A Modified Flower Pollination Algorithm for Fractional Programming Problems

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Abstract: Flower pollination algorithm is a new nature-inspired algorithm, based on the characteristics of flowering plants. In this paper, a new method is developed chaos-based Flower Pollination Algorithm (CFPA) to solve Fractional Programming Problems (FPPs). The proposed algorithm is tested using several ROP benchmarks. The test aims to prove the capability of the CFPA to solve any type of FPPs. The solution results employing the CFPA algorithm are compared with a number of exact and heuristic solution methods used for handling FPPs. Numerical examples are given to show the feasibility, effectiveness, and robustness of the proposed algorithm. The results obtained using CFPA indicated the superiority of the proposed technique among others in computational time.

Keywords: Flower Pollination Algorithm; Nature-Inspired Algorithm; Optimization; Chaos; Fractional Programming Problems.

1. Introduction

The general form of the fractional programming problems FPPs mathematical models as follows[1]

\[
\begin{aligned}
\min / \max \quad & z(x_1, \ldots, x_n) = \sum_{i=1}^{p} f_i(x) \\
\text{subject to} \quad & x \in S, x \geq 0 \\
& S = \left\{ x \in \mathbb{R}^n \mid h_k(x) \geq 0, \quad k = 1, \ldots, K; \right. \\
& m_j(x) = 0, \quad j = 1, \ldots, J; \\
& x^l_i \leq x_i \leq x^u_i, \quad i = 1, \ldots, n. \\
& g_i(x) \neq 0, \quad i = 1, \ldots, p. \\
& x_i \geq 0, \quad i = 1, \ldots, n.
\end{aligned}
\] (1)

where \( f_i(x) \), \( g_i(x) \), are supposed to be continuous functions. \( S \) is compact. Fractional programming problem is often the form (1) arise reality whenever rates such as the ratios (profit/revenue), (profit/time), (waste of raw material/quantity of used raw material), are to be maximized often these problems are linear concave-convex fractional programming.

Fractional programming problems is a nonlinear programming method that has known increasing exposure recently and its importance, in solving concrete problems, is steadily increasing. Furthermore, nonlinear optimization models describe practical problems much better than the linear optimization, with many assumptions, does. The fractional programming problems are particularly useful in the solution of economic problems in which different activities use certain resources in different proportions.

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While the objective is to optimize a certain indicator, usually the most favorable return on allocation ratio subject to the constraint imposed on the availability of resources. It also has a number of important practical applications in manufacturing, administration, transportation, data mining, etc. The solution methods to solve fractional programming problems can be broadly classified into exact and inexact approaches. Some examples of traditional approaches is that of ([2]) who introduced the parametric approach, ([3]) solved the linear fractional programming problems by converting Fractional Programming Problems FPP into an equivalent linear programming problem and solved it using already existing standard algorithms for Linear Programming. ([4], [5]) reviewed some of the methods that treated solving the FPP as the primal and dual simplex algorithm. The crisscross, which is based on pivoting, within an infinite number of iterations, either solves the problem or indicates that the problem is infeasible or unbounded. The interior point method, as well as Dinkelbach algorithms both reduces the solution of the Linear Fractional Programming LFP problem to the solution of a sequence of Linear Programming LP problems. Isbell’s Marlow method, Martos’ Algorithm, Cambini–Martein’s Algorithm, Bitran and Novaes Method, Swarp’s Method. Moreover, there are many recent approaches employing traditional mathematical methods for solving the Fractional Programming Problem FPPs such as: [6-7].

A few studies in recent years used heuristics approaches to solve fractional programming problems. ([8]) presented a genetic algorithm based method to solve the linear fractional programming problems. A set of solution point are generated using random numbers, feasibility of each solution point is verified, and the fitness value for all the feasible solution points are obtained. Among the feasible solution points, the best solution point is found out and then replaces the worst solution point. A pairwise crossover method is used for crossover and a new set of solution points is obtained. These steps are repeated.
for a certain number of generations and the best solution for the given problem is obtained. [9] developed a genetic algorithm for the class of bi-level problems in which both level objective functions are linear fractional and the common constraint region is a bounded polyhedron. [1] proposed an algorithm for the sum-of-ratios problems based harmony search algorithm. [10] developed neural networks for nonlinear fractional programming problem. The research proposed a new projection neural network model. It’s theoretically guaranteed to solve variational inequality problems. The multiobjectiveminmax nonlinear fractional programming was defined and its optimality is derived by using its Lagrangian duality. The equilibrium points of the proposed neural network model are found to correspond to the Karush Kuhn Tacker point associated with the nonlinear fractional programming problem. [11] presented a neural network method for solving a class of linear fractional optimization problems with linear equality constraints. The proposed neural network model have the following two properties. First, it is demonstrated that the set of optima to the problems coincides with the set of equilibria of the neural network models which means the proposed model is complete. Second, it is also shown that the model globally converges to an exact optimal solution for any starting point from the feasible region. [12] used particle swarm optimization algorithm for solving fractional programming problems.[13–16] introduced solution for integer fractional programming problem and complex variable fractional programming problems based swarm intelligence under uncertainty.

Flower pollination is an intriguing process in the natural world[17], [18]. Its evolutionary characteristics can be used to design new optimization algorithms. The algorithm obtained good results were dealing with lower-dimensional optimization problems[17], but may become problematic for higher-dimensional problems because of its tendency to converge very fast initially. This paper introduced an improved Flower pollination algorithm by integrating it with chaostio improve the reliability of the global optimality, also enhances the quality of the results.

This paper is organized as follows: after introduction, the original Flower pollination algorithm is briefly introduced. In section 3, the proposed algorithm is described. section 4 introduces the meaning of chaos, while the results are discussed in section 5. Finally, conclusions are presented in section 6.

2. The Original Flower Pollination Algorithm

Flower Pollination Algorithm (FPA) was founded by Yang in the year 2012. Inspired by the flow pollination process of flowering plants are the following rules:

**Rule 1:** Biotic and cross-pollination can be considered as a process of global pollination process, and pollen-carrying pollinators move in a way that obeys Le’viy flights.

**Rule 2:** For local pollination, a biotic and self-pollination are used.

**Rule 3:** Pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved.

**Rule 4:** The interaction or switching of local pollination and global pollination can be controlled by a switch probability \( p \in [0, 1] \), with a slight bias toward local pollination.

In order to formulate updating formulas, we have to convert the aforementioned rules into updating equations. For example, in the global pollination step, flower pollen gametes are carried by pollinators such as insects, and pollen can travel over a long distance because insects can often fly and move in a much longer range[17]. Therefore, Rule 1 and flower constancy can be represented mathematically as:

\[
x_i^{t+1} = x_i^t + \gamma \lambda(\lambda)(x_i^t - B)
\]  

(2)

Where \( x_i^t \) is the pollen i or solution vector \( x_i \) at iteration \( t \), and \( B \) is the current best solution found among all solutions at the current generation/iteration. Here \( \gamma \) is a scaling factor to control the step size. In addition, \( \lambda(\lambda) \) is the parameter that corresponds to the strength of the pollination, which essentially is also the step size. Since insects may move over a long distance with various distance steps, we can use a Le’viy flight to imitate this characteristic efficiently. That is, we draw \( L > 0 \) from a Levy distribution:

\[
L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi \lambda / 2)}{\pi} \frac{1}{S^{1+\lambda}}, (S >> S_0 > 0)
\]  

(3)

Here, \( \Gamma(\lambda) \) is the standard gamma function, and this distribution is valid for large steps \( S > 0 \). Then, to model the local pollination, both Rule 2 and Rule 3 can be represented as:

\[
x_i^{t+1} = x_i^t + U(x_j^t - x_i^t)
\]  

(4)

Where \( x_j^t \) and \( x_i^t \) are pollen from different flowers of the same plant species. This essentially imitates the flower constancy in a limited neighborhood. Mathematically, if \( x_j^t \) and \( x_i^t \) comes from the same species or selected from the same population, this equivalently becomes a local random walk if we draw \( U \) from a uniform distribution in \([0, 1]\). Though Flower pollination activities can occur at all scales, both local and global, adjacent flower patches or flowers in the not-so-far-away neighborhood are more likely to be pollinated by local flower pollen than those faraway.

In order to imitate this, we can effectively use the switch probability like in Rule 4 or the proximity probability \( p \) to switch between common global pollination to intensive local pollination.

To begin with, we can use a naive value of \( p = 0.5 \) as an initial value. A preliminary parametric showed that \( p = 0.8 \) might work better for most applications[17].

The basic steps of FPA can be summarized as the pseudo-code shown in Figure 1.

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**Flow pollination algorithm[17]**

**Define Objective function** \( f(x) , x = (x_1, x_2, ..., x_d) \)

**Initialize a population of n flowers/pollen gametes with random solutions**

Find the best solution \( B \) in the initial population

Define a switch probability \( p \in [0, 1] \)

while \((t < \text{MaxGeneration})\)

for \( i = 1 \) to \( n \) (all n flowers in the population)

if rand < \( p \),

Draw a \((d\text{-dimensional})\) step vector \( L \) which obeys a Levy distribution

Global pollination via \( x_i^{t+1} = x_i^t + L(B - x_i^t) \)

else

Draw \( U \) from a uniform distribution in \([0, 1]\)

Do local pollination via \( x_i^{t+1} = x_i^t + U(x_j^t - x_i^t) \)

end if

Evaluate new solutions

If new solutions are better, update them in the population

end for

Find the current best solution \( B \)

end while

---
Output the best solution found

Figure 1. Pseudo code of the Flower pollination algorithm

3. Chaos Theory

Chaos is a deterministic, random-like process found in nonlinear, dynamical system, which is non-period, non-converging and bounded. Moreover, it depends on its initial condition and parameters.[19-22]. Applications of chaos in several disciplines including operations research, physics, engineering, economics, biology, philosophy and computer science[23].

Recently chaos has been extended to various optimization areas because it can more easily escape from local minima and improve global convergence in comparison with other stochastic optimization algorithms [24]. Using chaotic sequences in flower pollination algorithm can be helpful to improve the reliability of the global optimality, and enhance the quality of the results.

3.1. Chaotic maps

At random-based optimization algorithms, the methods using chaotic variables instead of random variables are called chaotic optimization algorithms (COA) [20]. In these algorithms, due to the non-repetition and ergodicity of chaos, it can carry out overall searches at higher speeds than stochastic searches that depend on probabilities [25-26]. To achieve this issue, herein one-dimensional, noninvertible maps are utilized to generate chaotic sets. We will illustrate some of well-known one-dimensional maps as:

3.1.1 Logistic map

The Logistic map is defined by:

\[ Y_{n+1} = \mu Y_n (1 - Y_n) \quad \text{for} \quad 0 < \mu \leq 4 \]  

(5)

3.1.2 Sine map

The Sine map is written as the following equation:

\[ Y_{n+1} = \frac{\mu}{4} \sin (\pi Y_n) \quad \text{for} \quad 0 < \mu \leq 4 \]  

(6)

3.1.3 Iterative chaotic map

The iterative chaotic map with infinite collapses is described as:

\[ Y_{n+1} = \sin \left( \frac{\pi x_n}{Y_n} \right) \mu \in (0,1) \]  

(7)

3.1.4 Circle map

The Circle map is expressed as:

\[ Y_{n+1} = Y_n + \alpha - \frac{x_n}{2\pi \mu} \sin (2\pi Y_n) \mod 1 \]  

(8)

3.1.5 Chebyshev map

The family of Chebyshev map is written as the following equation:

\[ Y_{n+1} = \cos (k \cos^{-1} (Y_n)) Y_n \in (-1,1) \]  

(9)

3.1.6 Sinusoidal map

This map can be represented by:

\[ Y_{n+1} = \mu Y_n^2 \sin (\pi Y_n) \]  

(10)

3.1.7 Gauss map

The Gauss map is represented by:

\[ Y_{n+1} = \begin{cases} 0 & Y_n = 0 \\ Y_n \mod 1 & Y_n \neq 0 \end{cases} \]  

(11)

3.1.8 Sinus map

Sinus map is formulated as follows:

\[ Y_{n+1} = 2.3 (Y_n)^2 \sin (\pi Y_n) \]  

(12)

3.1.9 Dyadic map

Also known as the dyadic map, bit shift map, 2x mod 1 map, Bernoulli map, doubling map or sawtooth map. Dyadic map can be formulated by a mod function:

\[ Y_{n+1} = 2Y_n \mod 1 \]  

(13)

3.1.10 Singer map

Singer map can be written as:

\[ Y_{n+1} = \mu (0.36Y_n - 23.31Y_n^2 + 28.75Y_n^3 - 13.3Y_n^4) \]  

(14)

\[ \mu \] between 0.9 and 1.08

3.1.11 Tent map

This map can be defined by the following equation:

\[ Y_{n+1} = \begin{cases} \mu Y_n & Y_n < 0.5 \\ \mu (1-Y_n) & Y_n \geq 0.5 \end{cases} \]  

(15)

4. The Proposed Algorithm (CFPA) for Solving Fractional programming problems

In the proposed chaotic flower pollination algorithm, we used chaotic maps to tune the flower pollination algorithm parameter and improve the performance [19-20].

The steps of the proposed chaotic flower pollination algorithm for solving Fractional programming problems are as follows:

Chaotic Flower pollination algorithm

Define Objective function \( f(x) \), \( x = (x_1, x_2, ..., x_d) \)

Initialize a population of \( n \) flowers/pollen gametes with random solutions

Find the best solution Bin the initial population

Define a switch probability \( p_s \), where \( p \) has been chosen from chaotic sequence between \( [0,1] \)

Tuning of parameters using chaotic maps (L, \( L \), U) while (i < MaxGeneration) for i = 1 : n (all n flowers in the population)

if rand < \( p_s \),

Draw a (d-dimensional) step vector \( L \) which obeys a Lévy distribution

Global pollination via \( x_i^{t+1} = x_i^t + L \) (B - \( x_i^t \))

else

Draw \( U \) from a uniform distribution in \( [0,1] \)

Do local pollination via \( x_i^{t+1} = x_i^t + U (x_i^t - x_k^t) \)

end if

Evaluate new solutions

If new solutions are better, update them in the population

end for

Find the current best solution B

end while

Output the best solution found

Figure 2. Pseudo code of the Chaotic Flower pollination algorithm

5. Numerical Results

Ten diverse problems were collected from literature[27], [16] to demonstrate the efficiency and robustness of solving FPFPs. The obtained numerical results are compared to their relevance found in references; some examples were also solved using exact
method $f_1$ and $f_3$. Table 1 shows they attained the comparison result. In these problems, the initial parameters are set at $n = 50$ and the number of iterations is set to $t = 1000$, the selected chaotic map for all problems is the logistic map, according to the following equation:

$$ Y_{n+1} = \mu Y_n (1 - Y_n) $$

Clearly, $Y_0 \in [0, 1]$ under the conditions that the initial $Y_0 \in [0, 1]$, where $n$ is the iteration number and $\mu = 4$. The results of the CFPA algorithm are conducted from 50 independent runs for each problem. The comparison between the results determined by the proposed approach and the compared algorithms are reported in Table 1. The results have demonstrated the superiority of the proposed approach to finding the optimal solution.

All the experiments were performed on a Windows 7 Ultimate 64-bit operating system; processor Intel Core i5 760 running at 2.81 GHz; 4 GB of RAM and code was implemented in MATLAB.

5.1. Test problem 1

This problem is defined as:

$$ f_1: \max \ z = \frac{4x + 2y + 10}{x + 2y + 5} $$

subject to $x + 3y \leq 30$

$$ -x + 2y \leq 5; \quad x, y \geq 0 $$

5.2. Test problem 2

The two-dimensional Schaffer 2 function defined as:

$$ 0.5 + \frac{\sin \left( \sin \left( x^2 + y^2 \right) \right) - 0.5}{\left( 1 + 0.001 \left( x^2 + y^2 \right) \right)^2} $$

subject to $100 \leq x_i \leq 100; \quad i = 1, 2$

5.3. Test problem 3

This problem is defined as:

$$ f_3: \min \ z = \frac{x + y + 1}{2x - y + 3} $$

subject to $0 \leq x \leq 1; \quad 0 \leq y \leq 1$

5.4. Test problem 4

This problem is defined as:

$$ f_4: \max \ z = \frac{8x + 7y - 2.33(3x^2 + 4y^2)_{0.5}}{20x + 12y - 2.33(3x^2 + 2xy + 4y^2)_{0.5}} $$

subject to $2x + y \leq 18$

$$ x + 2y \leq 16; \quad x, y \geq 0 $$

5.5. Test problem 5

The two-dimensional Schaffer 4 function defined as:

$$ 0.5 + \frac{\cos \left[ \sin \left( x^2 + y^2 \right) \right] - 0.5}{\left( 1 + 0.001 \left( x^2 + y^2 \right) \right)^2} $$

subject to $100 \leq x_i \leq 100; \quad i = 1, 2$

5.6. Test problem 6

This two-dimensional sineEnvelope function defined as:

$$ f_6: \max \ z = -\sum_{i=1}^{n-1} \left[ \sin^2 \left( \frac{\sqrt{x_i^2 + x_{i+1}^2} - 0.5}{1} \right) \right] + 0.5 $$

subject to $-100 \leq x_i \leq 100$

5.7. Test problem 7

This problem is defined as:

$$ f_7: \max \ z = \frac{-x^2y^{0.5} + 2x^{0.5} - y^2 + 28x^4y + 75}{y^{1.5} + 1} $$

subject to $2x^{0.5} + xy \leq 4$

$$ x + 3x^{-1}y \leq 5; \quad x^2 - 3y^2 \leq 2; \quad 1 \leq x, y \leq 3 $$

5.8. Test problem 8

This problem is defined as:

$$ f_8: \max \ z = \frac{37x + 73y + 13}{13x + 13y + 13} + \frac{63x - 18y + 39}{13x + 26y + 13} $$

subject to $5x - 3y = 3$

$$ 1.5 \leq x \leq 3 \quad x, y \geq 0 $$

5.9. Test problem 9

This problem is defined as:

$$ f_9: \min \ z = \frac{2x + y}{x + 10} + \frac{2}{y + 10} $$

subject to $-x^2 - y^2 + 3 \leq 0$

$$ -x^2 - y^2 + 8y - 14 \leq 0$$

$$ 2x + y \leq 6$$

$$ 3x + y \leq 8$$

$$ x - y \leq 1$$

$$ 1 \leq x \leq 3; \quad 1 \leq y \leq 4 $$

5.10. Test problem 10

This problem is defined as:
Objective function value with other methods.

The obtained optimization value the proposed algorithm. Figures 2, 3 and 4 show that the proposed CPFA algorithm is able reach to global optimization in $f_2$, $f_3$, and $f_6$ though they have many local optimums.

Table 1: Comparison results of the CPFA with other methods.

<table>
<thead>
<tr>
<th>Test problem</th>
<th>Technique/Reference</th>
<th>Decision variable optimal value</th>
<th>Objective function value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$ (max)</td>
<td>C.C. Transformation “Exact Method”</td>
<td>$(x^<em>,y^</em>)=(30,0)$</td>
<td>$z^*=3.714286$</td>
</tr>
<tr>
<td></td>
<td>Dinkelbach algorithm “Exact Method”</td>
<td>$(x^<em>,y^</em>)=(30,0)$</td>
<td>$z^*=3.714286$</td>
</tr>
<tr>
<td></td>
<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(30,0)$</td>
<td>$z^*=3.7142857$</td>
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<tr>
<td>$f_2$ (min)</td>
<td>C.C. Transformation “Exact Method”</td>
<td>none</td>
<td>none</td>
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<tr>
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<td>Dinkelbach algorithm “Exact Method”</td>
<td>none</td>
<td>none</td>
</tr>
<tr>
<td></td>
<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(0.0008)$</td>
<td>$z^*=0.0056$</td>
</tr>
<tr>
<td>$f_3$ (min)</td>
<td>C.C. Transformation “Exact Method”</td>
<td>$(x^<em>,y^</em>)=(0.0)$</td>
<td>$z^*=0.333$</td>
</tr>
<tr>
<td></td>
<td>Dinkelbach algorithm “Exact Method”</td>
<td>$(x^<em>,y^</em>)=(0.0)$</td>
<td>$z^*=0.333$</td>
</tr>
<tr>
<td></td>
<td>[26] “Neural Network”</td>
<td>$(x^<em>,y^</em>)=(0.5,3)$</td>
<td>$z^*=4.5$</td>
</tr>
<tr>
<td></td>
<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(0.0)$</td>
<td>$z^*=0.333$</td>
</tr>
<tr>
<td>$f_4$ (max)</td>
<td>C.C. Transformation “Exact Method”</td>
<td>none</td>
<td>none</td>
</tr>
<tr>
<td></td>
<td>Dinkelbach algorithm “Exact Method”</td>
<td>none</td>
<td>none</td>
</tr>
<tr>
<td></td>
<td>[29] “Goal Setting and Approximation”</td>
<td>$(x^<em>,y^</em>)=(7.229,0)$</td>
<td>$z^*=0.084$</td>
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<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(1.0264,5.7391)$</td>
<td>$z^*=0.3383$</td>
</tr>
<tr>
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<td></td>
<td>$(x^<em>,y^</em>)=(1.025,6.268)$</td>
<td>$z^*=0.3385$</td>
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<td>$f_5$ (max)</td>
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<td>Dinkelbach algorithm “Exact Method”</td>
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<tr>
<td></td>
<td>CPFA</td>
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<td>C.C. Transformation “Exact Method”</td>
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<td>$f_7$ (max)</td>
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<td></td>
<td>[30] “Global Optimization”</td>
<td>$(x^<em>,y^</em>)=(1.1)$</td>
<td>$z^*=5.5167$</td>
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<tr>
<td></td>
<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(1.1)$</td>
<td>$z^*=5.5167$</td>
</tr>
<tr>
<td>$f_8$ (max)</td>
<td>C.C. Transformation “Exact Method”</td>
<td>none</td>
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</tr>
<tr>
<td></td>
<td>Dinkelbach algorithm “Exact Method”</td>
<td>none</td>
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</tr>
<tr>
<td></td>
<td>[31] “Global Optimization”</td>
<td>$(x^<em>,y^</em>)=(3,4)$</td>
<td>$z^*=5$</td>
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<tr>
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<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(3,4)$</td>
<td>$z^*=5$</td>
</tr>
<tr>
<td>$f_9$ (min)</td>
<td>C.C. Transformation “Exact Method”</td>
<td>none</td>
<td>none</td>
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<tr>
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<td>Dinkelbach algorithm “Exact Method”</td>
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<tr>
<td></td>
<td>[6] “Global Optimization”</td>
<td>$(x^<em>,y^</em>)=(1.1,4.1442)$</td>
<td>$z^*=0.48558$</td>
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<td>CPFA</td>
<td>$(x^<em>,y^</em>)=(1.1,4.14)$</td>
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<td>Dinkelbach algorithm “Exact Method”</td>
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<tr>
<td></td>
<td>[11] “HS”</td>
<td>$(x^<em>,y^</em>,v^*)=(1.5,1.5,1.1)$</td>
<td>$z^*=8.1207$</td>
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</tbody>
</table>

The numerical results obtained using the proposed algorithm are compared to exact methods and metaheuristic techniques as shown in table 1. Four exact methods were selected for solving the 10 benchmark functions and carrying out the comparison. The four methods are C.C. Transformation, Dinkelbach algorithm, Goal setting and approximation and global optimization. Neural network and harmony search are the other two metaheuristic intelligent techniques incorporated in the compare test. The some calculations are obtained out of the numerical solutions of all the ten functions. The obtained optimization value the proposed CPFA algorithm managed to explore new solution areas that benchmark problem results using exact methods couldn’t reach that could be clearly noticed from $f_2$ to $f_{10}$ in table (1).The optimization value results for the rest functions indicates a better achievement for CPFA algorithm. Boldface figures in the table indicates the best result(s) among the algorithms. Figures 2, 3 and 4. show that the proposed CPFA algorithm is able reach to global optimization in $f_2$, $f_3$, and $f_6$ though they have many local optimums.
Design of a Gear Train

Two best

Comparison results of the corrugated bulkhead design example

<table>
<thead>
<tr>
<th>Method</th>
<th>b(cm)</th>
<th>h(cm)</th>
<th>t(cm)</th>
<th>t(cm)</th>
<th>best</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFPA</td>
<td>57.69231</td>
<td>37.2659</td>
<td>57.69231</td>
<td>1.05</td>
<td>7.008391</td>
</tr>
<tr>
<td>CS</td>
<td>57.69231</td>
<td>37.36410</td>
<td>57.69231</td>
<td>1.05</td>
<td>7.014123</td>
</tr>
<tr>
<td>FA</td>
<td>57.69231</td>
<td>38.00000</td>
<td>57.69231</td>
<td>1.05</td>
<td>7.021597</td>
</tr>
<tr>
<td>PSO</td>
<td>57.69231</td>
<td>37.56410</td>
<td>57.69231</td>
<td>1.05</td>
<td>7.025944</td>
</tr>
</tbody>
</table>

The comparison result of minimum-weight and the statistical values of the best solution obtained by CFPA, CS, FA and PSO are given in Table (2). Accuracy performance is measured in terms of the best, mean, and standard deviation values of the solutions obtained by 20 independent runs. The best minimum-weight in this study is 7.008391 with thickness 1.05 cm.

5.12. Design of a Gear Train

The below figure (5) shows the gear train problem [16]. A gear ratio between the driver and driven shafts must be achieved when designing a compound gear train. The gear ratio for gear train is defined as the ratio of the angular velocity of the output shaft to that of the input shaft. It is desirable to produce a gear ratio as close as possible to 1/6.931. For each gear, the number of teeth must be between 12 and 60. The design variables $T_a$, $T_b$, $T_{ab}$ and $T_f$ are the numbers of teeth of the gears $a$, $b$, $d$, and $f$, respectively, which must be integers.

$$\bar{x} = (T_a, T_b, T_{ab}, T_f) = [x_1, x_2, x_3, x_4]^T$$

The optimization problem is expressed as:

$$\min z = \left(\frac{1}{6.931} - \frac{|T_d||T_b|}{|T_a||T_f|}\right)^2 = \left(\frac{1}{6.931} - \frac{|x_1||x_2|}{|x_3||x_4|}\right)^2$$

subject to

$$12 \leq x_i \leq 60 \quad i = 1, 2, 3, 4$$

![Figure 5: A gear train.](image-url)

The constraint ensures that the error between obtained gear ratio and the desired gear ratio is not more than the 50% of the desired gear ratio.

Table 3: Comparison results of the CFPA, CS, FA and PSO

<table>
<thead>
<tr>
<th>Method</th>
<th>Best</th>
<th>Mean</th>
<th>StdDev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFPA</td>
<td>2.7E-012</td>
<td>2.7E-012</td>
<td>0.00E+00</td>
</tr>
<tr>
<td>CS</td>
<td>2.7E-012</td>
<td>2.7E-012</td>
<td>1.04E-010</td>
</tr>
<tr>
<td>FA</td>
<td>2.7E-012</td>
<td>2.7E-012</td>
<td>7.6868E-012</td>
</tr>
<tr>
<td>PSO</td>
<td>2.7E-012</td>
<td>2.7E-012</td>
<td>7.6868E-012</td>
</tr>
</tbody>
</table>

The comparison result obtained by the CFPA, CS, FA and PSO algorithms are given in Table (3). The comparison in terms of the best, error, mean, standard deviation values, these values obtained out of 20 independent runs. The result indicates a better achievement for CFPA, with an objective function value of 2.7 E-012.

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5.11. Corrugated Bulkhead Design

Corrugated bulkhead design [32] are often used in chemical tankers and product tankers in order to help facilities cargo tank washing effectively. This problem is as an example of minimum-weight design of the corrugated bulkheads for a tanker. Four design variables of the problem are width $(b)$, depth $(h)$, length $(l)$, and plate thickness $(t)$ for minimum-weight design of the corrugated bulkheads for a tanker, the mathematical formula for the optimization problem as follows:

Minimize $f(b, h, l, t) = \frac{5.885(b + l)}{b + \sqrt{(l^2 - h^2)}}$

subject to

$$g_1 = t \left(0.4b + \frac{1}{6}\right) - 8.94 \left(b + \sqrt{(l^2 - h^2)}\right) \geq 0$$
$$g_2 = t \left(0.2b + \frac{1}{12}\right) - 2.2 \left(8.94 + \left(b + \sqrt{(l^2 - h^2)}\right)^4\right) \geq 0$$
$$g_3 = t - 0.0156b - 0.15 \geq 0$$
$$g_4 = t - 0.0156b - 0.15 \geq 0$$
$$g_5 = t - 1.05 \geq 0$$
$$g_6 = l - h \geq 0, \quad 0 \leq b, h, l \leq 100, \text{ and } 0 \leq t \leq 5$$
6. Conclusion

The paper presents a new approach to solve FPPs based on Fractional programming algorithm with chaos. Ten-benchmark problems were solved using the proposed algorithm and many other previous approaches. The results employing the proposed algorithm were compared with the other exact and metaheuristic approaches previously used for handling FPPs. The algorithm proved their effectiveness, reliability, and competences in solving different FPPs. The proposed algorithm managed to successfully solve large-scale FPPs with an optimal solution at a finite point and an unbounded constraint set. The features and capabilities of the proposed algorithm were more evident when dealing with large-scale problems and a solution is a regular space. The computational results proved that CFPA turned out to be superior to other algorithms for all the accomplished tests yielding a higher and much faster growing mean fitness at less computational time. The proposed algorithm can extend to handle multiobjective fractional optimization.

References


