Nature-Inspired Metaheuristic Multi-Optimal Global Resource Identification Mechanism for On-Demand Mobile Users

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Summary

The ability to effectively identify a potential resource in mobile environment is challenging and difficult. Managing and utilization of the resources depends ultimately on the mobile users to identify the best available resource within close proximity. The resources can be available but the ability to choose the optimal resource amongst global multiple resources needs highly efficient optimization scheme which dynamically adapts with the mobile environment and users as well. It is very obvious that the naturally inspired metaheuristic algorithms have had greater impact in optimization field. The natural phenomenon of the nature-inspired algorithms can be used in exploiting the optimal resource which satisfies the on-demand mobile user requirement and constraints. In this paper, a naturally-inspired resource identification scheme has been proposed to effectively identify the potential resource within close proximity to the on-demand mobile users. The simulation result shows that the proposed nature-inspired multi-optimal global resource scheme has been able to determine the global optimal resource amongst the available the multiple resources and it has improved the performance and reduce the computational time when compared to conventional firefly resource scheme.

Key words:

Nature-inspired optimization, Firefly algorithm, global optimal, mobile user, resource fitness, proximity

1. Introduction

For mobile users to identify the best resource within their domain requires high precision and accuracy especially where there are multiple global solutions. There has been an explosive growth in demand for resource management and optimization scheme in on-demand mobile user's environment especially with the alarming increase in users and limited resources needed to be shared amongst the users with different requirement. The users need to identify the potential resources available and subsequently utilize the resources effectively. Hence, the mobile user may be group into clusters according to the resource they related with. The fact that the clustering is applied in data analysis and evaluation in order to divide the set of objects based on particular parameters or similarity [1] – the object can be group into clusters. Most of the research activities on clustering focus on clustering static and dynamic collection of document. There is high demand for efficient clustering schemes to accurately cluster dynamically changing objects, document and users within a particular domain. More importantly, the clustering document has been used in organizing, retrieving and extracting information from different document. This can also be applicable to users in dynamically changing environment. By dividing users based on their requirement and demands, it will assist greatly in effective utilization of resources within a particular domain or environment.

The nature-inspired based optimization techniques have been gaining much attention over the past couple of years where they have been applied in solving linear and multidimensional problems in different fields – in which conventional optimization techniques could not be able to accomplish. Particle swarm and ant colony optimizations have been used in various fields to solve optimization problems. Swarm based optimization is a family of population optimization which primarily mimic the behavior of bee, fly, fish, ant, termite and birds to solve complex problems. These natural behaviors can be extended and applied to mobile environment where multiple users within a particular domain cooperatively work together to achieve some goals or objectives.

More interestingly, it is very obvious that different algorithms have been developed to tackle different problem in different fields. These nature inspired algorithms primarily includes the ant colony, particle swarm, bee colony, fire fly etc. The key important issue is the fact that each of the techniques has its own strength and weakness – some are better in solving particular problems than others. Hence, each can be applicable to solve some particular problems with relative ease and sophistication than others. Their principle of operation is based on the interaction of large of agents following certain criterion or rules. The nature-inspired algorithms are self-learning, self-organized, robust, flexible, modular and effective. Indeed, these keys features makes the nature-inspired suitable of dynamically changing environment since they can be able to adjust and adapt with the rapid changes. It is very important to note that all the aforementioned approaches are not appropriate for dynamically changing environment. This eventually pave away for more intensive research works in order to explore

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avenues to use the nature-inspired algorithms for solving multi-global optimal problems and clustering users within a particular domain as in fig 1. The mobile users are clustered based on their closeness and effectiveness of the resources. The naturally inspired algorithms have the capability to cluster together, but the ability to select the best resources seems to be more complex especially in dynamically changing environment. In this research, fire-fly based clustering approach has been proposed to identify and cluster dynamic users within a particular domain or network. The user proximity to the resources and the resource fitness has been used in identifying and clustering the best available resource.

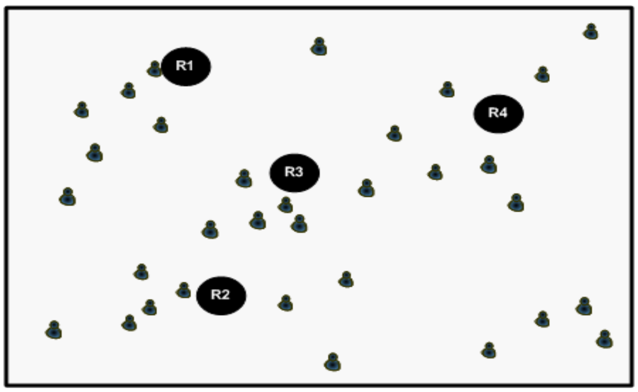


Fig. 1 Mobile users and available resources

In this paper, a multi-global optimal resource identification scheme for on-demand mobile users has been developed using the nature-inspired algorithm. Fire-fly algorithm is used to identify the available resources within close within a domain. The complexity of the optimal global resource has been effectively and efficiently solved using the natural phenomenon used by the fire-flies to detect the best global optimal resource amongst the potential resource.

The rest of the paper is organized as follows: Section 2 covers the related nature-inspired optimization and clustering works. In section 3, discusses the formulation and development of the proposed nature-inspired multi-optimal global resource identification scheme. Section 4 provides detailed experimental setup and results to measure the performance of the proposed scheme. The conclusion for the research has been drawn in Section 5.

2. Nature-Inspired Optimization & Clustering Algorithms

It is known fact that clustering has been a powerful tool for analyzing information which eventually helps in acquiring more details about a particular data and information. The primary objective for clustering is to classify data or users into domains of similar entities. This is done based on the similarity of the entities to be clustered. The need to cluster users within a domain is very important such that users could be served base on their requirements or constraints. Identifying and selecting the optimal resource would assist greatly in dealing with complex problems. Different algorithms have been developed in order to cluster data but less has been done to clustering mobile users. As mentioned earlier that clustering has initially been used to cluster document collection [2]. Subsequently, their used has been widely extended to both clustering data and document collections [3-5]. While there is dramatic need to select best resources and mobile user form cluster around resource which satisfy their requirements. The fact that metaheuristic methods were used in different fields and applications in order to achieve optimal solution in clustering domains but these algorithms need to be extended to dynamic environments. Naturally-inspired algorithms are highly efficient and effective to tackle very complex problems since they mimic the natural phenomenon and can be applicable to problems which are dynamic in nature.

In fact the firefly algorithm has been developed based on the behavior of fireflies – the algorithm has the capability of solving the global optimization problem and is highly effective. The firefly algorithm was developed by Yang Xin-She [6] and it is primarily based on the natural phenomenon of light flashing of the fire flies. In general, the firefly emits light which attracts other fireflies toward it. As the best firefly within the a particular domain attracts other flies close to it, all the flies moves toward the firefly with high brightness, it serves as best converging point for other flies and hence the algorithm selects the firefly as optimal solution for the optimization problem.

Having realized this amazing behavior of the fireflies, it can be applicable in dealing with complex problem such as identifying the best resource in on-demand multi user environment which is a bit challenging to determine the best resources in such situation - this is primarily due to the mobility of the users and the dynamic of the environment. It is very important to note that the information exchange between fireflies is pairwise while the attractiveness is associative. Thus, this will assist tremendously in sharing information and determining the best optimal resource available within the location of the mobile user. The firefly can be able to select the best possible resource even in an environment where many resources do exist based on the resource fitness and proximity.

In [7], it described that the modified firefly algorithm can be used for different applications. [8] and [9] have been used for clustering application. [10] mainly focused on the use of dynamic optimization to track changes in dynamic environment. In [11], it proposed two-tier architecture for computing platform in order to improve performance in cloud based and distributed response. Interestingly, the approach tackle the problem of mobility in cloud computing. [12] uses load balancing and task scheduling to improves the throughput and efficiency as well. A method for effective and efficient resource utilization has been proposed in [13]. It has clearly been shown in [14] that distributed resource policy can yield better job scheduling. Also, [15] proposed a model to ensure effective and efficient resource allocation.

A hybridized firefly algorithm has been used to solve the multimodal problem with many peaks in [16]. A multi swarm which uses firefly algorithm approach was reported to have been used for dynamic environment in [17]. More importantly, fire fly was used to determine the best size and optimal location for power distribution network [18]. In [19], fire fly is used in training radial basis function networks. Data objects were group using fire fly algorithm based on their attributed in [20].

The problem anticipated in finding solution in long distance has been tackle in [21] in order to avoid any premature convergence. In [22], the light intensity mechanism of fire fly was modified so that it could adjust itself depending on the problem. An approach for finding the global best for solving high dimensional problem has been proposed in [23] – this eventually reduces the time complexity. [24] has employed a technique which considers the neighbor of each population and exploration in order to enhance the overall performance.

2.1 Firefly Algorithm

Firefly algorithm is becoming an extremely important tool applicable in areas such as engineering, robotics and mathematics to solve complex problems. The firefly was initially formulated [6] as a metaheuristic search algorithm which mimics the behavior of the light of the fire flies. The fire fly is primarily based on the concept of attracting the mating partner through flashing the light. The fire fly with the highest light intensity attracts the neighboring flies toward it. This phenomenon of the fire fly can be adapted and utilized in solving very complex real world problems.

The two main component of the fire fly are the light intensity and attractiveness which serves as the criteria through the fire flies used to choose the best possible fire fly to move toward on. Both the light intensity and attractiveness depend greatly on the distance between the fire flies. The flies are assumed to attract one another base on their light intensity. The attractiveness is proportional to the light intensity (brightness). The brightness is dependent on the objective function. The light intensity can be express mathematically as follows

$$\boldsymbol{I_i = I_o e^{\sigma r_{jk}}} \tag{1}$$

I_o represents the fluorescence strength of the fire fly and r_{jk} is the distance between the flies j and k. More importantly, the attractiveness of a firefly i at the distance r can be calculated using the mathematical expression below

$$\boldsymbol{\beta_i = \beta_o e^{-\sigma r^2}} \tag{2}$$

Where B_0 is the attractiveness at the distance equal to zero (d=0). The distance between the fireflies i and j can be determine using equation (3) below. The mathematical expression in equation (3) has been used in computing the distance between two fireflies both located at the position x_i and x_j. Therefore, it can be represented as follows:

$$r_{ij} = \|x_i - x_j\| = (x_{i,k} - x_{j,k}) = \sqrt{\textstyle\sum_{k=1}^{d}(X_{i,k} - X_{j,k})^2} \tag{3}$$

The fireflies move toward another firefly based on equation (4). The movement of firefly i to firefly j can be determined using the equation as follow

$$x_i(t+1)= x_i(t)+\boldsymbol{\beta_o e^{-\sigma r_{ij}^2}}(x_i(t) - x_j(t)) + \alpha_t(t) \tag{4}$$

The position of the firefly at the time t+1 can be determined using the equation (4). The first term in the equation represents the current position of the firefly i at the time t. while the second term is the product of the attractiveness and distance **between the fireflies i and j.**

3. Multi-Optimal Global Resource Identification

In this section, the on-demand mobile user resource problem has been defined and formulated. In order to clearly define and formulate the problem through which the potential resource can be identified, there is need to critically understand the resource identification system and the function or role of each component within the mobile user environment. Fig 1 shows the typical mobile user environment with the resources placed at different distance which are surrounded by the mobile users.

3.1 Resource Identification Problem and Formulation

Initially, it has been considered that there are r set of resources available within the mobile environment. This can be represented mathematically as follows: $R = \{1, 2,..., r\}$. Also, the mobile users are assumed to be within the coverage area of the available resources. The number of mobile users are represented by $M = \{1, 2,…, m\}$, where m is the total number of mobile users tapping the resource (r) within their proximity. The connection between the mobile user and resource, and it is represented by $l \in L$. The proximity and fitness between the user and resource plays an important in determining the possibility the mobile users will connect or not. More importantly, it is assumed that all the mobile users have the prior knowledge about the resources available with their vicinity.

In this work much effort is dedicated to the development of efficient resource identification approach using the fire fly algorithm. This is mainly due to the fact there is clear connection between the aforementioned problems and how the firefly algorithm can deal with the problem through the application natural phenomenon by determining the global maximum resource amongst all the available resources. The primary goal is to effectively determine the best available within the mobile user environment based on the distance and fitness. The fitness can be compared with the firefly emitted light intensity. Indeed, adapting this interesting behavior of the fireflies would assist in dealing with the identification and assigning resources to the mobile users according to their proximity and requirement. Interestingly, it can be notice from fig 2 that more than one mobile user can connect to the nearby resource within its close proximity which has best fitness function. More importantly, it is assumed that the users (M) are mobile within the coverage area under investigation. This particular scenario will assist greatly in making analogy with the fireflies in which the brightest fly attracted other flies toward it – the resource with the highest fitness within the coverage area, attracts the users to it.

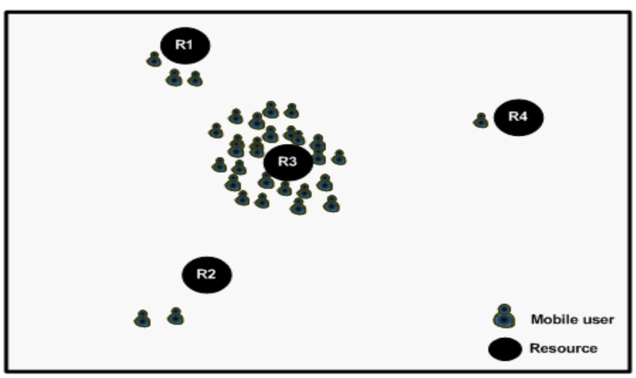


Fig. 2 System model of the available resources & mobile users.

In order to effectively represent the resource identification problem, the system model shown in fig 2 has been used. Initially, it is assumed that there are M mobile users within the area under study. This can be represented mathematically as follows:

$$M_i = \{M_1 \ldots\ldots\ldots\ldots\ldots\ldots M_N\} \quad (5)$$

Where M_i represents the number of mobile users (from 1 to N user).

It is very important to note that it has been assumed that each user has different degree of attraction to other users. In order to make more effective and simple, it is considered that the resource with higher degree of attraction are represented by R and the behavior of the resources is described by the objective function. The number of the resource is small when compared to the number of the mobile users ($Q \in M$). This can be expressed mathematically as follows:

$$R_i = [R_1, R_2 \ldots\ldots\ldots\ldots\ldots R_Q] \quad (6)$$

The value of Q is set to four (4) and it is relatively low compared to the number of the mobile users (M). More importantly, the available resources have different characteristics and qualities which the users choose from based on the resource fitness and proximity.

To determine the underutilized resources and identify the best will eventually require high precision and accurate scheme, thus the best global optimal resources can be identified with the relative ease and cost as well. Interestingly, the resources which have not been occupied can be immediately utilized by the potential users which require such services since they can be admitted easily. Also, this will assist in effective and efficient management of the users and resources especially where there are limited resources and the number of users is extremely high.

The fact that clustering mobile users based on their proximity to the available resources is extremely important in resource management and allocation. It will ultimately reduce burden on the network and provide decentralized system in which the needed resources are served by the nearest resource. This ensures effective and efficient resource utilization within the network and it reduces network complexity. The main primary objective for clustering users is to group users according to their closeness to the available resources and resource fitness as well. Suppose the number of resources to be access is *q* and the number of users to use the available resources at different proximities is represented by *i*. The number of user *i* can be distributed amongst the mobile users based on their proximities to the point through which the resources can be tapped. More importantly, it has been assumed that the available resources are limited and each has specific behavior described by the mathematical expression below. Hence, the resource identification problem can be described as follows based on equation (7).

$$Max \ \sum_{n=1} R_n \quad (7)$$

Subject to:

$$\sum_{n=j} \mathrm{d}_n \leq \mathrm{D}_j, \ \ \forall_j \in \mathrm{M} \quad (8)$$

$$\sum_{n=k} \mathrm{i}_n \leq \mathrm{I}_k, \ \ \forall_k \in \mathrm{M} \quad (9)$$

The primary object of equation (7) is to determine the best possible resource for a user based on the constraint in equation (8) and (9). Ultimately, this will ensure that the user identify and select the resource which satisfy the constraints. Hence, this will ensure effective utilization of the available resource since the mobile users are assigned based on their requirements. Equation (8) clearly describe that the distance of the mobile user should be within the maximum distance. Secondly, the fitness of the mobile user should be less than the fitness of the resource function.

3.2 Nature-inspired Metaheuristic Multi-Optimal Resource Identification Algorithm

In this section, the nature-inspired resource identification algorithm has been discussed in more detail. The nature-inspired metaheuristic multi-optimal resource identification algorithm is designed and proposed primarily to determine the best resource for users on demand in a mobile environment. Indeed, this is extremely difficult to accomplish due to the users mobility and the complexity of multi-global optimal resource identification problem. The detail procedure is described in the algorithm below:

Algorithm 1: Nature-inspired Metaheuristic Multi-Optimal Resource Identification Algorithm

```
01. Initialization: No of iterations, resources and fireflies,
    randomness, and absorption coefficient
02. Generate the number of fireflies X1, X2,.......XN
03. Set the resources and their positions
04. Sort all resources in the decreasing order of the fitness
05. Define the light intensity coefficient
06. Evaluate the fitness of the population
07. While (i < No of iterations) do
     for i = 1, 2, ...,N
       for j = 1, 2, ...,N
       Compute D and I for each user
          If ((1/N) Σ_1^N i_i ≤ I   AND   (1/N) Σ_{i=1}^N d_i ≤ D) then
    Vary the attractiveness based on the distance
    Update the value x(n+1) based on equation (4)
    Sort all the users in the decreasing order of Ii & Di
    Choose the best resource R and move toward it
          end
        end for
      end for
   end
```

3.2.1 Initialization step

To initialize the nature-inspired metaheuristic multi-optimal resource identification algorithm, the population of N size of fireflies is generated which represents the number of mobile users. These fire flies can be represented as X_1, X_2.....X_N as it has been shown in algorithm 1. Each of the generated fire fly has light intensity and attractiveness. Both the light intensity $I_i = (I_1, I_2 ...... I_N)$ and distance $D_i = (D_1, D_2 ..... D_N)$ have been taken into consideration as the key parameter used in determining the best resources. Eventually, we can make an analogy between light intensity of the fire flies and fitness of the resources. Each fire fly compared the intensity of its light with the fitness of the resource around it. Hence, the vector of the optimal resource can be represented as

$$R_i(I_i\, D_i) = [R_1\,(I_1 D_1),\, R_2\,(I_2 D_2) \ldots R_n(I_n\, D_n)] \quad (10)$$

3.2.2 Global optimal Resource search

Searching for global resource in multi-optimal environment is challenging due to fact that many global optimal do exist and require high precision technique in order to determine the best optimal resource. As it has been mentioned earlier, the flies compare their intensities regularly with the fitness of the resources as they move within the environment. The fitness of the resources is assumed to be higher than the fitness of the mobile users and hence the flies (mobile users) automatically move toward the resources.

The difference between the resources in terms of their fitness has successfully been achieved by ranking the resources based on their fitness. The fitness is directly proportional to the attractiveness. In a nutshell, the resource with higher fitness value would eventually attract the mobile user more when compared to the resource with low fitness. Each resource has different fitness and their attractiveness is entirely different as well. This can be noticed from fig 3 which shows all the four resources and their fitness. The maximum fitness is located at the center which indicated that there is every tendency that more mobile user would be attracted toward the maximum peak resource.

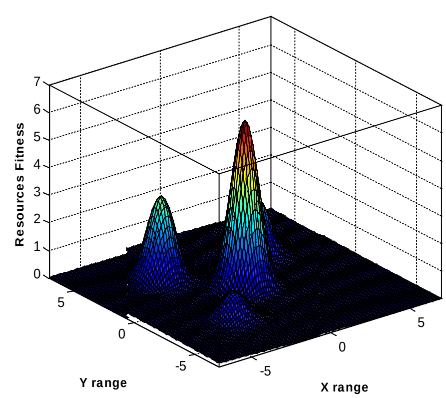


Fig. 3 Resource fitness & peaks

Each mobile user compares its fitness with the fitness of the resource. Once the best resource fitness has been determined, it moves toward it. This relationship is represented in matrix form shown as follows:

$$\begin{bmatrix} R_{I1} \\ . \\ R_{IN} \end{bmatrix} = \begin{bmatrix} I_{11} & \cdots & I_{1N} \\ \vdots & \ddots & \vdots \\ I_{N1} & \cdots & I_{NN} \end{bmatrix} \begin{bmatrix} I_1 \\ . \\ I_N \end{bmatrix} \quad (11)$$

Also, the distance between the resource and mobile user is taken into account in order to determine the best resource within its close proximity. The relation of the resource and mobile user in terms of distance can be represented in matrix form as follows:

$$\begin{bmatrix} R_{D1} \\ . \\ R_{DN} \end{bmatrix} = \begin{bmatrix} D_{11} & \cdots & D_{1N} \\ \vdots & \ddots & \vdots \\ D_{N1} & \cdots & D_{NN} \end{bmatrix} \begin{bmatrix} D_1 \\ . \\ D_N \end{bmatrix} \quad (12)$$

The resource fitness considered both the mobile user fitness and its distance to the resource – this serves as a major for selecting the best resource. The fitness of the resources is presented in matrix form as shown in equation (13).

$$\begin{bmatrix} F_1(I_1 D_1) \\ . \\ F_N(I_N D_N) \end{bmatrix} = \begin{bmatrix} I_{11} & \cdots & I_{1N} \\ \vdots & \ddots & \vdots \\ I_{N1} & \cdots & I_{NN} \end{bmatrix} \begin{bmatrix} D_{11} & \cdots & D_{1N} \\ \vdots & \ddots & \vdots \\ D_{N1} & \cdots & D_{NN} \end{bmatrix} \quad (13)$$

As can be seen from equation (13), it shows the matrix representation of the resource fitness in terms of the constraints of each mobile user. Each mobile user relates to the fitness of the available resources based on its constraint.

4. Numerical Experiments and Performance Analysis

In order to evaluate the performance of the developed nature-inspired multi-Optimal resource identification scheme, the scheme has been implemented on MATLAB environment and executed by 2.7GHz processor, 8 GB RAM and 64-bit operating system. Different test and experimentation were conducted to examine the capability of the developed scheme. The impact of various parameters on the developed scheme have been investigated to clearly the understand the behavior under different conditions. The experimentation was conducted based on the parameters and settings described in Table 1. These parameters were varied under different scenarios to determine the exact behavior of the developed algorithm when subjected to different conditions.

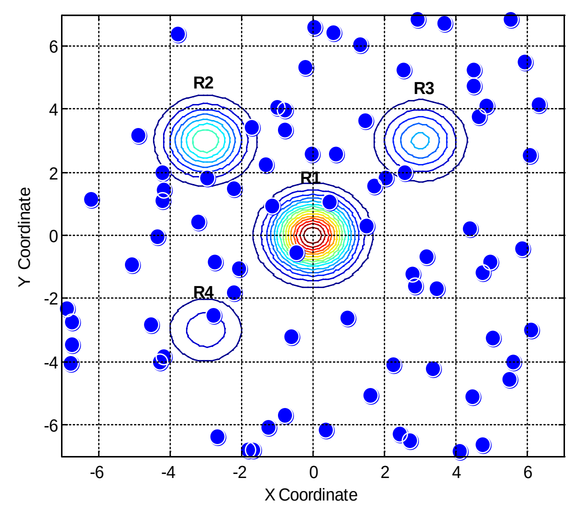
4.1 Parameters configuration

In this experimentation, the parameters used to test the performance of the developed algorithm are represented in Table 1. The parameters have been carefully chosen to meet up with the best optimal resource fitness and computational performance as well.

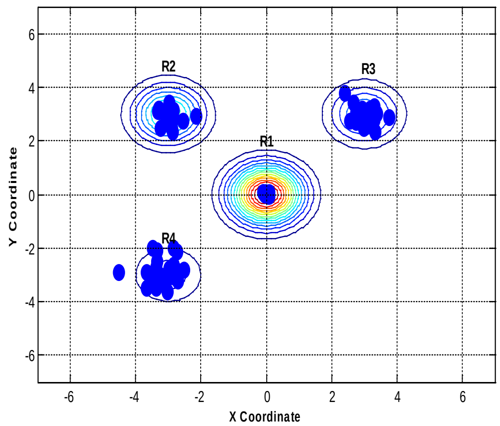
Table 1: Parameters setting

Parameter	Value
Number of fireflies	80
Number of iteration	80
Absorption coefficients	1
Number of resources	4
Randomness	0.2

The experimentation was conducted based on the above settings in table 1 and arrangement shown in fig 4(a). All readings used for performance evaluation were taken 10 times and the average value was considered. The available resources are stationary and all the users are mobile. The users mobility has been accomplish through setting their movement to be random. This is to ensure that the scenario is represented exactly as in real world situation. The resources are at the fixed position, but they all have fitness in which the mobile users make comparison. The mobile users have been randomly distributed over the environment under investigation. As it has been shown in fig 4(a), the blue filled rounded circles represent the mobile users while the bigger circles represent the four available resources which are the primary target for the on-demand mobile users.



(a)



(b)

Fig. 4 Resource and Users: (a) Initial stage (b) After several iterations.

As it can be seen from fig. 4(a), the initial stage both the users and the available resources are assumed to be deployed randomly across the environment. This typically mimic the real world scenario where by the users and resources are scattered. The four different resources were located at different coordinate and all the users can move freely within the environment. Each user can sense other users and resources within its limited range and move within the environment based on equation (2), (3), (4), (8) and (9). Each resource has different fitness function which describes its behaviour. It is assumed that the fitness is quantify in terms of attractiveness as the one exhibited by the users (Fire flies). All the flies can be able to move toward the best available resource within its close proximity. The attractiveness of the resources is much higher than the individual mobile users (flies). This is primarily to ensure and test the capability of the developed scheme when it comes to resource selection – it has been accomplished by looking at every resource as a function in which its fitness can be adjusted.

Fig 4(b) shows the mobile users clustered into four groups – each user select the best resource based on the distance and the fitness of the resource. More importantly, it can be notice that the best resource has attracted the mobile users toward it. The mobile users tend to move toward the best resource under each iteration. The resource with the best fitness has the highest concentration of the mobile users around it and has better convergence. It is very clearly that the mobile users have converged more toward the middle resource which is located at the center of the grid. This is primarily because it has the fitness which is much stronger than the other resources.

4.1 Fitness Comparison

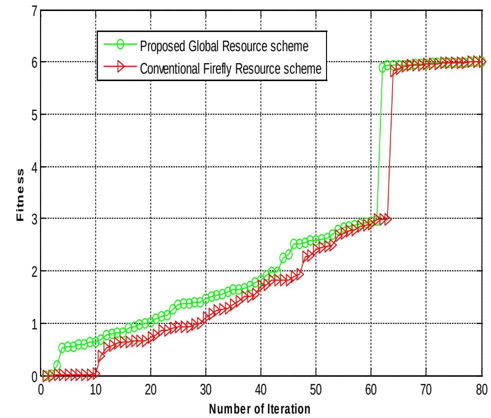


Fig. 5 Fitness and number of iteration.

Fig 5. shows how the fitness of the developed algorithm compared to conventional firefly resource scheme. increases with the increase in number of iterations. The performance of both the proposed nature-inspired metaheuristic algortihm and conventional firefly has been observed as the number of iteration changes. The maximum achievable target value for both scheme is represented by the red broken straight lines and the developed scheme progressively outperform the conventional firefly resource scheme from 0 to 63th iterations. Subsequently the fitness has been steadily increasing with the number of iterations. The developed scheme converges immediately to the maximum achievable fitness value before the conventional firefly resource scheme. As it can be notice, the nature-inspired multi-global resource identification remain relatively constant since the optimal solution has been reached. This clearly indicated how effective and efficient the proposed algorithm is in terms of convergence. In a nutshell, the proposed scheme converges faster and has high searching capability which leads to better performance and output as well.

More interestingly, the developed algorithm behavour has been examined based on the impact of increasing the users mobility (randomness) on the overall system behavour. Fig 6 demonstrated that when the randomness is low (0.1), the developed algorithm can achieve the desired target fitness much easily, but at the expense of higher number of iteration. This is very much clear and obvious that the users chance to determine the optimal resource value at relatively low randomness is more when compared to the situation when the randomness is high. Therefore, there is dramatic need to balance between accomplishing the required target and randomness as well. In a nutshell, the higher the randomness, the lower the chance or probability to determine the optimal resource available within the environment. As the randomness is increased from 0.2 upto 0.4, the capability of the developed scheme to convervege quickly to the optimal resource reduces as well. This can be seen clearly from fig 6 which shows the variation of randomness and convergence of the proposed scheme.

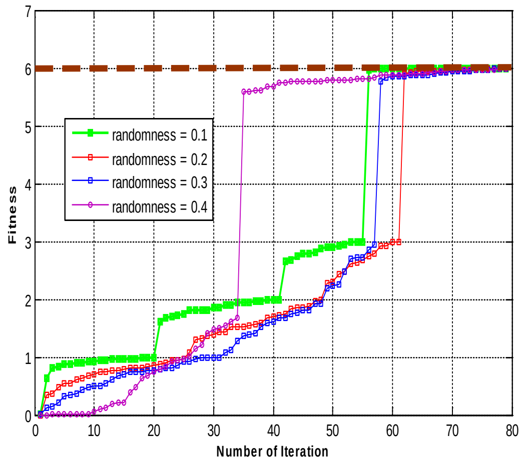


Fig. 6 Impact of higher users mobility (randomness) on the developed scheme convergence

4.2 Impact of Increasing the Number of Iteration

The impact of varying the number of iterations on the computational time for both schems has been studied in order to determine the algorithm with low computational cost. As it can be seen from fig 7, the computational time of the proposed and conventional firefly resource scheme were measured to determine the impact of increasing the number iterations on computational time needed to execute the algorithms. This is mainly to critcally analyse the relationship between the computational time and number of iterations. The computational complexity in terms time increases with the increase in number of iterations. The simulation results how clearly a linear relationship between the number of iteration and computational time. The computational time slightly increase as the number of iterations increases from 50 to 350. As can be seen in fig 7, the computational time of the proposed scheme is relatively low when compared to that of conventional firefly resource scheme. This clearly shows that the proposed algorithm can be executed within few milliseconds and hence it reduces the time computational burden as well. More importantly, the experimentation shows that the proposed algorithm has high convergence and searching capability even when dealing with complex problems.

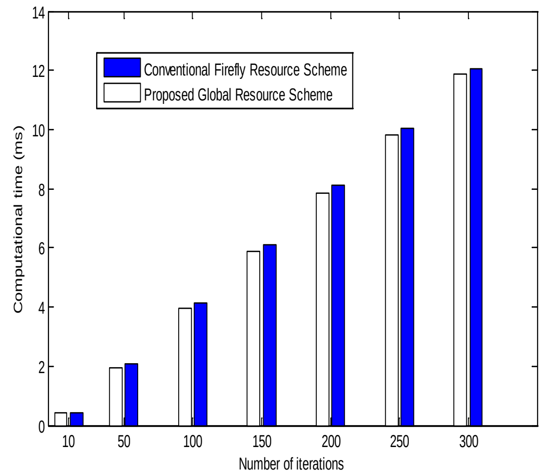


Fig. 7 Computational time and number of iterations

4.3 Impact of Increasing On-Demand Mobile users

Also, the impact of varying the number of mobile user on the computational time has been examined and observed. This is primarily to explore the relationship between the mobile users within a particular environment and the ability of the proposed to determine best resource for the users with fairness and high precision. As it can be noticed from fig 8 that the computational time is directly proportinal to the number of mobile users. Indeed, this very obvious looking at the fact that the proposed algorithm need to determine the resource which suit the on-demand mobile user requirement and constraint as well. More interestingly, it can be seen that the computational time for the scenario of increasing the number of mobile users is much higher when compared to the computational time for increasing the number of iterations. It is mainly due to the fact that it require more time and effort to search for best resource for the on-demand users.

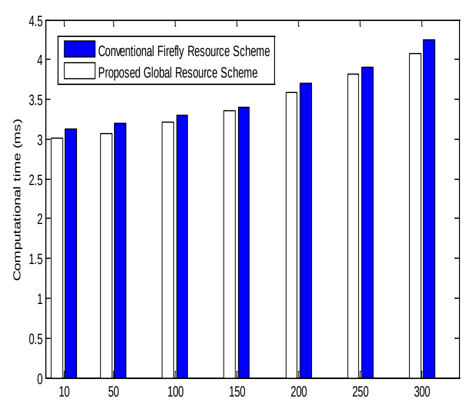


Fig. 8 Computational time and number of mobile users

The computational time for the proposed and conventional resource scheme were measured and critically analyzed as the number of mobile user's increases. From fig 8, it can be notice that the computational time for the proposed algorithm is low when compared to the conventional firefly resource scheme. This clearly indicated that the proposed nature-inspired multi-global optimal scheme has high searching and convergence capability when compared to the conventional firefly resource scheme. The results in fig 7 and 8 shows that the proposed scheme is energy efficient and it converges fast - it indicated that the performance of proposed scheme is better than the conventional resource scheme.

In order to keep track of the performance of the developed scheme, the square error for both schemes have been measured and analyzed critically as the number of iteration varies. The overall scheme rapidly reduces the square error over the period of time and this can be clearly seen in fig 9. It can be noted the nature-inspired metaheuristic scheme reduced the error difference between the targeted and achievable output as the number of iterations increases. Initially, the gap between the targeted and achievable error is much, but as the scheme converges, the error is minimized significantly. After several iterations, the overall error seems to be extremely negligible – this indicated that the error has been minimized and the algorithms have fully converged to zero. The error minimization is related to the ability of the algorithm to converge toward the targeted value. Indeed, the proposed algorithm due to its high convergence and searching capability can be reduce error to minimum better than the conventional firefly resource scheme.

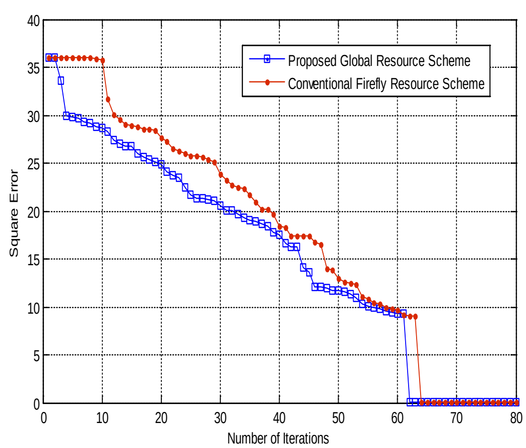


Fig .9 Square error and Number of Generations

Having developed, analyzed and evaluated the proposed algorithm for identifying the multi-optimal global resources, it is necessary to stress on the important features of the proposed scheme. Natural-inspired algorithms have tremendously assisted in dealing with many problems in optimization, classification and engineering. There is dramatic to explore more about its application in large scale optimization and its hybridization with other scheme in order to improve its capability and overall performance as well.

5. Conclusion & Future Works

In this paper, the nature-inspired multi-optimal global based resource identification scheme has been proposed to ensure effective identification and exploration of the optimal global available resources within a domain. The scheme primarily considers both the user physical proximity and resource fitness as the measures to determine the best available resource within its vicinity or coverage area. The capability of the scheme to ultimately determine the best resources even in a situation where the resources tend to have similar optimal maxima or solution is exceptional. Firstly, the resource and multi-user problem is formulated and developed. Subsequently, the nature-inspired metaheuristic has been used to solve the problem in very effective and energy efficient way. Also, the proposed scheme ultimately ensure fairness amongst clusters and users which is accomplish through allocating users based on the resource capability to accommodate the mobile users. Our future work will focus on using hybrid nature-inspired approach in order to decrease the complexity which consequently improves the efficiency and convergence of the proposed scheme while using it for resource allocations and other applications as well.

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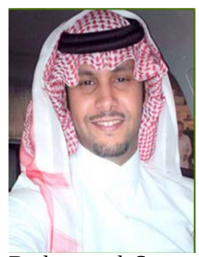

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