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Hybrid Inverse Weed Optimization Algorithm with Math-Flame Optimization Algorithm

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Abstract: In this work, two Meta-Heuristic Algorithms were hybridized, the first is the Invers Weed optimization algorithm (IWO), which is a passing multiple algorithm, and the second is the Moth-flame Optimization Algorithm (MFO). Which depend in their behavior on the intelligence of the swarm and the intelligence of society, and they have unique characteristics that exceed the characteristics of the intelligence of other swarms because they are efficient in achieving the right balance between exploration and exploitation. So the new algorithm improves the initial population that is randomly generated, A process of hybridization was made between the IWO and MFO Algorithm to call The new hybrid algorithm (IWOMFO). The new hybrid algorithm was used for 16 high-scaling optimization functions with different community sizes and 250 repetitions. The Algorithm showed access to optimal solutions by achieving the value Minority (f_{min}) for most of these functions and the results of this algorithm are compared with the basic algorithms IWO, MFO

Keywords: optimization, Invasive Weed Optimization Algorithm, Moth-Flame optimization Algorithm, Crossbred Algorithms

INTRODUCTION

Classical optimization techniques, based on derivatives, need a clear-define starting point and are remarkably close to the final solution or are very likely to falls into local solutions. The flaws in the calculations have prompted researchers to search for Meta-Heuristic algorithms that are based on simulating some natural phenomena in the past. (Basak, Pal, Das, Abraham, & Snasel, 2010).

Optimization is the process of searching for a solution to reduce the function according to the data of the problem, where the process is summarized by filtering the variables of the problem to reduce or increase the efficiency of the function for a purpose to the fullest extent, and most of the problems of classical algorithms are the time spent from creating to optimal solutions, despite the use of modern technologies , it may require several years to solve a big problem, and in recent years, post-intuitive algorithms have been developed as an acceptable solution to optimization problems, and many of them have been inspired by naturalness and can be defined as Meta-Heuristic algorithms, which are techniques that start with an initial set of variables. As an initial group of society and then ends to achieve the minimum or avoid falling into local solutions .(Razmjooy & Ramezani, 2014)

Almost non-linear Optimization problems arise in engineering problems, and most of their problems lack variables continuity, which is a major necessity for exploiting derived

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Optimization methods, For efficiency and improvement, scientists and engineers from various disciplines are forced to deal with the classical problems of global improvement by defining a set of parameters or variables for a situation that provides a *f mim* or *f max* for a cost worth, a function or a set of specific worths, so There has been an growing interest in applying algorithms Meta-Heuristic (Ahmadi & Mojallali, 2012; Basak, Maity, & Das, 2013). Often a post-intuitive algorithm, inspired by nature, can be classified into three categories: evolutionary intelligence, physics, and swarm intelligence. Since swarm intelligence is characterized by simplicity in the development and effective results of a set of problems, some of them have made them attractive and very popular .(حسن & خضر, 2019). Over the past two decades, researchers tend to use Meta-Heuristic algorithms, where the great majority of optimization techniques are either Heuristic algorithms or Meta-Heuristic algorithm.
Meta-Heuristic algorithms share combination factors between randomness and basis to simulate some natural phenomena, there are two closely related types of algorithms, first it is an Evolution Algorithm (EAS), the second is a swarm intelligence (SI) algorithm that is inspired by collective intelligence and emerging from the behavior of a group of insects (such as termites, bee and hornets) (Giri et al., 2010.)

Research Problem

The research problem dealt with finding a comprehensive optimum resolution to the problems of unconstrained optimization of high scale without falling into local solutions. Using the characteristics of algorithms

Importance Research

The aim of the Research is to propose A new hybrid Algorithm by linking The Invers Weed Optimization Algorithm, which depends on evolutionary computations with the swarm intelligence algorithm (Moth-flame Optimization Algorithm), to solve high scale optimization problems. , which are NP-hard problems.

LITERATURE REVIEW

Crossbred Algorithm

In analyzing collective behavior and the evolving properties of complex structures with a defined social structure, swarm intelligence has introduced an important aspect of artificial intelligence. Meta-Heuristic Algorithms and optimization techniques is Crossbred Algorithms, that which has brought out Anew type characterized by dynamic attitude and rise pliability, in transaction with problems in the actual world on a large-scale, although the process of combining Algorithms began in the eighties of the last century, Crossbred Algorithms has been acceptable in last years(Yaseen, Mitras, & Khidhir, 2018).
Within The framework Of combinatorial optimization (CO), algorithms can be classified into two types: complete or approximate algorithms. Working algorithms guarantee reaching the optimal solution for any harmonic optimization problem in a specific time. But if the harmonic optimization problems are of the type (NP-Hard), there is no polynomial time algorithm to solve them, and assuming that (P≠NP) therefore, complete algorithms may need time Exponential arithmetic in the worst case, and this often leads to very high computational times for practical purposes. In approximate methods such as post-intuitive, access to optimal solutions will be sacrificed in order to obtain good solutions and in much less time, and this is what made post-intuitive algorithms skip with more attention In the past 30 years
(حسن & خضر, 2019).
It was agreed to combine the components of research techniques and design trends of crossbred technologies adopted in the areas of operations research .(حسن & خضر, 2019).

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METHOD

Invasive Weed Optimization Algorithm

The emergence of problems of non-linear algorithms from a scientific and engineering point of view, and the inability to avoid falling into local solutions, so there has been a growing interest in presenting advanced algorithms, including Meta-Heuristic, to solve non-linear optimization problems, and because of their characteristics and characteristics inspired by nature. , (Ahmadi & Mojallali, 2012)

One of the characteristics of (IWO) is the method of spatial proliferation, dispersal and locative insularity.

The research process starts with making a sample, this means that the set of solutions is random, grows over the search area, then produces a sample of grains depending on the relative fitness in a sample, in other words, the number of grains for each sample person starts with a worth of S_min and increases linearly for the best individual S_max, spread These are grains at random over the search space by means of irregular numbers distributed naturally, The competitive exception is performed in the Algorithm after a number of reiteration up to the topmost , and it must by appoint to achieve this end the grains and the sample members are ranked better than the best.(Hajimirsadeghi & Lucas, 2009). These are inspired by the colonization of weeds which prove to be so strong and able to adapt to alteration in the ocean to mimic the conduct of grass. There are several basal characteristics of the operation including

1. Identifying a specific numeral of grains in the search space.
2. It grows essential with a blossom implant and output essential according to its function.
3. Randomly distribute the produced grains in the research area and grow new implants.
4. This process continues until the maximum number of plants is reached, and plants with low fitness are eliminated(Ahmadi & Mojallali, 2012)

One of the defects of the Weed Optimization Algorithm is the rapid convergence, and the working mechanism of the (IWO) Algorithm works on distributing the produced grains over the solutions area by classified random numerals similar to the average of The locations of the outputting implant, but this (IWO) Algorithm is located in the local solutions (Bai, Xiao, Liu, & Wang, 2012)

However, it is characterized by simplicity, and it has some affinities that try to avoid falling into local solutions (or convergence to the optimal level) through the use of basic characteristics for example grains, worth growth and competition(Sedighy, Mallahzadeh, Soleimani, & Rashed-Mohassel, 2010).

Algorithm Liens Weed

Algorithm liens

1. *Commence Population* :Create an initial sample of solutions and publish them on (d) of the dimensions in the search region with random postions and calculate The account of the expediency laber for this sample.

2. *.Reproduction :* The implant in a sample is allowed to produce grains (reproduction), depending on the account of its function, as well as the upper and lower limits, as the numeral of grains generated by the implant boost linearly from the lowest to the highest potential(Ahmadi & Mojallali, 2012)

The following equation shows the procedure of reproduction

$$Seed_i = floor\left(\frac{f_i - f_{min}}{f_{max} - f_{min}}(S_{max} - S_{min})\right) + S_{min} \quad (1)$$

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Floor: Round grains to the near whole number.
f_i**:** Represents a function of i of weeds.
$f_{max} - f_{min}$ **:** Lower and upper limits of the function.
$S_{max} - S_{min}$**:** Upper and lower limits of the grain .
neutralization (1) is the arithmetic relation amidst the numeral of grains and the worth of the weeds mission, as the numeral of grains diminution with the growing in the worth of the function, and the numeral of grains domain between S_{max} & S_{min}, and in a better way we assume that Weed 5 and Weed 1 are the best and worst weeds among 5 of the given weeds, so the number of grains around Weed 1 equals S_{max} and the number of grains around Weed 5 equals S_{min}

3. *Spatial Dispersal :*This step provides the Weeds Algorithm with a feature of randomness and adaptation, as the at random created grains are dispense over (d) of the distances in the search space by casual numerals that are naturally dispense at A rate (μ = 0) and a variable difference according to neutralization (2), and this agency that the grains will be Its distribution is casual so that it is located close to the parent plant, but the Standard Deviation (σ) of the random mission will decrease from A predetermined premier value (σ premier) to a last value (σ last) At each step (all obstetrics), the non-linear transformation in the simulation displayed a satisfying showing in the next neutralization:

$$iter = \frac{(iter_{max} - iter\ )^n}{(iter_{max})^n}(\sigma\ initial - \sigma\ final) + \sigma\ final \quad (2)$$

as
σ iter: represents the standard deviation.
$iter_{max}$: appears the upper numeral of repetitions.
n: represents the non-linear transformation index (Sedighy, Mallahzadeh, Soleimani, & Rashed-Mohassel, 2010).
And now calculate the position of the new grains through the following equation:

$$x_{son} = x_{parent} + Sd = x_{parent} + rand(0,1) * \sigma\ iter \quad (3)$$

as
x_{son}: Represents the position of the offspring,
x_{parent}: represents the location of the parents,
Random: generates scalar naturally distributed random numbers (1,0).

4. *Competitive Exception :* If the implant does not reproduce, it will become extinct, so there is a requirement for a type of contest between implants in the colony P_{max}, by excluding implants with weak function for that generation, where the exclusion technique doing as follow up: When the extreme numeral of Weeds in the settlement is extended, All Weed is allowed to output seed, and then the output grain are allowed to prevalence in the position , when all the grain have found their positions in the search space, they are arranged with their origin (as a settlement of Weeds). Then seeds with low function are removal to reach the extreme allowable limit for the sample in the settlement.

In this way, grain and their progeny are arranged both and the element with the best function will survive while allowing the process of repetition within the Algorithm. This mechanism gives an opportunity for grain with low function to reproduce, and the community dominance technique is used to the progeny also until of finish the a certain stage, which achieves Competitive Exclusion(Mehrabian & Lucas, 2006).

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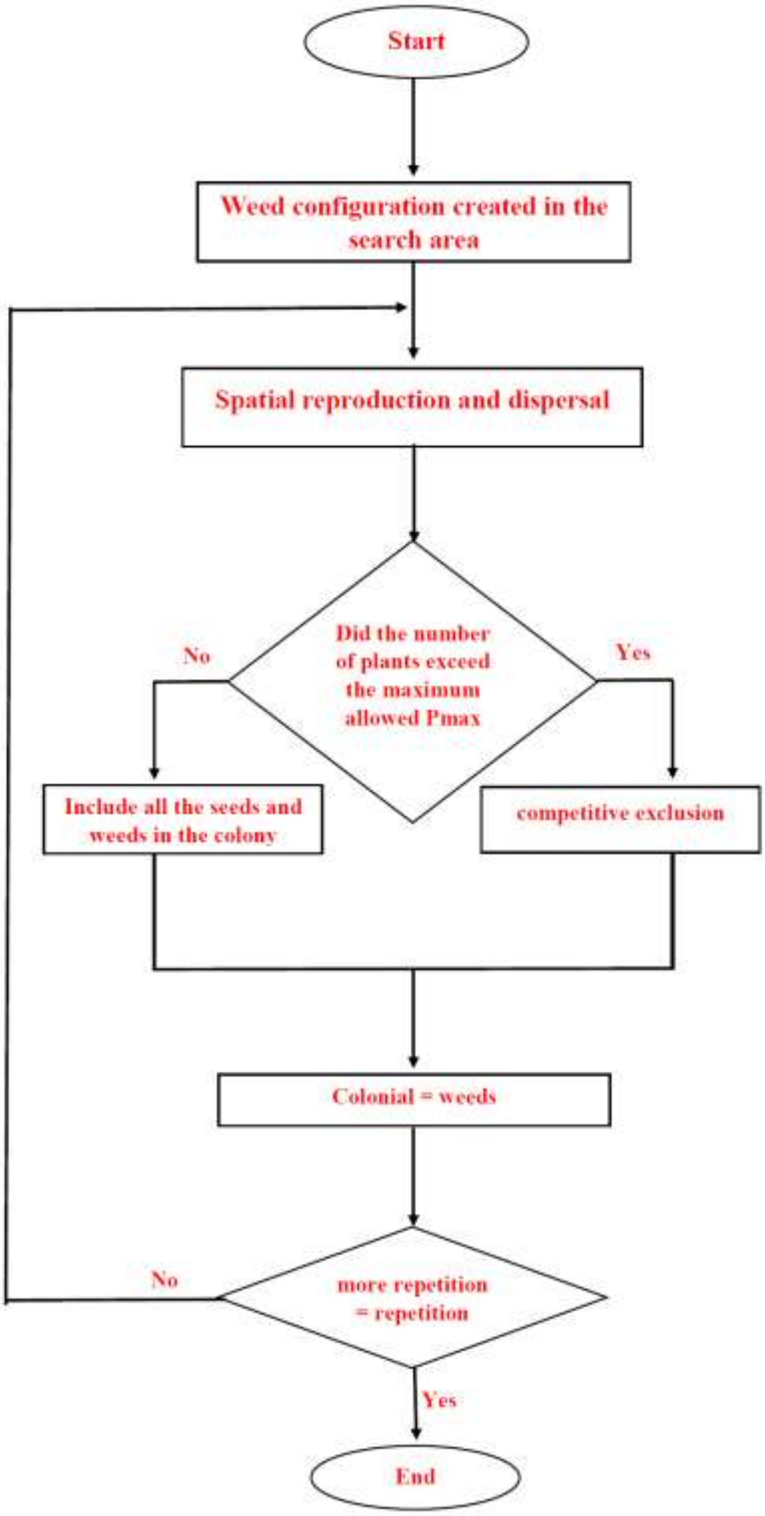

Flowchart of Inverse Weed optimization Algorithm

The aim of this diagram is to clarify the steps of the Inverse Weed algorithm and how to moving in the initialization of the primary community to spatial reproduction and dispersal, and whether the desired goal has been achieved or not

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Moths Algorithm

1. .Inspiration Moths are a set of bug very comparable to butter flies, and one of the extreme enjoyable and unique behaviors of Moth is the saltworks path to traveling all ranges in a upright rang , they travel by maintaining a constant corner with esteemt to the moonlight (Khalilpourazari & Khalilpourazary, 2019). This insect is characterized by a styled of movement in air . Moth-fly at dark by preserving a constant corner (Mirjalili, 2015). This active way is called (Transverse Orientation). The actively of the cross trendrely on the path of the illumination exporter (Artificial light), for example when the illumination exporter is close to a Moth.

The Moths begins to fly in a spiral path around the light, and eventually leads to the approximation of the Moth to the light (Khalilpourazari & Khalilpourazary, 2019).There are more than 160,000 different species of this insect in nature. They have two main stages in their life cycle, which are larvae and adult larvae, and the larvae turn into mites by pupae. The most interesting fact about moths is their special navigation methods at night. They have evolved to fly at night using moonlight. The following figure shows an understandable transverse orientation(Mirjalili, 2015)

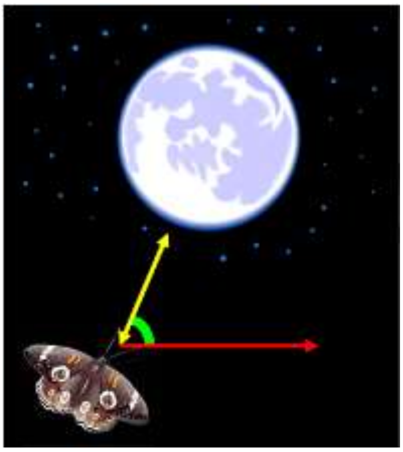

Figure (1). (Transverse orientation)

In spite of the active of the cross trendrely, generally noting that Moth-Flame travel winding about the illuminations. In truth, the Moth were played by synthetic illuminations. Such conducts appear due to the inactive of the cross trendrely. Where it is only useful to move to (Mirjalili, 2015)

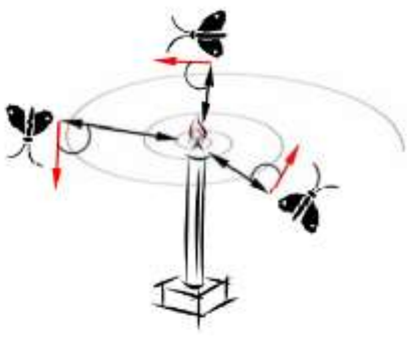

Figure (2). Spiral flight path around near light

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Moths-Flame Algorithm

1. *Moths-Flame Algorithm*

The Moth Algorithm is a sample-based Algorithm, and changes are the status of a Moth in space. The Moth is appeared by a array containing (n) the numeral of Moths and (d) represents the dimensions as pursues [17].

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \vdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \vdots & m_{2,d} \\ \vdots & \vdots & \cdots & \vdots \\ m_{n,1} & m_{n,2} & \vdots & m_{n,d} \end{bmatrix} \quad (4)$$

A function with the number of moths stored in the array is calculated as

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \quad (5)$$

(n): Represents the number of moths.

The Artificial light array has the same dimensions as the moth array, and the light array also shops the function account accordingly as a numeral of light. Both the mite and the artificial light are ornaments, but the mite is the search area and the artificial light is the best placement for the mite, and the artificial light is the one that the mite falls on during the search process, and it moves around this area and makes a selection accordingly. For this reason, mites do not lose the best solutions [17].

The location of the Moth-flame is updated according to the equation shown as follows:

$$M_{i\,j} = S(M_i, F_i) \quad (6)$$

Where as

M_i : Represents mites

F_i: Represents light

S :Represents helical motion

The motion of the insect's spiral is like a spiral logarithm and is given by the equation:

$$S(M_i, F_i) = D_i \cdot e^{bt} \cos(2\pi t) + F_i \quad (7)$$

Where b a constant that defines the shape of the helical moves and t is the casual numeral in the area [-1,1].

The light is compressed using the numeral from the following equation

$$= round\left(N - l * \frac{N-1}{T}\right) \quad (9)$$

Where

l :Is the current number of iterations

T :Is the extreme number of repetitions

N :Is the extreme number of light

The goal of this diagram is to clarify the Moth-Flame Optimization Algorithm steps and how to prepare the initial population, how to calculate fitness, calculate distance and light, then rearrange fitness and re-iteration if the required condition is met, offer the best value

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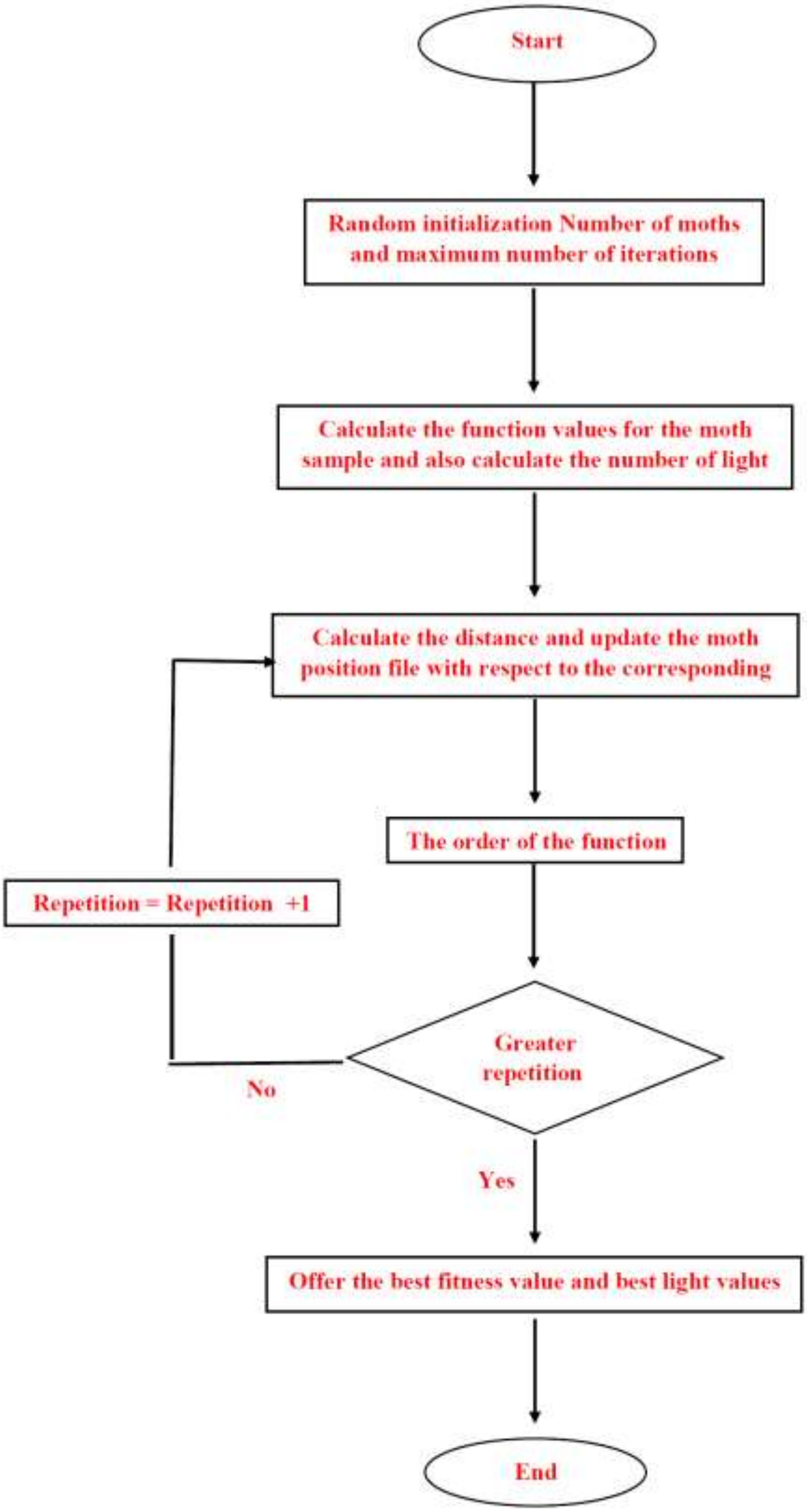

Flowchart 2. Moth-Flame Optimization algorithm

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Place Of Hybrid
Hybrid Algorithm

Flock cleverness is a section of synthetic cleverness that projects mass conduct, emerging, characteristics of the compound, ego -organizing, and decentralized control with a friendly frame. Central control and cumulative behavior are traits imposed in the flock. They have the ability to respond to environmental changes and decision-making capabilities.

In this paragraph, I propose a new hybrid Algorithm by connecting Meta-Heuristic ideas inspired by nature. In general, the (IWO) algorithm has been hybridized with (MFO), which uses flock cleverness to get it the overall Optimal settling to the Optimization problems. The new proposed algorithm was named (IWOMFO).

The IWO algorithm is distinguished from other evolutional algorithms by three ownerships: cloning, locative stampede, and competitive exemption, and the templant interest from these ownerships was completed when performing the crossbreeding style.

The lines of the hybrid Algorithm (IWOMFO) are:

1. Initializing an initial sample by produce an first sample of settlements and studied a function worth for this sample.
2. Propagation and production of new grain using equation No. (1), as it allows the property of propagation to produce the new generation (children).
3. Spreading essentials in the search space (locative stampede). This feature confers the IWO algorithm the capability to adjust and casual to use the plain allocation and norm perversion (SD), which is studied from neutralization No. (2), whom lets the seed to prevalence in the space.
4. Determining the location of the offspring in the space using neutralization No. (3). Then the fathers and sons are gathered with to form a settlement of herbs.
5. The colony consisting of origins and offspring is entered with in step (4) as an first sample for the MFO algorithm, and it is considered a random sample for the MFO algorithm, then a function is calculated for this sample time the optimization styles has started. next the better settling (solution) is obtained, the MFO algorithm performs several iterative steps until the stop condition is met These steps are as follows:

   First: Main Transaction Update of the MFO Algorithm.

   Second: Random values are generated and parameters represented by n, d are initialized, where n is the number of moths and d is the solution space

   Three: solutions are blocked from going leaving the confines of the space. list, the algorithm restoration the better settlement acquired as an parataxis to the overall optimal solution.
6. After completing all the steps of the MFO algorithm, the last sample is used, which gave the best worth for the target function in the MFO Algorithm, and considered it as a settlement of herbs to be reintroduced to the IWO algorithm, and then deem the efficiency task for this people next it has been amended.
7. The best sample is ordered setup on the worth of a task.
8. next arranging the best sample arrives the part of the third special of the IWO algorithm, which is (competitive exemption). When the extreme permissible numeral of implants in the settlement, $P_{max,}$ is scoped, the elements with lower function are excluded, and the style is refined till the optimal settling is scoped or till the case is met Stop.
9. After initializing the initial population in the Weed Algorithm and calculating the function of Reproduction, Production and Seed dissemination, we enter it into the Moth-Flame Algorithm sample and calculate the value of the function. Then we work on the improved sample and form a colony by referring it to the Weed Algorithm, arranging the sample and calculating the value of the function.

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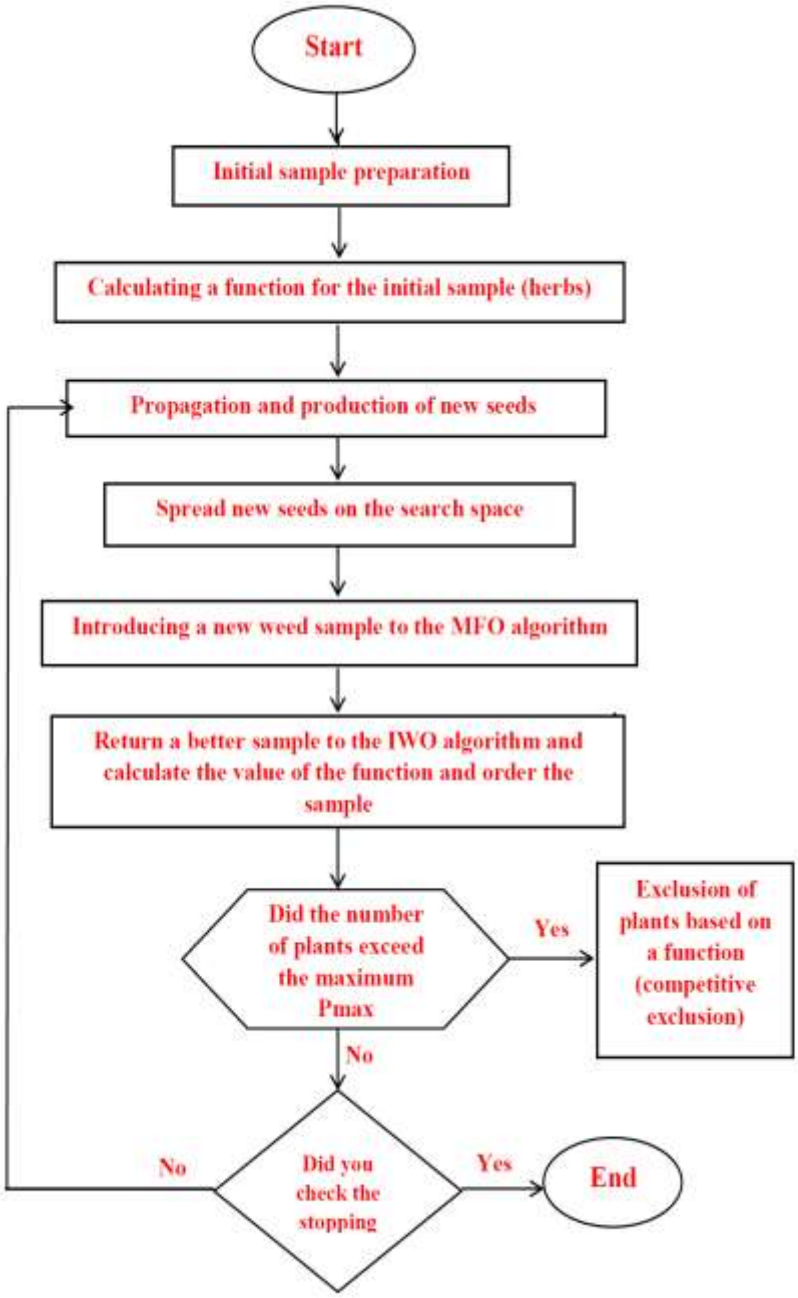

Flowchart3. illustrates the steps of the new algorithm (IWOMFO)

Function details, number of iterations and type of functions
Practical side
The efficiency of the new proposed algorithm (IWOMFO) was tested by using it to solve (16) problems of numerical optimization of high scale. (2) The details of the test functions as well as the special range, min worth (fmin) for each function, lower bounds and upper bounds for each function. The new proposed algorithm (IWOMFO) is a combination of IWO and MFO examples, so it contains parameters These two algorithms are shown in the numbered table.(1)

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Table 1. Algorithms parameters to be determined before starting the program

Parameter	The Description	IWO	MFO	IWOMFO
MaxIt	Maximum number of repetitions	250	250	250
npop0	Primary sample size	10	10	10
Npop	Maximum sample size	25		25
Smin	Minimum number of seeds	0	—	0
Smax	Maximum number of seeds	5	—	5
n	Nonlinear Transformation Indicator	2	—	2
σ_{initial}	The initial value of the standard deviation	0.5	—	0.5
σ_{final}	The final value of the standard deviation	0.001	—	0.001

Table 2. Details of the test functions and the minimum value of each function

Function	Dim	Range	*Fmin*
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	$[-100,100]$	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$	30	$[-10,10]$	0
$F_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_i)^2$	30	$[-100,100]$	0
$F_4(x) = \max_i\{\lvert x_i\rvert . 1 \le i \le n\}$	30	$[-100,100]$	0
$F_5(x) = \sum (100 * (x_{i+1}: \dim \quad) - (x_i: \dim \quad)^2 + ((x_{i+1}: dim - 1) - 1)^2$	10	$[-30,30]$	
$F_6(x) = \sum_{i=1}^{n} ([x_i \quad + 05])^2$	30	$[-100,100]$	0
$F_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$	30	$[-1.28,1.28]$	0
$F_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i\rvert})$	30	$[-500,500]$	-418.9829
$F_9(x) = \sum_{i=1}^{n} \lvert x_i^2 - 10\cos(2\pi x_i) + 10\rvert$	30	$[-5.12,5.12]$	0
$F_{10}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	30	$[-32,32]$	0
$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	30	$[-600,600]$	0

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$F_{12}(x) = \frac{\pi}{n}\{10\sin(\pi y_i) + \sum_{i=1}^{n-1}(y_i-1)^2[1 + 10\sin^2(\pi y_{i+1}) + (y_n-1)^2\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i+1}{4} u(x_i, a, k, m) = \begin{cases} k(x_i-a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i+a)^m & x_i < a \end{cases}$	30	$[-50,50]$	0
$F_{13}(x) = 1.0\{\sin^2(3\pi x_i) + \sum_{i=1}^{n-1}(x_i-1)^2[1 + \sin^2(\pi x_{i+1}) + (x_n-1)^2[1 + \sin^2(2\pi x_n)]\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)\}$	30	$[-50,50]$	0
$F_{14}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1 - (b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^4$	4	$[-5,5]$	0.00030
$F_{15}(x) = 4x_i^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	$[-5,5]$	-1.0316
$F_{16}(x) = \left[1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)\right] * \left[30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 2x_2^2)\right]$	2	$[-5,5]$	-1.0316

RESULT

Results of the work and comparisons of the hybrid algorithm with the original algorithms

Table 3. Comparison of results between the hybrid IWOMFO Algorithm, the IWO Inverse Weed Optimization Algorithm and the MFO algorithm to find ($f_{\_min}$) and the number of iteration 250

Function	MFO	IWO	MFOIWO
F1	5.8844e-31	287.0192	0
F2	1.5876e-19	0.0014718	1.5842e-06
F3	1.7176e-06	1.3906e-07	0
F4	0.00027629	0.00050418	5.4500e-252
F5	556.6125	10.4898	3.9308
F6	6.9642e-31	320.4223	0
F7	0.0058086	0.00059557	0.0014

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F8	-3060.1026	-1235.0134	-1.6181e+03
F9	10.9445	2.985	6.9647
F10	4.4409e-15	14.8131	4.4409e-15
F11	0.22393	27.6281	0.1551
F12	1.2577e-31	23.2638	9.4233e-32
F13	2.0893e-32	1.7245e-07	3.7095e-31
F14	0.00078266	0.00061782	3.0749e-04
F15	-1.0316	-1.0316	-1.0316
F16	3	3	3

DISCUSSIONS

Discussion of Numerical Results

The results in the previous table display the victories of the crossbred algorithm (IWOMFO) in feedback the optimal settling for 16 high-scaling standard test functions in comparison with the IWO algorithm again and again with the MFO algorithm, and this confirms the success of the hybridization process. The proposed (IWOMFO) algorithm gave Better results than the algorithm IWO and MFO, the functions (F6,F3,F1) have given a perfect solution, the best of the algorithm itself, that is, there is a clear convergence. As for the functions (F13,F8,F2), we have seen in them no improvement and may be bad with the stability of the convergence value at Hybridization has a difference with the Moth-flame Algorithm. As for the function (F10), the result is equal between the hybridization algorithm and the Moth-flame Algorithm, with the knowledge that there is an improvement in it compared to the weed algorithm. As for the functions (F14, F12, F4) there is an improvement after the hybridization, but the improvement is small compared to The rest of the functions are algorithms. As for the two functions (F16, F15), there is stability of results in all algorithms, whether in hybrids or others.

CONCLUSIONS

The hybridization of the evolutionary algorithm with the meta-heuristic algorithm contributed to improving the performance of the singular post-intuitive algorithm by increasing the speed of convergence to the zero value, which is the optimal value, and also led to an improvement in the quality of the resulting solutions by increasing its exploration capabilities. And the best research, as the numerical results showed the ability of the hybrid algorithm to solve different optimization problems. The results and algorithm of weeds were compared with the algorithm of Moth-flame, which led to obtaining excellent results, as the overall optimal solution was obtained for most of the test functions.

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