Metaheuristic algorithm approach to solve non-linear equations system with complex roots

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Abstract. Non-linear equations system is a collection of some non-linear equations that will find the best solution. Finding the solution of non-linear equations system usually by using analytical method, but there are some complex cases that cannot be solved analytically, so new methods are needed to solve them. One method that can be used to solve non-linear equations system is by using metaheuristic algorithm. This research aims to solve non-linear equations system with complex roots by using metaheuristic algorithm. The metaheuristic algorithm used in this research is Particle Swarm Optimization (PSO), Firefly Algorithm (FA) and Cuckoo Search (CS). The input of this research is non-linear equations system that will be tested and parameters of the PSO, FA, and CS algorithm. Non-linear equations system which is the object of problem is polynomial function and transcendent function, which include logarithmic function, first degree trigonometric function and exponential function. The resulting output is an approximation of the complex roots and function value. Then the obtained solution of non-linear equations system compared with the result of accuracy by finding the value of the function f(x) which is closer to zero. The result of this research obtained by comparing the value of the function produced by each algorithm showed that Particle Swarm Optimization (PSO) algorithm is better at solving non-linear equations system with complex roots because the value of the resulting function is close to zero.

1. Introduction

The problem that often arises in the field of mathematics is finding solutions of an equations system. The form of the equations system is divided into two, namely linear equations system and non-linear equations system. Non-linear equations system is a collection of several non-linear equations are sought for solution. Non-linear equations are equations that have a variable with the smallest rank of one or in the form of a transcendent function. Finding a solution from non-linear equations system is usually by using analytic methods, but there are some complex cases that cannot be solved analytically and must use numerical methods to solve them.
Numerical methods are methods used to formulate mathematical problems so that they can be solved by arithmetic or arithmetic operations. Numerical calculations offer estimation results that are close to solutions of analytical methods with small errors. Solutions from numerical methods are generated from repeated calculation processes until convergence is achieved. The most frequent method used to solve systems of non-linear equations is the Newton-Raphson method. Newton-Raphson method is a method that is faster in solving the system of non-linear equations, but still has weaknesses where this method requires to calculate the function $f(x_n)$ as well as determining the initial value of $x_n$ which is difficult and does not always find the root. Weaknesses in these methods have encouraged researchers to conduct research in order to find the most effective method for solving non-linear systems of equations, one of which is to use a metaheuristic algorithm.

The metaheuristic algorithm has an optimal search solution speed that is better than the heuristic algorithm because this algorithm will always try to get out of the local optima solution [3]. Although there is no guarantee that the answer found is the optimal solution, the solution saw will always approach the optimal solution. Some metaheuristic algorithms used include the Particle Swarm Optimization (PSO) algorithm, Firefly Algorithm (FA), and Cuckoo Search (CS).

2. Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) is a population-based swarm intelligence algorithm, discovered by Kennedy and Eberhart in 1995. The PSO algorithm is inspired by the social behavior of a herd of fish or a group of seagulls that fly together in search of food or nests. The PSO algorithm can easily reach a global or optimal point because of its ease of application to solve problems and have consistent performance. PSO algorithm is proven to be a good and effective algorithm to solve optimization problems [2].

In PSO systems, each particle has the position $z_i = [z_{i1}, z_{i2}, \ldots, z_{iN}]$ and the speed $v_i = [v_{i1}, v_{i2}, \ldots, v_{iN}]$ in the dimension N search space, where $i$ represents the ith and N particles representing search space dimensions or number of variables that are not yet known in the non-linear equation system. The initialization of the PSO algorithm begins by randomly setting the initial position of the particle and then finding the optimal value by updating its position. At each iteration, each particle updates its position following the two best values. The best solution that has been obtained by each particle is pbest and the best solution in the population is gbest. After getting the two best values, the position and speed of the particles are updated using the following equation:

$$
\begin{align*}
v_i^{t+1} &= \theta v_i^t + c_1 r_1 (pbest_i^t - z_i^t) + c_2 r_2 (gbest_i^t - z_i^t) \\
z_i^{t+1} &= z_i^t + v_i^{t+1}
\end{align*}
$$

(1)

where $v_i^t$ is the i-th particle velocity in the t-iteration, and $z_i^t$ is the i-th solution (position) on the t-iteration. $c_1, c_2$ are positive constants, in general the values $c_1 = c_2 = 2$ and $r_1, r_2$ are two random variables that are uniformly distribute between 0 to 1. In the above equation $\theta$ is the weight coefficient of inertia which shows the effect of changes in velocity from the old vector to new vector [5]. Here, $\theta$ is the weight coefficient of inertia used to reduce speed. The weight coefficient of inertia formulate as follows:

$$
\theta = \theta_{\text{max}} - i \frac{\theta_{\text{max}} - \theta_{\text{min}}}{\text{t}_{\text{max}}}
$$

where $\theta_{\text{max}}$ and $\theta_{\text{min}}$ are the initial value and the final value of the inertia weight coefficient, $\text{t}_{\text{max}}$ is the maximum number of iterations used and $i$ is the iteration.

Particle Swarm Optimization Algorithm can be seen in the Figure 1.
Start

Initial Position Initialisation, Particle Initial Speed and Max Iteration

Evaluate the Purpose Function Value and Fitness Value for Each Particle

Determine Initial pbest and Initial gbest

Update Speed ($\omega$)

Update New Individual Positions ($z$)

Re-Evaluate Values $f(z)$

Determine The New pbest and gbest Values

Iteration = Max Iteration?

No

Yes

Sorting and Find the Best Solution

End

Figure 1. Flowchart particle swarm optimization algorithm
3. Firefly Algorithm (FA)

Firefly Algorithm (FA) was first developed by Xin-She Yang in late 2007 to 2008 at Cambridge University, which is base on flashing patterns and the behavior of fireflies. FA uses three rules that are considered ideal [6], i.e.:

a. Fireflies are unisex, so one fireflies can be attracted to other fireflies without looking at their sex.

b. Interest in fireflies will be proportional to the level of brightness of the fireflies. Provided that the farther the distance between fireflies, the brightness level of fireflies will decrease or disappear. So for each blinking firefly, the dimmer fireflies will approach the lighter fireflies. If none of the fireflies are brighter, the fireflies will move randomly.

c. The objective function of the problem will determine the brightness in fireflies.

In the FA algorithm, there are two important problems, namely variations in light intensity and the formulation of attractiveness. Brightness in fireflies will be determined by the objective function and attractiveness is proportional to brightness. Thus for every two flashing fireflies, fireflies with less bright light will move towards fireflies that are brighter. The intensity of the light in fireflies is influenced by the objective function. The level of light intensity for the problem of minimizing a firefly $x$ using the following equation (2).

$$ I(x) = \frac{1}{1+f(x)} $$

Equation (2)

Attractiveness ($\beta$) is of relative value, because the light intensity must be seen and assessed by other fireflies. Thus, the results of the assessment will differ depending on the distance between the fireflies one with the other $r_{ij}$. In addition, the intensity of light will decrease from the source due to absorbed by the media, such as air. So that attractiveness ($\beta$) can be determined with the distance $r$ as follows:

$$ \beta = \beta_0 e^{-\gamma r^2} $$

Equation (3)

where $\beta_0$ is the attraction when there is no distance between the fireflies ($r = 0$) and $\gamma \in [0,100]$ is the coefficient of light absorption. Most of the Firefly Algorithm implementations using $\beta_0 = 1$.

The distance between the fireflies $i$ and $j$ at the $z_i$ and $z_j$ positions respectively is the Cartesian distance formulated as in equation (4).

$$ r_{ij} = \|z_i - z_j\| = \sqrt{\sum_{t=1}^{n}(z_{i^t} - z_{j^t})^2} $$

Equation (4)

with $z_{i^t}$ is the $t$-component of $z_i$ on firefly $i$ and $z_{j^t}$ is the $t$-component of $z_j$ on firefly $j$.

Movement is a movement made by firefly $i$ because of interest in another firefly $j$, the intensity of the light is brighter. With the movement, the firefly’s position or solution of the firefly will change according to equation (5).

$$ z_i^{t+1} = z_i^t + \beta (z_j^t - z_i^t) + \alpha \left( rand - \frac{1}{2} \right) $$

Equation (5)

with the first term being the old position of firefly, the second term occurs because of interest, the third term is the random firefly movement where $\alpha$ is the coefficient of the random parameter and rand is the random number in the interval $[0,1]$. Firefly Algorithm can be seen in the Figure 2.
Start

Initial Position Initialisation, \( \gamma \), \( \beta_0 \), and MaxGen

Randomly Generating Initial Populations

Calculate the Light Intensity of Each Firefly \( I(x) \)

\[ i = 1/n \\
\]

\[ j = 1/n \]

No

\[ I(x) > I(x) \]

Yes

Update Movement Firefly

Determine \( g_{best} \)

Comparing the Best Firefly with \( g_{best} \)

Update Movement on the Best Firefly

Iteration = MaxGen?

No

Yes

Sorting and Find The Best Solution

End

Figure 2. Flowchart firefly algorithm
4. Cuckoo Search (CS) Algorithm

Cuckoo search is a metaheuristic algorithm developed by Xin-she Yang and Suash Deb in 2009. This algorithm is inspired by the parasitic nature of several cuckoo species that lay their eggs in other host bird nests (from other species). Some host birds can be in direct conflict with a disturbing cuckoo. For example, if a host bird finds an egg that is not their own, it will either throw the foreign egg or just leave the nest and build a new nest somewhere else. Some cuckoo species such as the New World brood-parasitic Tapera have evolved such that the color and pattern of their eggs mimic some of the selected host species [4].

Yang and Deb [7] formulated Cuckoo Search (CS) by utilizing Lévy Flights which is the development of random walks. Lévy Flights is a random walk distributed by Lévy. Lévy Flights is proven to be able to map fruit flies in search of food. Fruit flies in search of food will concentrate at one point then if the fruit flies feel the food there is gone, it will look elsewhere. the research also explained that Lévy Flights helps CS algorithm in search because the search step is getting wider. CS algorithm using Lévy Flights has better accuracy than other optimization algorithms in determining the optimum point.

Yang and Deb in their research revealed that there are several rules that must be met in the use of this algorithm, including:

a. Each bird lays an egg at a time and then discards the egg in a randomly chosen nest.

b. Bird nests that are considered the best will be continued for the next generation.

c. The number of bird nests in one colony is fixed.

d. The opportunity to recognize cuckoo eggs ($P_a$) placed in the nest of the original owner is 0 to 1.

The last rule can be approximated by the $P_a$ parameter to determine the worst solution of $n$ nests that will be randomly replaced with new nests. In the matter of maximization, to simplify its application a simple representation can be used that each egg in the nest represents a solution, and the egg represents a new solution. The aim is to use a new solution that is potentially better to replace the solution in the hive. Then the eggs in the nest will be selected and evolved by removing eggs that are considered less good. In some circumstances, the original mother nest may have two eggs, so in other words a nest can contain more than one solution. But to simplify the problem, a hive can only save one solution.

To produce a new generation $z^{(t+1)}$, the randomization process with Lévy Flights will be used which can be seen as follows:

$$z_i^{(t+1)} = z_i^t + s \odot \text{Lévy} (\alpha, \beta, \gamma, \delta)$$

where $z_i^{(t+1)}$ is a new solution, $z_i^t$ is an old solution, $s$ is the step size associated with the level of the problem being worked on and the $\odot$ sign which has a meaning of times or multiplied. Lévy Flights or so-called Lévy Stable Distribution in matlab has several parameters, including:

a. Alpha ($\alpha$), is the first form parameter.

b. Beta ($\beta$), is the second form parameter.

c. Gamma ($\gamma$), is the scale form parameter.

d. Delta ($\delta$), is the location form parameter.

Cuckoo Search Algorithm can be seen in the Figure 3.
5. Results

In this research several non-linear equation systems will be solved which are referred from several sources. The non-linear equation system used is a non-linear problem system that contains complex roots that are solved using a metaheuristic algorithm. Solving a system of non-linear equations by applying a metaheuristic algorithm that includes the Particle Swarm Optimization (PSO), Firefly Algorithm (FA), and Cuckoo Search (CS) algorithms into the form of a program in MATLAB software.
Comparing the obtained solution from each algorithm, to find a solution is considered to be the best solution. The input used is in the form of a non-linear equation system to be solved, the parameters to be used are adjusted to the algorithm to be applied. The output produced in this study is a solution of a non-linear equation system that contains complex roots. The output exposure is in the form of the best function value and convergence graph. The function value is formulated with \( f(x) = |f_1(x_1, x_2, \ldots, x_n)| + |f_2(x_1, x_2, \ldots, x_n)| + \cdots + |f_n(x_1, x_2, \ldots, x_n)| \), where the value of the function \( f(x) \) is obtained by substituting each variable on an individual to the function in the form \( z = x + iy \). The value of \( x \) is a real number element and \( y \) is an imaginary number element. While the modulus of \( z \) is obtained from the formula \( |z| = \sqrt{x^2 + y^2} \). The metaheuristic algorithm approach is said to be good, if the output produced is a function value that is close to 0.

5.1 Comparison PSO, FA and CS algorithms

Non-linear equation system that will be solved in this study consists of two, three, and four variables. The solution obtained in the form of \( x \) and \( y \) values for two variable functions, \( x \), \( y \) and \( z \) for three variable functions and \( x_1 \), \( x_2 \), \( x_3 \) and \( x_4 \) for four variable functions.

Table 1. Comparison of results of improving equations system using PSO, FA, and CS algorithms

| NO | EQUATIONS SYSTEM | SOLUTION | PSO | FA | CS |
|----|-----------------|----------|-----|----|----|
| 1  | \( e^x + xy - y - 0.5 = 0 \)  
\( \sin(xy) + x + y - 1 = 0 \) | \( x = 0.139581 - 0.0000000i \)  
\( y = 0.755203 + 0.0000000i \) | \( x = 0.139394 + 0.000000i \)  
\( y = 0.755272 - 0.000303i \) | \( x = 0.135946 + 0.008250i \)  
\( y = 0.746879 + 0.002312i \) |
| 2  | \( x^2 - 10x - y^2 + 8 = 0 \)  
\( xy^2 + x - 10y - 8 = 0 \) | \( x = 0.821210 + 0.0000000i \)  
\( y = -0.679916 - 0.0000000i \) | \( x = 0.821185 + 0.000181i \)  
\( y = -0.680054 - 0.000403i \) | \( x = 0.135946 + 0.008250i \)  
\( y = -0.682014 - 0.013216i \) |
| 3  | \( x + \cos(xy) - x^2 - 1.1 = 0 \)  
\( x^2 - 10y - e^{17} + 0.8 = 0 \)  
\( xy + y^2 - x - 0.3 = 0 \) | \( x = 0.267600 + 0.000044i \)  
\( y = -0.012505 - 0.000028i \)  
\( z = -0.409383 - 0.000531i \) | \( x = 0.426967 + 0.034005i \)  
\( y = -0.001806 + 0.002780i \)  
\( z = -0.571537 - 0.031370i \) | \( x = 0.167964 - 0.202391i \)  
\( y = -0.021490 - 0.009468i \)  
\( z = -0.292085 + 0.186998i \) |
| 4  | \( 2x^2 + y - z^2 - 10 = 0 \)  
\( 3x^2 + 6y - z^2 - 25 = 0 \)  
\( x^2 - 5y + 6z^2 - 4 = 0 \) | \( x = 2.182854 - 0.000712i \)  
\( y = 2.047349 + 0.001906i \)  
\( z = -1.256443 - 0.000839i \) | \( x = 2.183751 - 0.000836i \)  
\( y = 2.043397 + 0.003432i \)  
\( z = 1.254594 + 0.001230i \) | \( x = 2.173322 - 0.016029i \)  
\( y = 2.049876 - 0.038148i \)  
\( z = 1.256634 - 0.005217i \) |
Figure 4. SPNL function value graph No. 1 in Table 1

Figure 5. SPNL function value graph No. 2 in Table 1

Figure 6. SPNL function value graph No. 3 in Table 1

Figure 7. SPNL Function Value Graph No. 4 in Table 1

Figure 8. SPNL Function Value Graph No. 5 in Table 1
Table 2. Comparison of the accuracy results of the PSO, FA, and CS algorithms

| No | PSO | FA | CS |
|----|-----|----|----|
| 1  | 874 | 762 | 799 |
| 2  | 894 | 20  | 29 |
| 3  | 1000| 949 | 765|
| 4  | 1000| 497 | 755|
| 5  | 892 | 471 | 393|

5.2 Effects of parameters on PSO, FA and CS algorithms

The parameters that exist in the Particle Swarm Optimization algorithm, Firefly Algorithm, and Cuckoo Search are quite numerous. The main parameters in the Particle Swarm Optimization algorithm, Firefly Algorithm, and Cuckoo Search are the population = Pop, upper limit = ub, lower limit = lb, and maximum iteration = Maxiter. The parameters that will be discussed in this study are Pop of 20, 50, 100 and 200, and the initial value is randomly constructed from lb = -1 and ub = 1 with Maxiter = 500. The non-linear equation system used is:

\[ x^2 - y^2 + 3 \log(x) = 0 \]
\[ 2x^2 - xy - 5x + 1 = 0 \]

Table 3. Effects of main parameters on the PSO algorithms

| No | Pop | Solution | Value of Function | Converging Iterations to | Computational Time (seconds) |
|----|-----|----------|-------------------|--------------------------|----------------------------|
| 1  | 20  | \[ x = 1.000000 - 0.000000i \]
   |     | \[ y = -1.000000 + 0.000000i \] | \[ 2.897964495212821 \times 10^{-10} \] | 499 | 10.3233 |
| 2  | 50  | \[ x = 1.000000 + 0.000000i \]
   |     | \[ y = -1.000000 - 0.000000i \] | \[ 4.68643544159241 \times 10^{-13} \] | 500 | 27.6338 |
| 3  | 100 | \[ x = 1.000000 - 0.000000i \]
   |     | \[ y = -1.000000 + 0.000000i \] | \[ 8.57200759022556 \times 10^{-15} \] | 499 | 38.0622 |
| 4  | 200 | \[ x = 1.319206 - 0.000000i \]
   |     | \[ y = -1.603557 + 0.000000i \] | \[ 5.34905726184719 \times 10^{-15} \] | 500 | 92.5826 |
Comparison of Particle Swarm Optimization, Firefly Algorithm, and Cuckoo Search algorithms in completing the five equations systems results the function value. Comparing the function value obtained from each algorithm show that Particle Swarm Optimization algorithm is considered to have the best results. The function value produced by Particle Swarm Optimization algorithm is getting closer to zero compared to the Firefly Algorithm and Cuckoo Search algorithm.

### 6. Conclusions

Comparison of Particle Swarm Optimization, Firefly Algorithm, and Cuckoo Search algorithms in completing the five equations systems results the function value. Comparing the function value obtained from each algorithm show that Particle Swarm Optimization algorithm is considered to have the best results. The function value produced by Particle Swarm Optimization algorithm is getting closer to zero compared to the Firefly Algorithm and Cuckoo Search algorithm.

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**Table 4. Effects of main parameters on the FA algorithms**

| No | Pop | Solution | Value of Function | Converging Iterations to | Computational Time (seconds) |
|----|-----|----------|-------------------|--------------------------|-----------------------------|
| 1  | 20  | \( x = 1.000125 + 0.000090i \) \( y = -0.999503 - 0.000331i \) | 2.20016072993615 \( \times 10^{-3} \) | 347 | 86.7591 |
| 2  | 50  | \( x = 1.000181 - 0.000115i \) \( y = -1.000895 + 0.0000576i \) | 2.55169590174889 \( \times 10^{-3} \) | 257 | 480.4257 |
| 3  | 100 | \( x = 1.000031 + 0.000160i \) \( y = -0.999588 + 0.000271i \) | 2.01621396333706 \( \times 10^{-3} \) | 231 | 1464.5087 |
| 4  | 200 | \( x = 1.319050 - 0.000046i \) \( y = -1.603172 + 0.000100i \) | 1.31464061404475 \( \times 10^{-3} \) | 84 | 7932.1816 |

**Table 5. Effects of main parameters on the CS algorithms**

| No | Pop | Solution | Value of Function | Converging Iterations to | Computational Time (seconds) |
|----|-----|----------|-------------------|--------------------------|-----------------------------|
| 1  | 20  | \( x = 0.993863 - 0.001703i \) \( y = -1.006385 - 0.028711i \) | 0.104697719424556 | 295 | 9.6073 |
| 2  | 50  | \( x = 0.986025 - 0.011642i \) \( y = -0.965922 + 0.029949i \) | 8.242184244075163 \( \times 10^{-2} \) | 296 | 18.7713 |
| 3  | 100 | \( x = 1.002736 - 0.016476i \) \( y = -1.004486 + 0.035236i \) | 8.19550559869661 \( \times 10^{-2} \) | 359 | 27.7745 |
| 4  | 200 | \( x = 0.183517 - 0.086748i \) \( y = -0.306500 + 2.212700i \) | 1.070056319623024 \( \times 10^{-2} \) | 499 | 71.0541 |

The table above is the result of the influence of the large population of Pop, and the initial value obtained randomly from lb = -1 and ub = 1. The Pop parameter is the number of Particle populations. The greater the number of Pop, the time required is also greater or longer. Pop is very influential on the value of the function; the more population the function value will be closer to zero.
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