function)

Test Statistics[a]

	CostFunction
Mann-Whitney U	.000
Wilcoxon W	465.000
Z	-6.653
Asymp. Sig. (2-tailed)	.000

a. Grouping Variable: Group

Table 8: Specifications of the computer used to compare the results

System

Processor:	Intel(R) Core(TM) i5-2450M CPU @ 2.50GHz 2.50 GHz
Installed memory (RAM):	6.00 GB (5.85 GB usable)
System type:	64-bit Operating System, x64-based processor
Pen and Touch:	No Pen or Touch Input is available for this Display

Table 9: Comparison of the average results of 30 times implementation of the Qashqai optimization algorithm (QOA) and genetic algorithm (GA) on test functions (cost function)

Function name	**Cost Function (Average)**		**P-Value**	**Standard error**	**Test result assumption**
	QOA	**GA**			
Sphere	2.01E-290	1.90E-02	0	α=0.05	H_0 is rejected
Rastrigin	0	1.94E+00	0	α=0.05	H_0 is rejected
Rosenbrock	3.98E+00	7.13E+00	0.008	α=0.05	H_0 is rejected
Griewank	0	4.53E-02	0	α=0.05	H_0 is rejected
Ackley	8.88E-16	2.58E-01	0	α=0.05	H_0 is rejected
EggHolder	8.24-E+02	-7.38E+02	0.156	α=0.05	H_0 is not rejected
Michalewicz	-1.51E+00	-1.75E+00	0	α=0.05	H_0 is rejected
Six-Hump Camel	4.77E-01	7.57E-03	0	α=0.05	H_0 is rejected
Levy	3.89E-01	1.07E-01	0	α=0.05	H_0 is rejected
Rotated Hyper-Ellipsoid	4.65E-55	1.44E+00	0	α=0.05	H_0 is rejected
Shubert	-1.37 E+02	-1.79E+02	0	α=0.05	H_0 is rejected

Table 10: Comparison of the average results of 30 times the Qashqai optimization algorithm(QOA) and Genetic algorithm on the test functions (computational time)

Function name	**Computational Time (Average)**		**P-Value**	**Standard error**	**Test result assumption**
	QOA	**GA**			
Sphere	2.87E-01	1.86E+00	٠	α=0.05	H_0 is rejected
Rastrigin	2.74E-01	1.83E+00	0	α=0.05	H_0 is rejected
Rosenbrock	2.76E-01	1.68E+00	0	α=0.05	H_0 is rejected
Griewank	2.77E-01	1.70E+00	0	α=0.05	H_0 is rejected
Ackley	2.80E-01	1.72E+00	0	α=0.05	H_0 is rejected
EggHolder	2.70E-01	2.50E+00	0	α=0.05	H_0 is rejected
Michalewicz	2.33E-01	1.78E+00	0	α=0.05	H_0 is rejected
Six-Hump Camel	2.89E-01	1.62E+00	0	α=0.05	H_0 is rejected
Levy	3.37E-01	1.57E+00	0	α=0.05	H_0 is rejected
Rotated Hyper-Ellipsoid	2.86E-01	1.60E+00	0	α=0.05	H_0 is rejected
Shubert	2.48E-01	1.58E+00	0	α=0.05	H_0 is rejected

To obtain the following tables, we continued the above procedure to compare the particle swarm algorithm (PSO) and the Qashqai optimization algorithm (QOA). The average of 30 consecutive runs of the Qashqai optimization algorithm and particle swarm algorithm and recording the algorithm's cost and computational time function are shown in Tables 11 and Tables 12.

Table 11: Comparison of the average results of 30 times implementation of the Qashqai optimization algorithm (QOA) and particle swarm algorithm (PSO) on test functions (cost function)

Function name	**Cost Function (Average)**		**P-Value**	**standard error**	**Test result assumption**
	QOA	**PSO**			
Sphere	2.01E-290	2.34E-07	0	α=0.05	H_0 is rejected
Rastrigin	0	4.41E+00	0	α=0.05	H_0 is rejected
Rosenbrock	3.98E+00	2.00E+00	0	α=0.05	H_0 is rejected
Griewank	0	2.27E-02	0	α=0.05	H_0 is rejected
Ackley	8.88E-16	5.71E-02	0	α=0.05	H_0 is rejected
EggHolder	8/24-E+02	-5.56E+02	0	α=0.05	H_0 is rejected
Michalewicz	-1.51E+00	-1.80E+00	0	α=0.05	H_0 is rejected
Six-Hump Camel	4.77E-01	4.69E-08	0	α=0.05	H_0 is rejected
Levy	3/89E-01	1.88E-01	0	α=0.05	H_0 is rejected
Rotated Hyper-Ellipsoid	4.65E-55	2.68E-06	0	α=0.05	H_0 is rejected
Shubert	-1.37 E+02	- 1.87E+02	0	α=0.05	H_0 is rejected

Table 12: Comparison of the average results of 30 times the Qashqai optimization algorithm(QOA) and particle swarm algorithm (PSO) on the test functions (computational time)

Function name	**Computational Time (Average)**		**P-Value**	**standard error**	**Test result assumption**
	QOA	PSO			
Sphere	2.87E-01	2.56E-01	0	α=0.05	H_0 is rejected
Rastrigin	2.74E-01	2.99E-01	0.081	α=0.05	H_0 is not rejected
Rosenbrock	2.76E-01	2.57E-01	0	α=0.05	H_0 is rejected
Griewank	2.77E-01	2.53E-01	0	α=0.05	H_0 is rejected
Ackley	2.80E-01	2.51E-01	0	α=0.05	H_0 is rejected
EggHolder	2.70E-01	2.46E-01	0	α=0.05	H_0 is rejected
Michalewicz	2.33E-01	2.51E-01	0	α=0.05	H_0 is rejected
Six-Hump Camel	2.89E-01	2.41E-01	0	α=0.05	H_0 is rejected
Levy	3.37E-01	2.54E-01	0	α=0.05	H_0 is rejected
Rotated Hyper-Ellipsoid	2.86E-01	2.48E-01	0	α=0.05	H_0 is rejected
Shubert	2.48E-01	2.28E-02	0.69	α=0.05	H_0 is not rejected

We continued the above procedure to obtain the following tables to compare the Differential Evolution (DE) and the Qashqai optimization algorithm (QOA). The average of 30 consecutive runs of the Qashqai algorithm and Differential Evolution (DE) algorithm and recording the algorithm's cost and computational time function are shown in Table 13 and Table 14.

Table 13: Comparison of the average results of 30 times implementation of the Qashqai optimization algorithm (QOA) and Differential Evolution (DE) algorithm on test functions (cost function)

Function name	**Cost Function (Average)**		**P-Value**	**Standard error**	**Test result assumption**
	QOA	**DE**			
Sphere	2.01E-290	1.67E-04	0	α=0.05	H_0 is rejected
Rastrigin	0	9.18E-01	0	α=0.05	H_0 is rejected
Rosenbrock	3.98E+00	2.23E+00	0	α=0.05	H_0 is rejected
Griewank	0	1.28E-01	0	α=0.05	H_0 is rejected
Ackley	8.88E-16	2.44E-01	0	α=0.05	H_0 is rejected
EggHolder	-8.24E+02	-8.13E+02	0.941	α=0.05	H_0 is not rejected

Function name	**Cost Function (Average)**		**P-Value**	**Standard error**	**Test result assumption**
	QOA	**DE**			
Michalewicz	1.51E+00 -	-1.80E+00	0	α=0.05	H_0 is rejected
Six-Hump Camel	4.77E-01	1.15E-05	0	α=0.05	H_0 is rejected
Levy	3/89E-01	5.81E-07	0	α=0.05	H_0 is rejected
Rotated Hyper-Ellipsoid	4.65E-55	2.24E-04	0	α=0.05	H_0 is rejected
Shubert	-1.37 E+02	-1.84E+02	0	α=0.05	H_0 is rejected

Table 14: Comparison of the average results of 30 times the Qashqai optimization algorithm(QOA) and Differential Evolution (DE) algorithm on the test functions (computational time)

Function name	**Computational Time (Average)**		**P-Value**	**Standard error**	**Test result assumption**
	QOA	**PSO**			
Sphere	2.87E-01	2.64E-01	٠	α=0.05	H_0 is rejected
Rastrigin	2.74E-01	2.58E-01	0.001	α=0.05	H_0 is rejected
Rosenbrock	2.76E-01	2.40E-01	0	α=0.05	H_0 is rejected
Griewank	2.77E-01	2.44E-01	0	α=0.05	H_0 is rejected
Ackley	2.80E-01	3.05E-01	0	α=0.05	H_0 is rejected
EggHolder	2.70E-01	2.62E-01	0.09	α=0.05	H_0 is not rejected
Michalewicz	2.33E-01	2.37E-01	0	α=0.05	H_0 is rejected
Six-Hump Camel	2.89E-01	2.41E-01	0	α=0.05	H_0 is rejected
Levy	3.37E-01	2.57E-01	0	α=0.05	H_0 is rejected
Rotated Hyper-Ellipsoid	2.86E-01	2.38E-01	0	α=0.05	H_0 is rejected
Shubert	2.48E-01	2.40E-01	0	α=0.05	H_0 is not rejected

Table 15 summarizes the results of Tables 9 to 14.

Table 15: Summary of the results of the Qashqai optimization algorithm (QOA) and PSO and DE algorithm 11 test functions

Statistical hypothesis testing	Cost Function (Number of H0 is rejected)	Computational Time (Number of H0 is rejected)
(GA)vs (QOA)	10	11
(PSO)vs (QOA)	11	9
(DE)vs (QOA)	10	10

Therefore, we can conclude that genetic (GA), particle swarm optimization (PSO), and differential evolution (DE) algorithms cannot overcome the Qashqai optimization algorithm (QOA) in terms of optimal solution quality and computational time.Fig1١ shows the performance of the Qashqai optimization algorithm (QOA) compared to the other meta-heuristic algorithms, such as genetic algorithm (GA), particle swarm optimization (PSO), and differential evolution (DE) algorithm.

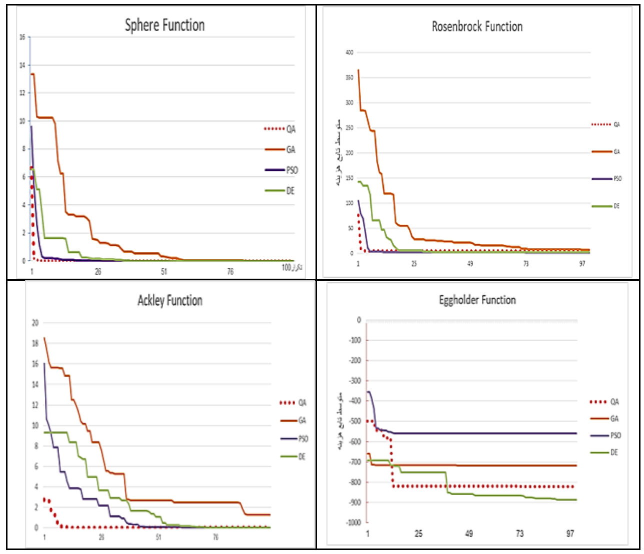

Fig. 11. Comparison of the performance results of the Qashqai Optimization Algorithm (QOA) on the test function

4- Solving the Facility Layout Problem using Qashqai Optimization Algorithm (QOA)

The facility layout problem (FLP) is one of the most critical issues in manufacturing plants. Proper layout of equipment will significantly reduce the cost of transporting the material and thus the total cost of production. Armour and Buffa first introduced this problem as a mathematical model. [12]
Researchers have always sought heuristic and meta-heuristic approaches to solving this problem, given the NP-hardness of the problem. [13, 50-54] The mathematical model of facility layout problem according to Formula Three.

$$\mathrm{Min} \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} \sum\nolimits_{k=1}^{n} \sum\nolimits_{l=1}^{n} F_{ik} D_{jl} X_{ij} X_{kl}$$

Subject to

$$\sum_{i=1}^{n} X_{ij} = 1 \qquad 1 \le j \le n$$

$$\sum_{j=1}^{n} X_{ij} = 1 \qquad 1 \le i \le n$$

$X_{ij} \in \{0, 1\} \;\; 1 \le i, j \le n$

Formula Three

Table 16 represents the Indices and parameters of the facility layout problem.

Table 16: Parameters of the facility layout problem

Indices and parameters	Description
i ,k	Departments in Layout
j , l	Candidate places for departments in layout
n	Number of departments and locations
Djl	Distance between Departments l and j
Fik	The distance between the places i and k
Xij	Equals one if department i is assigned to location j and otherwise equals zero

Table 18 exhibits the results of the facility layout problem with the assumed problem information in Table 17. It should regard that nPop = 10 and MaxIt = 100 take into account.

Table 17: Specifications of the facility layout problems

The problem	Workshop length	Workshop width	Machine length	Machine width
P1	W=100	H=80	h=[12.22.17.25.25.12.25.25]	w=[18.14.11.20.24.12.24.23]
P2	W=150	H=100	h=[13.14.16.28.29.21.22.18]	w=[24.18.20.15.26.30.22.27]
P3	W=200	H=150	h=[24.22.32.35.33.18.24.25]	w=[25.22.15.20.24.15.24.28]
P4	W=220	H=180	h=[27.8.9.15.16.27.27.16]	w=[24.15.10.11.12.16.12.10]
P5	W=200	H=240	h=[23.26.19.22.27.30.25.16]	w=[15.7.20.11.12.28.25.21]

Table 18: Results of solving facility layout problem with Qashqai Optimization Algorithm (QOA) and Particle Swarm optimization (PSO)

The problem	**QOA**		**PSO**	
	Answers average	**Mean Standard deviation of responses**	**Answers average**	**Mean Standard deviation of responses**
P1	1.22E+05	1.01E+04	1.23E+05	1.23E+05
P2	1.29E+05	1.25E+04	1.29E+05	1.41E+04
P3	1.32E+05	1.46E+04	1.34E+05	1.90E+04
P4	1.01E+05	7.12E+03	1.02E+05	8.32E+03
P5	1.15E+05	7.09E+03	1.18E+05	7.24E+03

The results of Table 18 shows that the responses of the Qashqai optimization algorithm (QOA) for solving facility layout problems (FLP) are as good as the algorithm of particle swarm optimization (PSO) and have a lower standard deviation.

• Results and Discussion

In this article, we designed a new meta-heuristic algorithm inspired by collaborative migration, collective intelligence, and nomadic elitism. Pseudo-code of this algorithm showed in Table 3. After that, we implemented the algorithm in MATLAB software. We applied a computer with this configuration: CPU 2.5 GHz, processor core i5-2450, 6.00 GB RAM, and 64-bit operating system. Finally, the proposed algorithm was implemented 30 times using the well-known optimization functions given in Table 5.
Comparisons concerning the hypothesis tests listed in Table 6 indicate that genetic (GA), particle swarm optimization (PSO), and differential evolution (DE) algorithms cannot overcome the Qashqai optimization algorithm (QOA) in terms of optimal solution quality and computational time. (See Tables 9 to 15). Fig11 shows the performance of the Qashqai optimization algorithm (QOA) compared to the other meta-heuristic algorithms, such as genetic algorithm (GA), particle swarm optimization (PSO), and differential evolution (DE) algorithm. Moreover, the facility layout problem was solved using Qashqai Optimization Algorithm (QOA). The results show that the responses of the Qashqai optimization algorithm (QOA) for solving facility layout problems (FLP) are as good as the algorithm of particle swarm optimization (PSO) and have a lower standard deviation. (c.f Table 18)

• Managerial Insights and Practical Implications

This research focuses on presenting a novel metaheuristic algorithm inspired by nomads' cooperative life and migration. We proposed that this metaheuristic algorithm used low parameters and did not need gradient information. Moreover, it is elite-oriented, concatenates particular importance to swarm intelligence, and can evade local optimal points. Low parameters in an algorithm require low parameter tuning and reduce computational complexity and time. This algorithm showed excellent convergence speed to the optimal solutions. The proposed algorithm could be applicability in solving a vast scope of problems such as supply chain, factory facility layout, Flow Shop Scheduling, vehicle routing, JIT sequencing, economic load dispatch problem, assembly sequence planning, maintenance scheduling, robot path planning, cloud computing, image processing & segmentation, data clustering, feature selection, association rules mining, ANFIS training, neural network training, etc.

5- Conclusion and Outlook

Nature-inspired Meta-heuristic algorithms are increasingly introducing. The range of applications of these highly diverse, high performance, low-cost algorithms has opened a new horizon for humanity in computing and solving complex problems in a reasonable time. In this paper, the literature review of the meta-heuristic algorithms presented from the beginning have reviewed. Then the Qashqai optimization algorithm (QOA) has been proposed to solve the optimization problems. The Qashqai algorithm does not require gradient information due to the use of random search. One of the exciting parts of the proposed algorithm is that it well simulates the behavior of nomads and can adjust the parameters C_1 and C_2 using experimental studies. These parameters considered to be the advantage of the Qashqai meta-heuristic algorithm over other meta-heuristic algorithms.

The results of the algorithm implementation for eleven well-known optimization functions showed that genetic(GA), particle swarm optimization(PSO), and differential evolution(DE) algorithms do not overcome the Qashqai optimization algorithm (QOA) both in terms of convergence to the optimal solution and computational speed.

As well, the results of the facility layout problem(FLP) using the Qashqai optimization algorithm (QOA) show that the responses of this algorithm are as good as the particle swarm algorithm and have a less standard deviation.

Some of the advantages of the Qashqai optimization algorithm (QOA) are as follows:

- Ability to search the answer space extensively.
- Ability to solve a vast span of optimization problems.
- Find the optimal global answer or the near-optimal solution.
- Crossing local optimization.
- The high-speed execution of the algorithm.
- The simplicity of the algorithm structure and implementation for solving complex optimization problems.
- The excellent convergence speed to the optimal solutions.
- The ability to evade local optimal points.
- The low standard deviation of the final solutions.
- It does not require gradient information.
- Requires few parameters to adjust.
- It is elite-oriented and concatenates particular importance to swarm intelligence.

The application of the Qashqai algorithm in various combinatorial optimization problems is one of the possible areas of research. Furthermore, it suggests to present an optimal strategy for the initial distribution of nomads and adjust the algorithm parameters for future research. For future research, suggested that the Qashqai optimization algorithm (QOA) utilized to solve various problems of continuous and discrete optimization, data clustering, feature selection problem, distribution of power generation and systems, design and optimization of communication networks, digital signals processing, and pattern recognition, design Automated and robotic systems, forecasting of economic models.

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