Drift Analysis for MPSO based MUD

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Abstract
Evaluation of an algorithm is an important aspect to check the performance of an algorithm and when one or more alternatives perform the same then it is necessary to analyze them further on the basis of some more traits. Mutant Particle Swarm Optimization (MPSO) and its two variants with and without weight relations performed the same in terms of Bit Error Rate (BER) and convergence rate for the selected MC-CDMA based system. So, evaluation of them is necessary to find out the best out of these. In this research, drift analysis is used for time complexity analysis. Simulation results have shown that MPSO with weight relation-based MC-CDMA system less complex as compared to MPSO without weight relation-based MC-CDMA system.
Key words:
MPSO, MIMO, BER, MC-CDMA

1. Introduction

Modern communication systems are now not only the source of communication (making phone calls and texting messages) but they provide a lot more. As time goes on, more emerging technologies and techniques are striving for getting to be a part of modern communication systems as these developments demand high computation speed, bandwidth, more storage capacity with low costs and accommodation of as many users as possible [1, 2]. The survival of these is usually associated with providing better data rates and improved system [3].

1.1 Multiple Access Schemes

The communication systems use multiple access schemes in their design to increase the capacity of a channel as well as to accommodate as many users as possible with the provision of a sufficient level of quality of services [1, 4, 5]. There are different schemes developed for this purpose. The former one is Frequency Division Multiple Access (FDMA) used by analog wireless systems and 1G cell phones, then Time Division Multiple Access (TDMA), Code Division Multiple carrier Access (CDMA) and Direct-Sequence CDMA (DS-CDMA) used by 2G and Wideband Code-Division Multiple Access (W-CDMA) for 3G systems [6,7,8]. But due to the use of larger bandwidth, frequency-selective multipath fading occurs [9,10,11,12] narrowband signals evolved and techniques like MC-CDMA and OFDMA schemes have been developed for 4G and even 5G systems. And some systems are using a hybrid version of these schemes [14, 15, 16].

1.2 Multiple Input Multiple Output (MIMO)

It is one of the smart antenna technologies used in recent communication systems. As in typical MIMO systems, the digital signal coming from different antennas interfere at the receiver end [17, 18, 19]. The MIMO receiver uses MUD techniques to separate them, which provides significant improvements in performance and promises better data rates and channel capacity in the MUD environment [19, 20, 21].

1.3 Multi User Detection (MUD)

The increased use of multimedia and wireless internet services increases the demand for improved data rates by minimizing the interference of signals (as it is unavoidable in such systems), so there arises a need for an efficient MUD in such an environment [22,23,24]. MUD deals with the demodulation of mutually interfering digital signals in areas like digital television, wireless communication, satellite communication, DSL, etc. [25,26,27,28]. This approach takes signals from multiple users and do joint detection, which minimizes the multiple access interference and results in a capacity increase [12]. But it is too simple for CDMA hybrids alone. Other classical algorithms like Recursive Least Square (RLS) and Least Mean Square (LMS) are used in typical multicarrier systems for multiuser detection [16, 20]. But they overheads at the receiver end due to their slow convergence rates and high BER [16, 20].

1.4 Swarm Intelligence (SI)

SI first introduced by Gerardo Beni and Jing Wang in 1989 while studying cellular robotic systems [16]. It is a discipline that deals with the natural and AI-based systems. It is inspired by the behavior of social organisms like Ant Colony, Flock of birds, school of fish, etc. There are some meta-heuristics, algorithms and their variants which belong to this domain like Evolutionary algorithms [17,18]. These techniques can be used in robotics, data mining, etc.

1.5 Particle Swarm Optimization (PSO)

PSO is an SI based heuristic method that was invented by Kennedy and Eberhard in 1995 when they were trying to simulate the movement of swarms of birds for a socio-cognitive study research idea of "united brainpower" [16]. In this method, Initial Swarm (randomly generated set of solutions) spreads now the examiner universe [16]. Over a number of iterations, the particles of swarm move towards the optimal solution. The movement is based on no. of constraints: mainly the information about the surroundings (the area under consideration) and the sharing of information by all particles of swarm [16].
This heuristic method is an international optimization line, melded on the community conduct of natural organisms; groups of birds, schools of fish, ant's colony, etc. Their movement is stimulated due to any reason like to find a rich source of food, escaping danger, avoid predators, etc. and sharing information among each other and then finding an optimal result, which will be followed by all the members of the swarm [16].
They have tested three different methods initially to check that how much iterations are needed to curtail objective to a certain level; Global Best, Local Best and the other variant of Local Best. Global Best expands the search space and new areas can be explored and it is better in terms of convergence [16, 21,22,28].
Over the last few years, different variants of PSO were developed other than conventional PSO, Binary PSO, and Discrete PSO, Mutant PSO, Partial PSO, TOMPSO, POMPSO, PFO, OPFO, Feedback Mutation PSO (FBPSO). Most of these are studied for MUD on MC-CDMA & OFDMA system and they perform better as compared to others [16].

2. System Model

In this article, two transmit antennas and one receiving antenna are used with the MC-CDMA system. The received signal vector for two consecutive symbols is given by Seo et al. [3,4], Khan et al. [16,17,18] and Ali et al. [23] as follows:

$$\beta\,(j) = [r^T(2j-1)r^H(2j)]^T \qquad (1)$$

$$\beta\,(j)= {}^{U}\sum_{i=1}\{\boldsymbol{\mu}_{i,1}di(2j-1) + \boldsymbol{\mu}_{i,2}di(2j)\}+ \mathbf{N}(j) \qquad (2)$$

In the overhead calculation, S, d, and N signify the network reply, conveyed signs and stabilizer white Gaussian sound, individually. The smallest nasty four-sided error (MMSE) of the uplink headset is accomplished by reducing the equation proposed in [16].

$$\beta[\mu_0, 1, \mu_{0,}2] = \arg\beta\,(\,\mu\,1, \mu\,2)$$

$$\beta[\mu_0, 1, \mu_{0,}2] = \{\beta_1(\,\mu\,1), \beta_2\,\mu\,2)\} \qquad (3)$$

The succeeding affiliation is planned in Seo et al. [4], Khan et al. [16, 18, 19, 20].

$$\mu_{1,2} = \mu^*_{2,3} \;and\; \mu_{1,4} = -\mu^*_{1,1}$$

The better actors purpose W can be printed as:

$$\beta\,\alpha = \beta\,\alpha\,1(\,\mu_{a,}\;\mu_b) + \beta_{z,2}(\mu_{a,}\;\mu_b) \qquad (4)$$

Where

$$\beta_{z,1}\,(\mu_a\,,\mu_b) = \in [|\mu^H\,\Omega(2j-1) + \mu_b^T\Omega * (2xj) - d_1\,(2j-1)|^2]$$

And

$$\beta_{z,2}\,(\mu_a\,,\mu_b) = €[|\mu^{\overset{H}{b}}\,\Omega(2j-1) + \mu_a^T\Omega * (2j) - d_1\,(2j-1)|^2] \qquad (5)$$

MPSO is very regularly recycled in nonlinear glitches by the optimization algorithm professionally. The MPSO is used for lessening the unruly assumed in Eqs. (4) and (5). The first one is the key cost role, and the second is the enhanced cost role.

3. Particle Swarm Optimization

In conventional PSO, few constraints need to be set. Though its conjunctions a then it sprays into limited optimal simply. To overcome this shortcoming, different approaches are developed like the Gaussian mutation PSO algorithm [16], random mutation algorithm and FBPSO [16] etc.
The mutation PSO algorithm proposed using a mutation operator. It is based on controlled mutation. The mutation process is carried out after the evaluation of fitness function. Then the fitness of the mutated population is evaluated. The positional values and velocities will be updated. These processes continue still the set criteria meet or the no. of repetitions will complete.
Opposition-based learning (OBL) was first presented by [26, 27, 28]. It was applied by [21, 22, 28] on a variety of problems effectively. The OBL concept is also used by [16] to estimate the current and opposite solutions to find improved approximation in Opposition-based Artificial Bee Colony (OABC). In OBL, the estimation of positions and opposite positions of particles is compared to analyze the current situation. The two variants of MPSO were proposed and compared by [16, 17, 18, 19] which based on partial and total opposition based computation to optimize the solution [23, 25]. These are:
calculated by

$$\overline{\boldsymbol{\beta}}_{\boldsymbol{o}}(\boldsymbol{i}) = \sum_{\boldsymbol{j=1}}^{\boldsymbol{A}} \frac{\boldsymbol{v_{ji}}}{\boldsymbol{A}}$$

4. Mutant Particle Swarm Optimization (MPSO) Algorithm:

Mutant PSO is based on controlled mutation. The elements used in MPSO are Particle, Fitness function, Limited top unit (LP), International top unit (GP), velocity update, position update, Mutation operator (MO), the fitness of mutated particles and population update [14]. These all will repeat until the set condition is satisfied as shown in figure 1.

The initial value of the mutation operator $\overline{M}_o$ is 4.

Evaluation of an algorithm means to check the computational complexity of it. It is an important aspect in the sense it predicts how efficient an algorithm is. An algorithm can be analyzed in multiple ways like cost models (one-step performance), runtime analysis (to estimate the increase in runtime as input exceeds), space complexity (the memory required), function performance (upper bounds estimation) and time complexity (the amount of time it used to run), etc. Usually, natural units are taken for the functions [21, 22, and 28]. The most commonly used complexity measures are Time complexity which refers to the total time of execution taken by an algorithm and space complexity which describes the total amount of space required by an algorithm while execution.

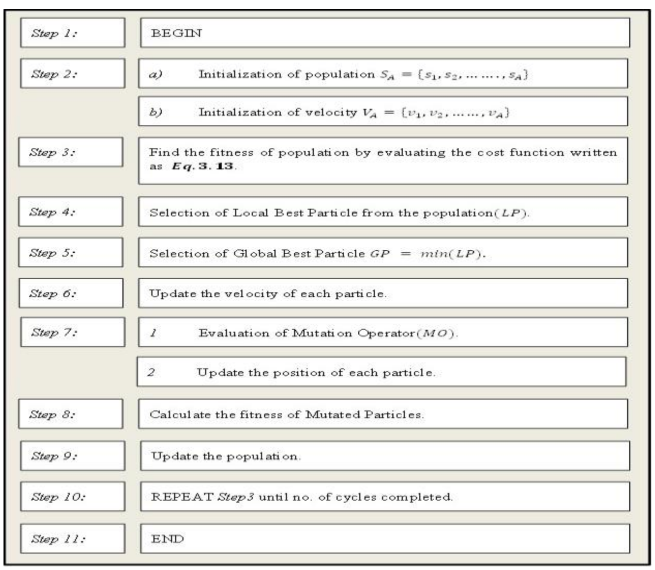

Fig. 1 Mutant Particle Swarm Optimization (MPSO) Algorithm

4.1 TIME Complexity of MPSO Based MC-CDMA SYSTEM

In an algorithm, the solution of a problem is organized systematically (sequenced) the infinite number of steps. Each step is done by computer and takes some time and occupies some space in memory. If two or more algorithms perform the same and give the same quality of results then another way to analyze the performance is complexity analysis on the basis of other factors like runtime, space utilization, etc. [26]. To find out the best out of them [16, 17, 18, 19].

As described earlier, the MPSO variants give the same BER for the system under study so, further research is done to check and compare the behavior of each on the basis of other factors. Time complexity analysis is used to check how much an algorithm is working fast or slow [20]. In this section, the time complexity analysis is represented for MPSO and its variants: un-weighted relation and weighted relation [23, 30].

4.2 Time Complexity Analysis based on Un-Weighted Relation

In un-weighted relations, all the participants are considered equally in the population of interest [26, 27]. This way of analysis is used to see the individual behavior of each participant in the system and un-weighted data considered best due to reduced standard errors, consistent and being unbiased [28]. Different steps of the MPSO and its variants are analyzed as follows:

4.3 Time Complexity Analysis of Mutant Particle Swarm Optimization (MPSO)

In this section time, complexity of each step will be calculated individually, to find out the total time used by MPSO algorithm asα_{MPSO}.

Step 2:

Step 2 represents the initialization of α_{S_A} andα_{V_A}. Here α_{S_A}represents a Time complexity of population (μ_A) and α_{V_A} represents Time complexity of velocity of each particle(Ω_A). In this research, population size depends upon 5K users and 2N no. of carriers.

$$\boldsymbol{\alpha_{S_A} = \sum_{i=1}^{5K} \sum_{j=1}^{2N} (1) = \sum_{i=1}^{5K} 2N}$$

Where,

$$\boldsymbol{2N \sum_{i=1}^{5K} (1) = 2N5K = 10\ KN}$$

So,

$$\boldsymbol{\alpha_{V_A} = \sum_{i=1}^{5K} \sum_{j=1}^{2N} (1) = 10\ KN}$$

Step 3:

After the initialization of population and velocity, the next step is the evaluation of cost function.

$$\alpha_{CF} = \sum_{i=1}^{5K} (1) = 5K$$

Step 4:

In this step time complexity of the local best particles is to be computed. In this research for the required population; first, the local best particles (LP) are sort out using merge sort in ascending order. The time complexity of the merge sort according to this problem is given below [18].

For M elements

$$\alpha_m = \begin{cases} 1, & If\ m = 1 \\ 3T\left(\frac{m}{4}\right) + m, & o.w \end{cases}$$

Assume m to be a power of 4.

$$m = 4^{\gamma}$$

$$\gamma = \log_4 m$$

$$\alpha_M = 3\alpha\left(\frac{m}{4}\right) + m$$

$$= 3\left[3\alpha\left(\frac{m}{16}\right)\right] + \left(\frac{m}{4}\right) + m$$

Similarly,

$$= 3^K\alpha\left(\frac{m}{4^K}\right) + 3^{K-1}\left(\frac{m}{4^{K-1}}\right) + \cdots + a\left(\frac{m}{16}\right) + 3\left(\frac{m}{16}\right) + m = 3^{\gamma}\alpha\left(\frac{m}{4^{\gamma}}\right) + \sum_{i=0}^{\gamma-1}\frac{3^i}{4^i}m$$

With $m = 4^{\gamma}$ and $T(1) = 1$

$$\alpha(m) = m^{\log_4 3} + \sum_{i=0}^{\log_4 m-1}\frac{3^i}{4^i}m$$

$$\therefore\ a^{\log_b m} = m^{\log_b a}$$

$$\alpha(m) = m^{\log_4 m} + m\sum_{i=0}^{\log_4 m-1}\left(\frac{3}{4}\right)i$$

$$= \sum_{i=0}^{\beta} x_i = \frac{x^{\beta+1}-1}{x-1}$$

$x = \frac{3}{4}$ and $\beta = \log_4 m - 1$

$$\alpha(m) = m^{\log_4 m} + m\frac{\left(\frac{3}{4}\right)^{\log_4 m-1} - 1}{\left(\frac{3}{4}\right) - 1}$$

Applying the log identity once more

$$\left(\frac{3}{4}\right)^{\log_4 m} = m^{\wedge}\log_4\left(\frac{3}{4}\right) = \frac{m^{\log_4 3}}{m}$$

Then put in A

$$\alpha(m) = 4m - 3m^{\log_4 3}$$

$$\log_4 3 = 4m - 3m^{0.79}$$

In this research,

$$m = 5K$$

Then,

$$\alpha_S(K) = 4.5K - 3(5K)^{0.79}$$

$$= 20K - 10.69K^{0.79}$$

$$= 20K - 11K^{0.79}$$

$$\alpha_S(K) \approx 9K$$

And for N Column

$$\alpha_S(K) \approx 9K[2N]$$

$$\alpha_{LP} = 18KN$$

Step 5:

After the assessment of local best particles, the next step is to find out the time complexity of the global best particle (GP) of the population.

$$\alpha_{GP} = constant$$

Step 6:

Below $Eq.$ 12 shows the time complexity of updating the velocity of particles.

$$\alpha_{UV} = 5K2N = 10KN$$

Step 7:

When the velocities are updated, then mutation operator is calculated using mutation operator $\overline{M}_o$ as described earlier. The time complexity of finding the mutation is taken asT_M.

$$\alpha_M = \sum_{K=1}^{5K}\sum_{j=1}^{2N}(1) = 10KN$$

After finding the mutation, the positions of each particle is calculated, the time complexity of updating the positions of particles is referred to as α_{UP}

$$\alpha_{UP} = 10KN + 10KN$$

$$\alpha_{UP} = 20KN$$

Step 8:

Now the fitness of mutated particles will be calculated as in Step 3. So, the time complexity of finding fitness is as:

$$\alpha_{MCF} = 5K$$

Step 9:

After evaluation of cost function, the positions of the population will be updated as in Step7 (b). The time consumed in this will be calculated as 20KN.

$$\alpha_{MUP} = 20KN$$

4.4 Total time Complexity of the MPSO based on Un-Weighted Relation:

Total time of execution of MPSO can be written as:

$$\alpha = \alpha_{S_A} + \alpha_{V_A} + \alpha_{CF} + [\alpha_{LP} + \alpha_{GP} + \alpha_{UV} + \alpha_M + \alpha_{UP} + \alpha_{MCF} + \alpha_{MUP}]M$$

$$\alpha_{MPSO}(N,K,M) = 5K(4N+1) + [(78N+5)K+C]M$$

So, by summarizing all we get the following result:
The above equation shows the total time complexity of the MPSO based MUD Without Weighted MC-CDMA system [31].

4.5 Time Complexity Analysis based on Weighted Relation

In un-weighted relation, sometimes the participants can be badly influenced whereas weighted parameters are nearly impartial for the population [12].
We use half the population and the rest of the population can be calculated.
The Time complexities of MPSO without weight relation is:

$$\boldsymbol{\alpha_{MPSO}(N,K,M) = 5K[4N+1] + [(78N+5)K+C]M}$$

And time complexity of MPSO with weight relation is given below:

$$\alpha_{MPSO}(N,K,M) = 5K[2N+1] + [(39N+5)K+C]M$$

Putting the value of $\frac{N}{2}$ in place of N in the above equations, weighted relations of each will be as [23].

5. Simulation & Results

Matlab is used for simulation purposes. Figure 2 -4 shown the time complexity of the MPSO based MC-CDMA system.
Figure 2 shown the time complexity of MPSO with respect to the Number of Users (K) and with different Number of Cycles like 100, 200 & 300. Topmost, middle & lower curves showed the time complexity of the MPSO based MC-CDMA system with the Number of cycles are 300, 200 & 100 respectively. It observed that the complexity of MPSO based MC-CDMA based receiver is increased when the number of users is increased. It also observed that the time complexity of the MPSO is also increased with the increase of the Number of Cycles from 100 to 300.
Figure 3 shown the time complexity of the MPSO based MC-CDMA system with respect to a different number of Cycles(M) and Different Number of Carriers (N). It clearly observed that the time complexity of MPSO is directly proportional to the number of cycles as well as a number of carriers.
Figure 4 shown the time complexity of the MPSO based MC-CDMA system with respect to different numbers of Cycles (M) and Different Number of Users (K). It clearly observed that the time complexity of MPSO is directly proportional to the number of cycles as well as the number of Users.

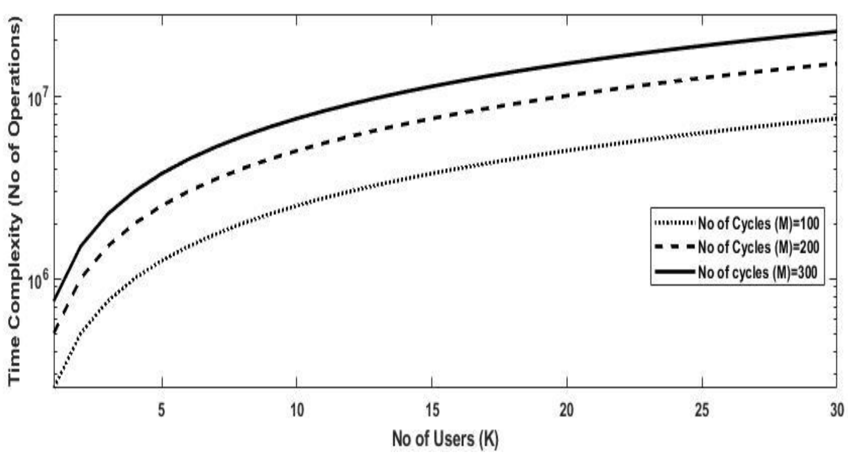

Fig. 2 Time Complexity of MPSO w.r.t K & M

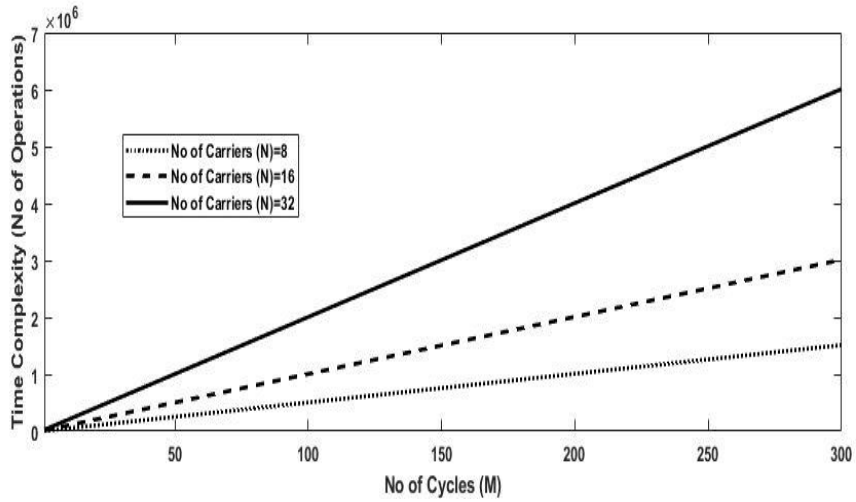

Fig. 3 Time Complexity of MPSO w.r.t M & N

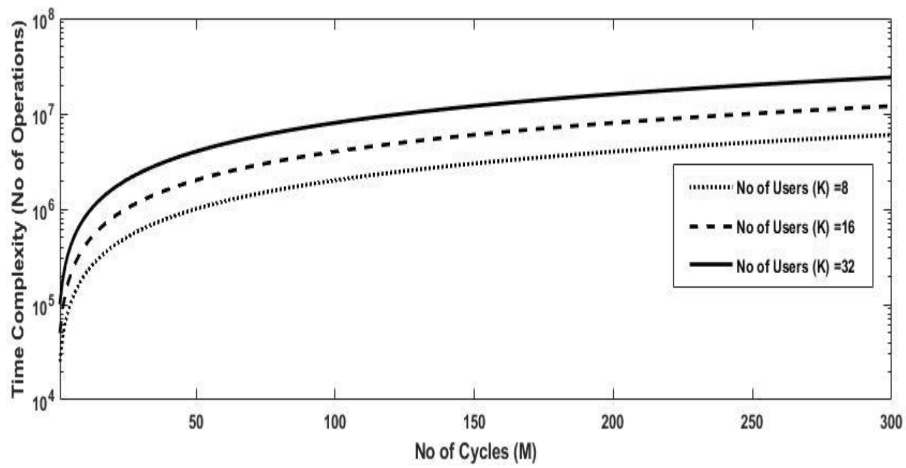

Fig. 4 Time Complexity of MPSO w.r.t M & K

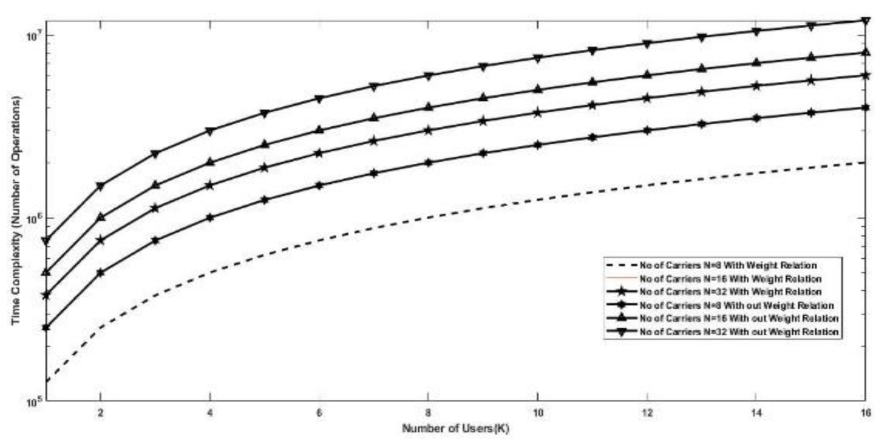

Fig. 5 Time Complexity of MPSO w.r.t M & K

Figure 5 shown the time complexity of the MPSO based MC-CDMA system with respect to different Number of Users (K) and a different number of Carriers (N) with & without weight relationship. It clearly observed that the time complexity of MPSO is increase when no of users is increased as well as a number of carriers. It also observed that MPSO with weight relationship-based MC-CDMA system complexity is less as compared to MPSO without a weight relationship-based MC-CDMA system.

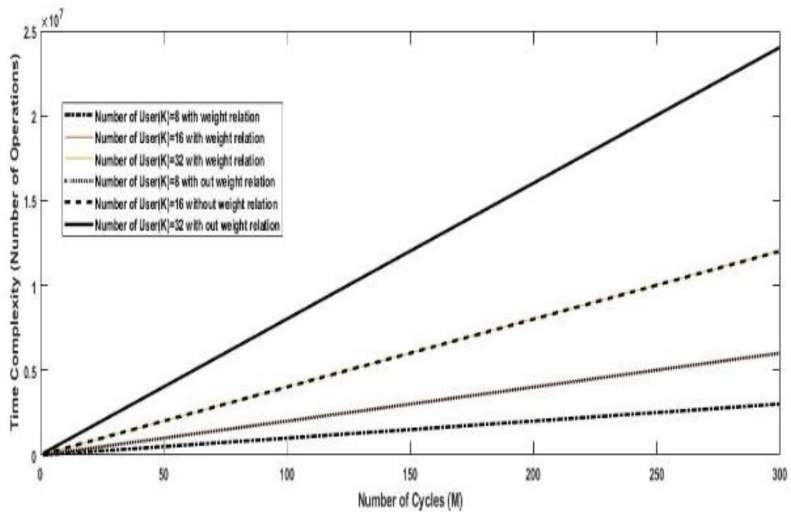

Fig. 6 Time Complexity of MPSO w.r.t M & K

Figure 6 shown the time complexity of the MPSO based MC-CDMA system with respect to different Number of Cycles (M) and a different number of Users (N) with & without weight relationship. It clearly observed that the time complexity of MPSO is increase when no of cycles is increased as well as a number of the users. It also observed that MPSO without weight relationship-based MC-CDMA system complexity is more as compared to MPSO with a weight relationship-based MC-CDMA system.

6. Conclusion

Complexity plays an important role in the selection of the best candidate solution. In this article, drift analysis is used for time complexity for the MPSO based MC-CDMA system. Simulation results showed that MPSO with weight relation gives less complexity as compared to MPSO with an unweighted relation-based MC-CDMA system.

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