

Received:  
25 September 2018  
Revised:  
11 February 2019  
Accepted:  
21 February 2019

Cite as: Swati Swayamsiddha, Prateek, Sudhansu Sekhar Singh, Smita Parija, Dilip Kumar Pratihar.  
Reporting cell planning-based cellular mobility management using a Binary Artificial Bat algorithm.  
Heliyon 5 (2019) e01276.  
doi: [10.1016/j.heliyon.2019.e01276](https://doi.org/10.1016/j.heliyon.2019.e01276)



# Reporting cell planning-based cellular mobility management using a Binary Artificial Bat algorithm

Swati Swayamsiddha<sup>a,b</sup>, Prateek<sup>b</sup>, Sudhansu Sekhar Singh<sup>b</sup>, Smita Parija<sup>c</sup>,  
Dilip Kumar Pratihar<sup>a,\*</sup>

<sup>a</sup> Indian Institute of Technology, Kharagpur, India

<sup>b</sup> Kalinga Institute of Industrial Technology, Bhubaneswar, India

<sup>c</sup> National Institute of Technology, Rourkela, India

\* Corresponding author.

E-mail address: [dkpra@mech.iitkgp.ac.in](mailto:dkpra@mech.iitkgp.ac.in) (D.K. Pratihar).

## Abstract

This paper attempts to present a novel application of Binary Artificial Bat algorithm for more effective location management in cellular networks. The location management is a mobility management task, which involves tracking of the mobile stations to locate their exact positions so that an incoming call or data can be routed to the intended mobile user. The location management cost comprises of the costs incurred by two processes, namely location registration and location search. This work focuses on network cost optimization, using Binary Artificial Bat algorithm for reporting cell planning strategy, which has not been reported yet. Results of the proposed algorithm have been compared with that of Binary Particle Swarm Optimization (BPSO) and Binary Differential Evolution (BDE) for some reference and realistic networks. The proposed approach is found to perform as good as other state-of-art techniques reported in the literature in terms of accuracy in solution, but it shows perceptible improvement in convergence speed.

Keywords: Computer science, Electrical engineering

## 1. Introduction

There has been a sea change in wireless communication as multiple users within the same house can now have a personal connection, as compared to a single fixed network per home (Wong and Leung, 2000). It is often the case that the user is not active and using the network throughout the day. Thus, there is a need for periodic interaction of the user's whereabouts within the network, called network management. Such interaction can be either from the user end (known as Location update) or from the network end (known as Paging) (Mukherjee and De, 2016). Various ways of location management have been studied in the literature that consolidates the freedom of the user within the network to varying extents (Prateek et al., 2018; Subrata and Zomaya, 2003b). Location management is a mobility management task, which involves tracking of mobile terminals, so that an incoming call or message can be routed to the intended user. To cater to the objective of minimizing the mobile location management (MLM) cost, which comprises of location update cost and paging cost, reporting cell planning-based cellular mobility management is researched upon. In this paper, the cells of the network have been categorized as "reporting" or "non-reporting", by taking clues from nature derived meta-heuristic techniques (Bettencourt, 2004; Subrata and Zomaya, 2003a, 2002; Taheri and Zomaya, 2007a).

The modified Differential Evolution (DE) developed by incorporating novel probability estimation operator (PEO) based on the distribution of estimation algorithm was found to perform better than ordinary DE because of an improved balance between exploration and exploitation (Swayamsiddha et al., 2017a,b; Wang et al., 2012). Optimum DE parameter values enabled Almeida-Luz et al. (2011) to ward off MLM cost inflation. In Kim et al. (2012), reporting cells were of paramount importance, whereas the normalized percentile dwell time distribution incorporated into the bio-inspired optimization techniques, such as GA and BPSO (Parija et al., 2017a,b) had been used for optimizing the location management cost in Swayamsiddha et al. (2017a,b). The Hopfield centric results of Taheri and Zomaya (2007b) were found to be superior as compared to that of GA. Hybrid swarm intelligence algorithms are formulated in Chaurasia and Singh (2015) to approach the network management issue. The recent algorithm developed based on bats (Yang, 2010) has a tremendous scope (Parija and Sahu, 2018) beyond the confines of usual non-communication related domains (Gao et al., 2016; Hossein Gandomi and Yang, 2012; Premkumar and Manikandan, 2015; Rahimi et al., 2016; Svecko and Kusic, 2015; Yang and He, 2013).

The span of this article picks up Binary Artificial Bat Algorithm (BABA) and puts it into the realm of cellular networks (both real and reference ones (Almeida-Luz et al., 2011; Kim et al., 2012; Subrata and Zomaya, 2002) to output the relevant cells to be designated as "reporting" to optimize cellular cost. The performance of BABA has

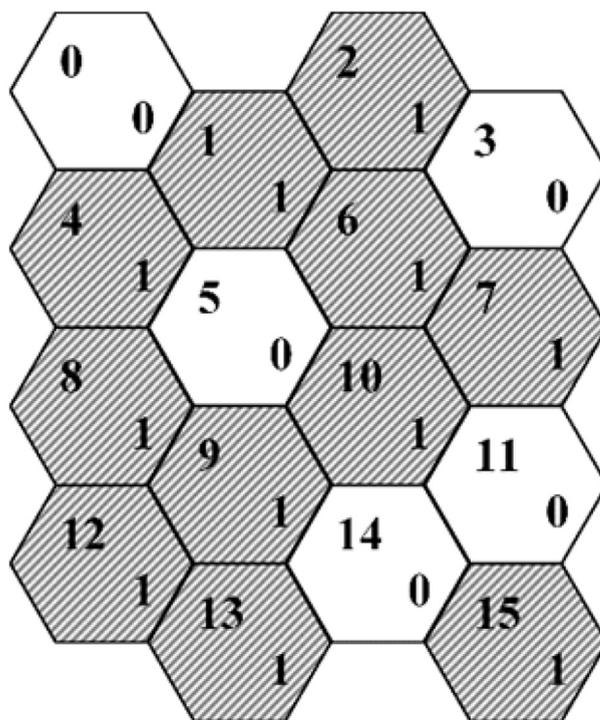
then been compared with that of the existing approaches like BDE-PEO (Binary Differential Evolution with Probability Estimation Operator) and BPSO in terms of convergence speed and the quality of the solution. This type of performance comparison has not been attempted so far on the said problem.

The remaining part of the text is organized as follows: Section 2 deals with the development of a system model based on the RCP problem. Section 3 establishes the link between MLM and BABA. The experimental simulation results, comparative analysis, and discussion are given in Section 4. Finally, some concluding remarks have been made in Section 5.

## 2. Theory/calculation

Once the cells are determined as “reporting” (Almeida-Luz et al., 2011; Kim et al., 2012), they are designated as binary 1, whereas the rest of the cells are unshaded (binary 0), as shown in Fig. 1.

The location management issue has been addressed in this paper by taking the help of reporting cell planning strategy, which also includes the concept of vicinity factor “ $v(i)$ ” for reporting and non-reporting cells (Almeida-Luz et al., 2011; Kim et al., 2012; Swayamsiddha et al., 2017a,b). The mobile location management (LM) cost is computed by adding the weighted location update cost and paging cost given in Eq. (1).



**Fig. 1.** A sample RCP configuration.

$$LM = C \times N_{LU} + N_P \quad (1)$$

where  $N_{LU}$  is the cost of location update and  $N_P$  denotes the paging/search cost (Almeida-Luz et al., 2011). The ratio of location update cost to that of paging cost is denoted by  $C$  and this factor generally takes the value of 10 (Kim et al., 2012). The location update cost depends on mobility coefficient ( $w_{mi}$ ) and the paging cost depends on the call arrival coefficient ( $w_{ci}$ ), where “ $i$ ” is the  $i^{\text{th}}$  cell of the network, as shown in Eqs. (2) and (3), respectively.

$$N_{LU} = \sum_{i \in R} w_{mi} \quad (2)$$

where  $R$  is the total RCs in the cellular network.

$$N_P = \sum_{k=0}^M w_{ck} \times v(k) \quad (3)$$

where  $M$  is the size of the network,  $w_{ck}$  and  $v(k)$  denote the call arrival coefficient and vicinity value associated with that cell, respectively. The total mobile location management cost ( $LM$ ) is calculated as the sum of Eq. (2) and Eq. (3) and is given by Eq. (4):

$$LM = C \times \sum_{i \in R} w_{mi} + \sum_{k=0}^M w_{ck} \times v(k) \quad (4)$$

The cost per call arrival ( $F$ ) is computed as a ratio of the total location management cost ( $LM$ ) to the sum of call arrivals ( $\sum_{k=0}^M w_{ck}$ ), which is represented by Eq. (5) as follows:

$$F = \frac{LM}{\sum_{k=0}^M w_{ck}} \quad (5)$$

Here, the fitness function of the optimization algorithm is  $F$  and once this function is minimized, the optimal RCP configuration is obtained.

### 3. Methodology

As mobile location management is a difficult optimization problem, bio-inspired algorithms may be useful to solve it. Bat-Algorithm was proposed by Yang (2010) in 2010, which works based on the principle of echolocation used by the bats for navigation. The beauty of this method lies in the fact that just by altering the parameters of loudness and pulse rate, it becomes possible for the bats to move as well as identify the objects in front of them. Generally, during echolocation, the bats radiate the signals and control their movement by continuously altering the frequency and detecting the echo to perceive the objects surrounding them. In Parija and Sahu (2018),

the simulations were performed to compare BPSO with bat algorithm, whereas this paper further extends the comparison to BDE-PEO, also. A detailed performance comparison analysis in terms of cost-per-call arrival, convergence speed, percentage improvement in convergence rate and scalability of the algorithms is studied.

### 3.1. Brief idea on bat algorithm

The echo-location characteristic of a bat is described briefly through the following steps:

#### 3.1.1. Echo-location

The time taken for the emitted sound pulse to return to the bats enables them to judge the expected distance to point of incidence of the echo.

#### 3.1.2. Parameter initialization

The parameters are pictorially represented in Fig. 2.

#### 3.1.3. Parameter updating

Eqs. (6), (7), and (8) represent the parameter update equations.

$$q_i = q_{\min} + (q_{\max} - q_{\min})\delta \tag{6}$$

where  $\delta$  is a random value and  $\delta \in [0, 1]$ .

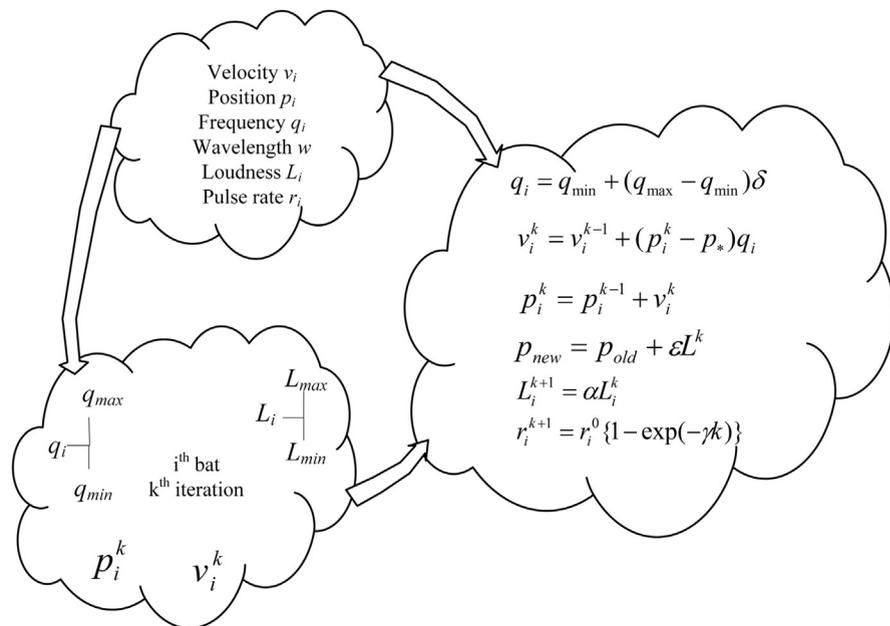


Fig. 2. BABA parameters.

$$v_i^k = v_i^{k-1} + (p_i^k - p^*)q_i, \tag{7}$$

$$p_i^k = p_i^{k-1} + v_i^k \tag{8}$$

where the most appropriate performance is  $p^*$ . Eq. (9) depicts the next possible bat position.

$$p_{new} = p_{old} + \varepsilon L^k \tag{9}$$

where  $\varepsilon \in [-1, 1]$ ,

$L^k = \langle L_i^k \rangle$  is the average loudness of all bats at  $k^{th}$  iteration.

Loudness modulation is performed and Pulse rate is altered in accordance with Eqs. (10) and (11).

$$L_i^{k+1} = \alpha L_i^k \tag{10}$$

$$r_i^{k+1} = r_i^0 \{1 - \exp(-\gamma k)\} \tag{11}$$

where  $\alpha$  and  $\gamma$  are the constants, whose values have been assumed to be as follows:  $\alpha = \gamma = 0.9$ (Yang, 2010).

### 3.2. Binary Artificial Bat Algorithm (BABA)

There are many variants of standard Bat Algorithm like fuzzy logic-based bat algorithm, multi-objective bat algorithm, K-means bat algorithm, chaotic bat algorithm, binary bat algorithm etc (Yang and He, 2013), which have been applied to multi-fold domains of research. However, this paper presents the application of BABA, a discrete version of Bat algorithm, to mobile location management using RCP strategy, which is considered as non-deterministic polynomial-time hard (NP-hard) and modeled as a combinatorial optimization problem. The binary variant of Bat algorithm, BABA, however, uses the sigmoid function to confine the bat’s new position to only binary values (refer to Eq. (12)), and for position update, Eq. (13) is used instead of Eq. (8).

$$S(v_i^k) = \frac{1}{1 + e^{-v_i^k}} \tag{12}$$

$$p_i^k = \begin{cases} 1 & \text{if } S(v_i^k) > \sigma \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where  $\sigma \sim U(0, 1)$  represents a uniform distribution in the range of (0, 1).

The implementation flowchart of the BABA is given in Fig. 3 and the pseudo-code is presented in Table 1.

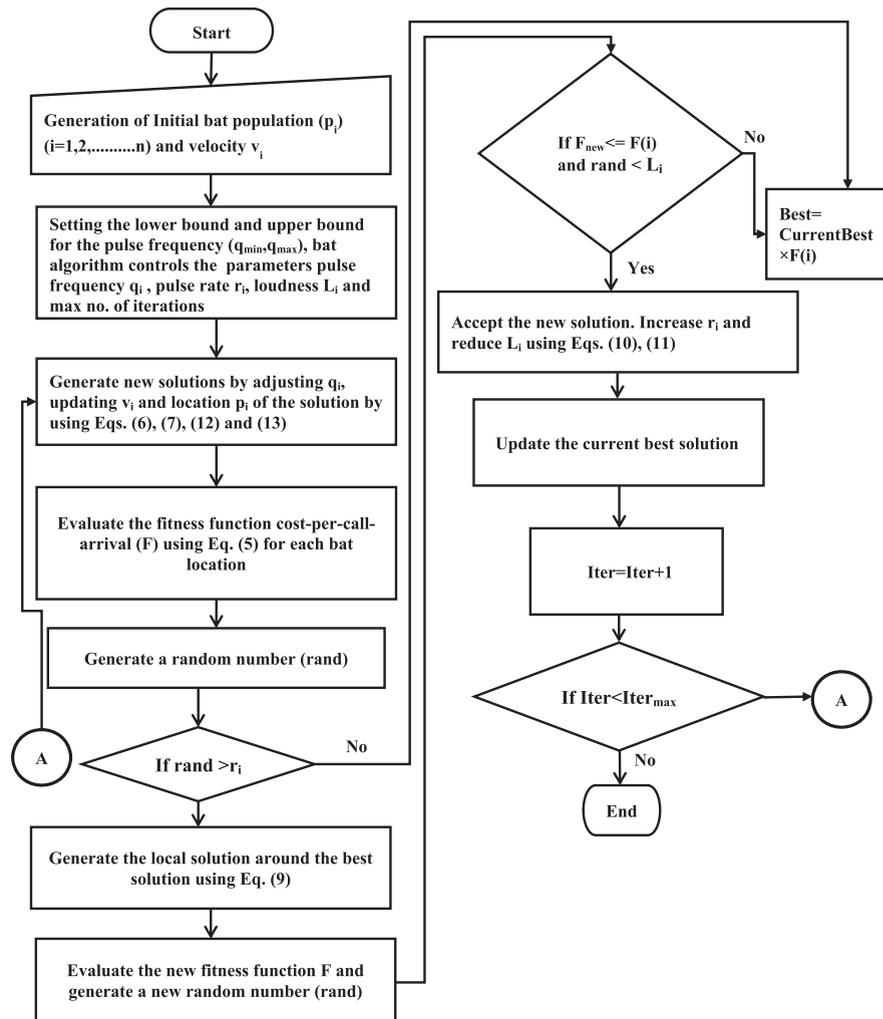


Fig. 3. Flowchart of BABA for RCP problem.

## 4. Results & discussion

Simulations are carried out for both reference as well as realistic networks of sizes  $4 \times 4$ ,  $6 \times 6$  and  $8 \times 8$  to gauge the ability of the proposed BABA with respect to the existing ones, such as BDE-PEO (Almeida-Luz et al., 2011; Bettencourt, 2004; Swayamsiddha et al., 2017a,b) and BPSO (Kim et al., 2012). The control parameters used in the BABA, BPSO, and BDE-PEO are outlined in Table 2.

### 4.1. Study on cost-per-call-arrival of the algorithms

A comparative study has been conducted here in terms of cost-per-call-arrival of three algorithms for some reference and realistic networks, as discussed below.

**Table 1.** Pseudo-code for BABA.

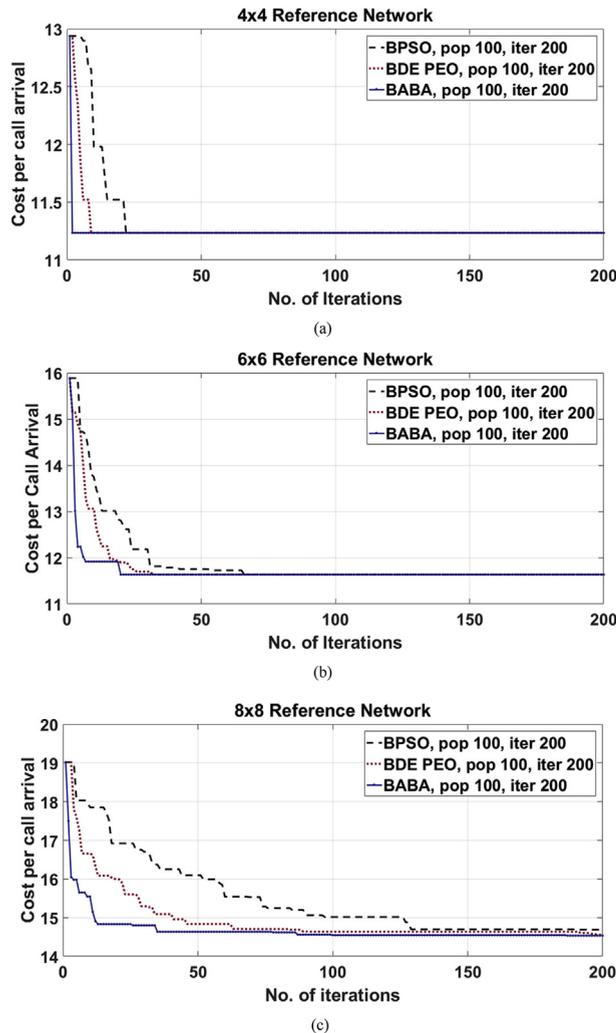
1:	Define the positional fitness function
2:	Generate randomly the binary bat population with position $p_i$ , ( $i = 1, 2, \dots, n$ ) and velocity $v_i$
3:	Define the control parameters; Pulse rate $r_i$ , Pulse frequency $q_i$ , and loudness $L_i$
4:	While ( $k < \text{max. no of iterations}$ )
5:	Generate new solutions by adjusting the frequency and updating velocities and positions
6:	If ( $\text{rand} > r_i$ )
7:	Select the solution among the best solutions; And
8:	Generate location solution from the selected best solution
9:	End if
10:	If ( $\text{rand} < L_i$ and $f(x'_i) < f(x_i)$ )
11:	Store the new solutions.
12:	Increase $r_i$ and Decrease $A_i$
13:	Update rand A
14:	End if
15:	Rank the bats and find the current best position $x^*$

**Table 2.** Values of simulation parameters for BABA/BPSO/BDE-PEO.

	Definition	Parameter	Value
BABA/BPSO/BDE-PEO	Population size	Pop size	100
	Number of iterations	Num of Ite	200
BABA	Minimum frequency	$q_{\min}$	0
	Maximum frequency	$q_{\max}$	2
	Loudness	L	0.3
	Pulse rate	R	0.2
BPSO	Inertia weight factor	W	1.5
	Cognitive parameter	$c_1 \times r_1$	1
	Social parameter	$c_2 \times r_2$	0.7
	Mapping probability range	Q [ $V_{\min}, V_{\max}$ ]	[-4,4]
BDE-PEO	Crossover ratio	Cr	0.15
	Mutation factor	F	0.5
	Bandwidth factor	B	20

#### 4.1.1. Cost analysis using reference data networks

The convergence patterns of the proposed BABA and existing BPSO and BDE-PEO algorithms for the reference networks of sizes  $4 \times 4$ ,  $6 \times 6$  and  $8 \times 8$  (by using the number of call arrivals and location update weight values of (Almeida-Luz et al., 2011; Subrata and Zomaya, 2002)) are shown in Fig. 4. It is interesting to note that the proposed BABA is able to achieve the faster convergence compared to BPSO and BDE-PEO algorithms.

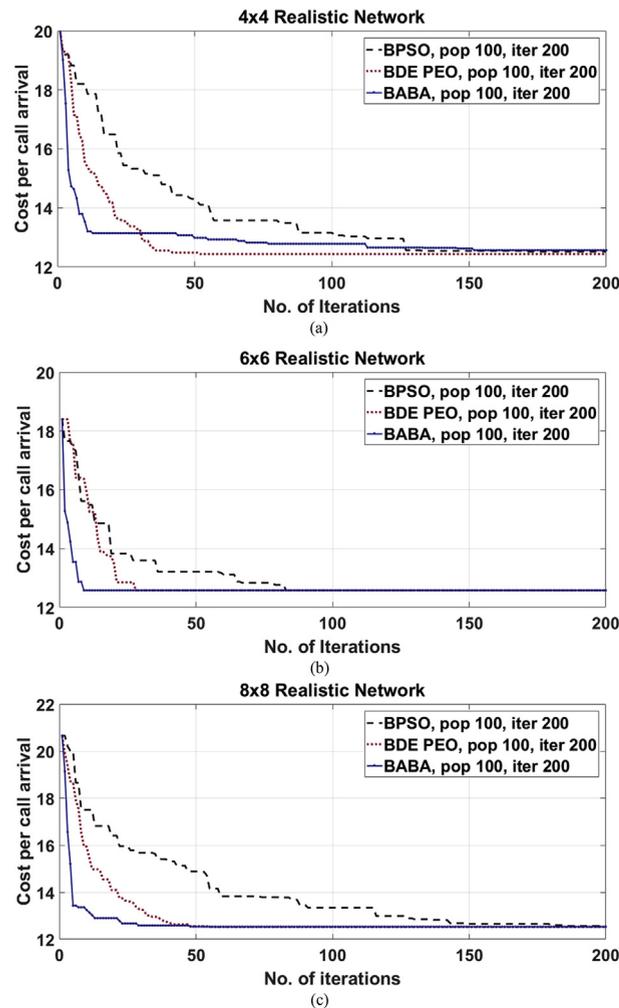


**Fig. 4.** Convergence patterns of MLM cost using BABA, BPSO, and BDE-PEO for reference networks of sizes (a)  $4 \times 4$ , (b)  $6 \times 6$  & (c)  $8 \times 8$ .

#### 4.1.2. Cost analysis using realistic networks

Fig. 5 displays the convergence floors of the proposed BABA and existing BPSO and BDE-PEO algorithms by utilizing the number of call arrivals and location update weight values of realistic networks of sizes  $4 \times 4$ ,  $6 \times 6$  and  $8 \times 8$ . Out of the three realistic networks studied here, the proposed BABA is able to yield the faster convergence in two problems compared to the existing algorithms.

Figs. 6 and 7 compare the cost-per-call-arrival obtained by the BABA, BPSO and BDE-PEO for the reference and real networks, respectively. From these graphs, it may be observed broadly that the proposed BABA performs nearly at par with BPSO and BDE-PEO, with the results being marginally distinct as we approach the larger network sizes (specifically  $8 \times 8$ ). Our results are then compared with



**Fig. 5.** Convergence floors of MLM cost using BABA, BPSO, and BDE-PEO for realistic networks of sizes. (a)  $4 \times 4$ , (b)  $6 \times 6$  & (c)  $8 \times 8$ .

the existing costs from the literature, which have utilized various other bio-algorithms, in Table 3.

## 4.2. Study on the convergence rate of the algorithms

To dive deeper into where exactly BABA shines, the rate of convergence should be looked into closely by observing the number of iterations required to reach a stable final cost value, as shown in Fig. 8. It is quite clear from the graph that the proposed BABA shoots its way past other algorithms by converging to the minimum cost in the lowest number of iterations. In other words, the rate of convergence of the proposed BABA is the fastest for the three network sizes considered for reference networks. On a side note, a trend observed in Fig. 9 quite naturally is that the number of iterations required to converge increases monotonically, as we go from the smaller to the larger network size (that is, from  $4 \times 4$  to  $8 \times 8$  through  $6 \times 6$ ).

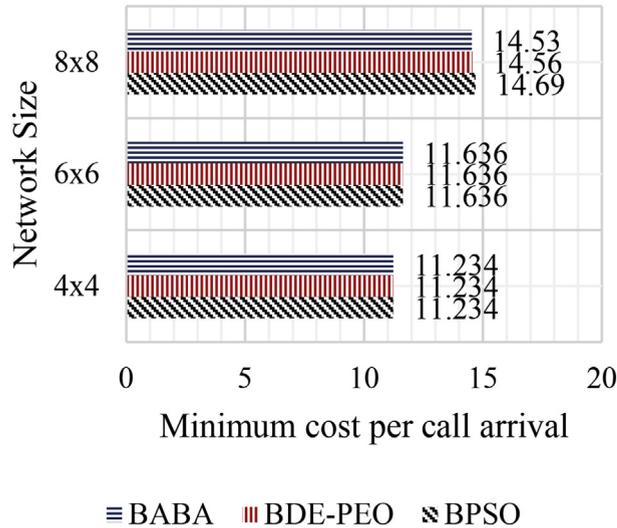


Fig. 6. Comparison in terms of cost-per-call-arrival for reference networks.

Further, the question arises: how much faster is the proposed algorithm? The answer to this question lies in Fig. 9. For the smaller reference networks, the proposed BABA is found to exhibit as high as 1000% and 350% faster rate of convergence than BPSO and BDE-PEO, respectively. At the very least, BABA is seen to be 2% ahead of the curve in the competition, when dealing with the larger networks (compared to BDE-PEO for 8 × 8 network).

A similar type of observation has been made on the data concerned with the realistic networks, as shown in Figs. 10 and 11. Here also, a similar pattern is seen with BABA

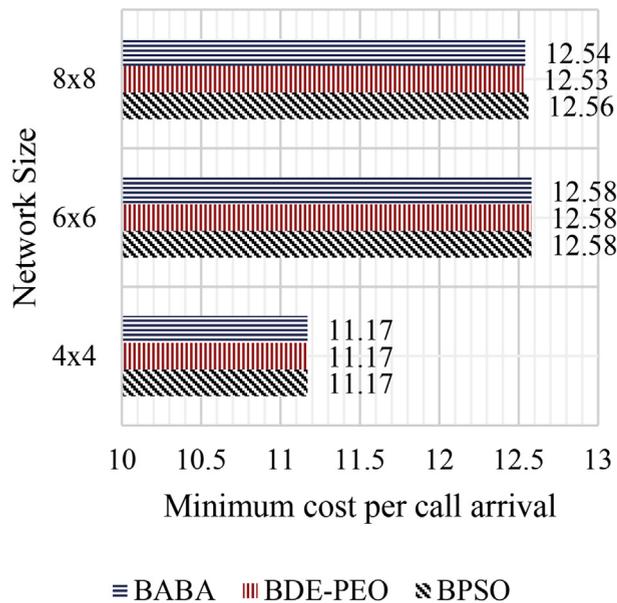


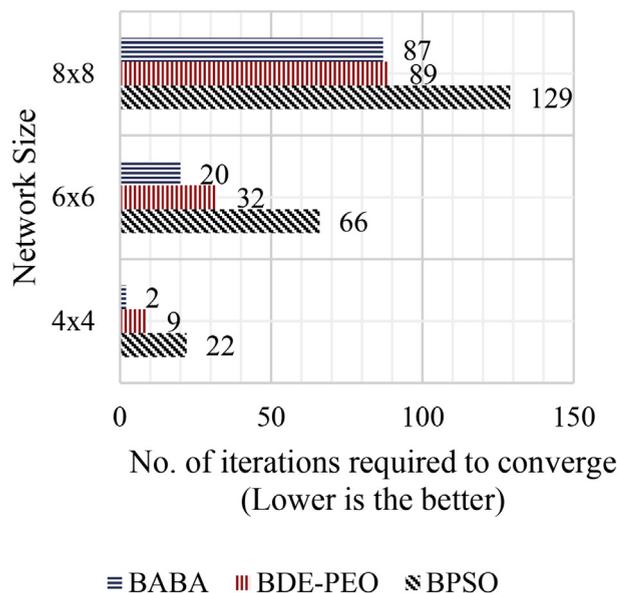
Fig. 7. Comparison in terms of cost-per-call-arrival for realistic networks.

**Table 3.** Comparison analysis of BABA with previous studies in terms of minimum cost-per-call-arrival for some reference networks.

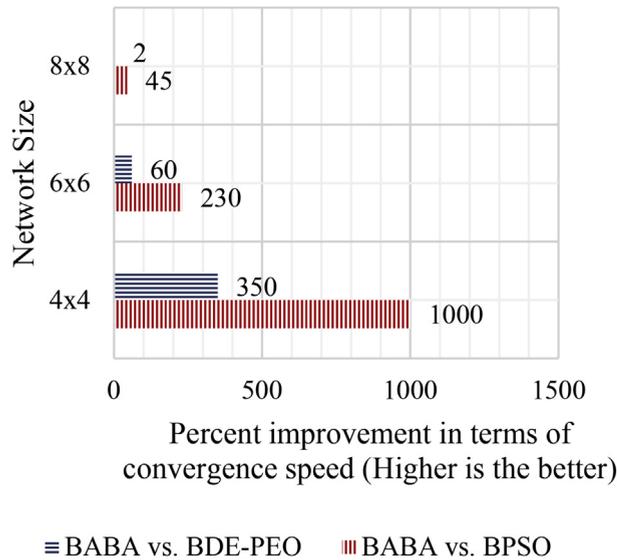
Proposed BABA Approach in Comparison with existing BDE-PEO and BPSO	Ref. network	4 × 4	6 × 6	8 × 8
	BABA	11.234	11.636	14.530
	BDE-PEO	11.234	11.636	14.560
	BPSO	11.234	11.636	14.690
(Subrata and Zomaya, 2002)	GA	12.252	12.464	13.782
	ACO	12.252	11.471	13.801
	TS	12.252	11.471	13.782
(Almeida-Luz et al., 2011)	DE	NA	11.471	13.782
(Kim et al., 2012)	BPSO	NA	11.471	13.782
(Taheri and Zomaya, 2007b)	MHN	NA	11.471	NA

leading the pack by requiring the least number of iterations to converge to an optimal value. Fig. 10 shows the number of iterations required for suitable convergence, whereas Fig. 11 highlights the increment in performance achieved by the proposed BABA over the other two algorithms for realistic network scenarios. For realistic network scenarios, the proposed BABA can spike as high as 822% (over BPSO at 6 × 6 network) and 17% at the very least (over BDE-PEO at 8 × 8 network).

Yet another pattern that may be observed through Figs. 9 and 11 is that the gains yielded by the proposed BABA are more effective over other algorithms, when dealing with the smaller networks and that these gains diminish, as we increase the network size. As a matter of fact, this law of diminishing returns holds true for the other algorithms as well, so to complain about the same for BABA would be nitpicking.



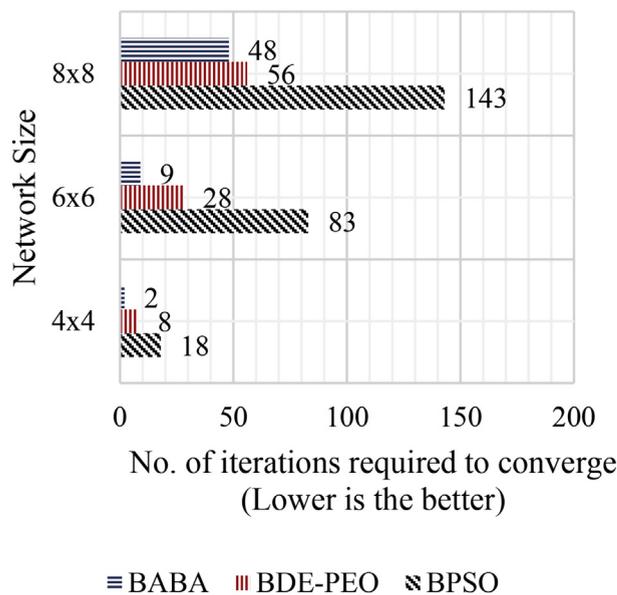
**Fig. 8.** Comparison in terms of convergence rate for reference networks.



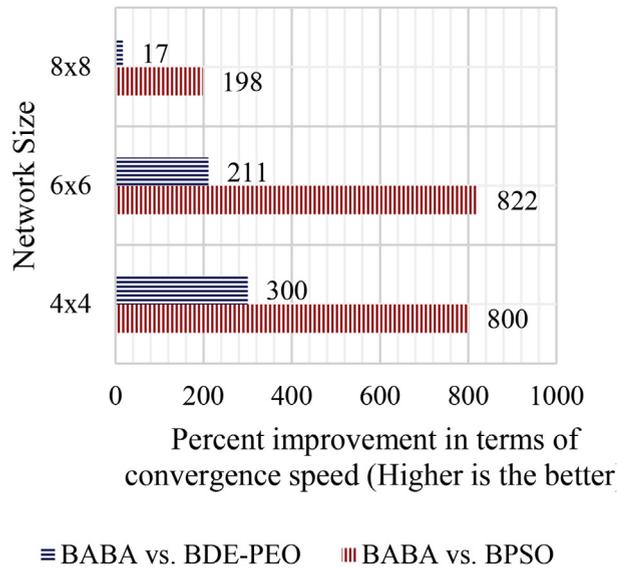
**Fig. 9.** Comparison of the algorithms in terms of percent improvement in convergence speed for reference networks.

### 4.3. Study on scalability of the algorithms

Fig. 12 specifies the percent increase in cost-per-call-arrival, while moving from the smaller to the larger network size, for each algorithm (for reference networks). Here, it is seen that almost all algorithms are neck-to-neck, whenever a particular type of scaling is considered (for example,  $4 \times 4$  to  $6 \times 6$ ). The peaks are in the vicinity of the hair's width, as shown in Fig. 12. This is true as well for realistic



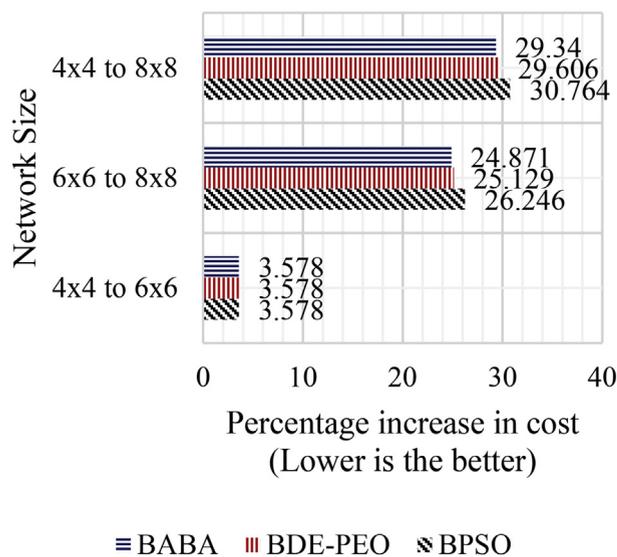
**Fig. 10.** Comparison in terms of convergence rate for realistic networks.



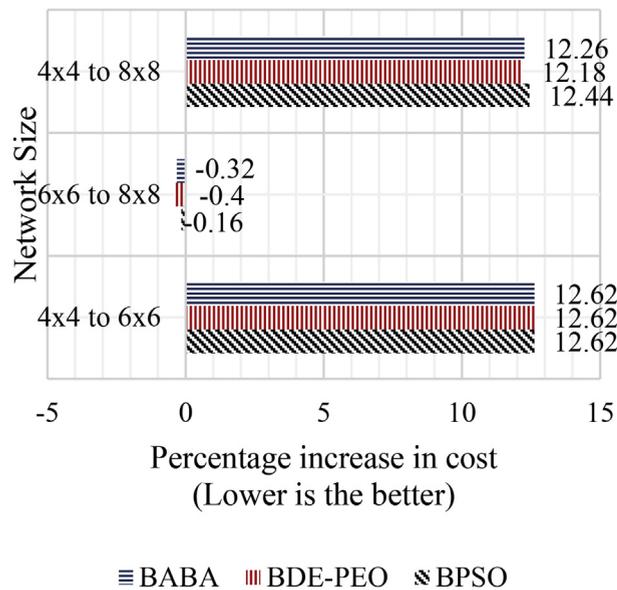
**Fig. 11.** Comparison of the algorithms in terms of percent improvement in convergence speed for realistic networks.

scenarios, depicted in Fig. 13. Interestingly, a regression is observed, while moving from  $6 \times 6$  to  $8 \times 8$  (refer to Fig. 13), which simply means that the performance efficiency aims to hit a sweet spot for all the three algorithms (including the proposed BABA) at  $6 \times 6$  size.

Thus, it may be noted that the proposed BABA performs well in terms of convergence speed, while being at par with the established algorithms in terms of minimum cost achieved for a fixed number of iterations. The reasons behind the



**Fig. 12.** Comparison in terms of scalability of algorithms for reference networks.



**Fig. 13.** Comparison in terms of scalability of algorithms for realistic networks.

improved performance of BABA compared to other existing techniques are the frequency tuning capability, automatic zooming and parameter control features of Bat algorithm, which are attributed in the updated equations. In BABA, by varying the frequency, it mimics the true function in reality. The faster convergence rate is an outcome of automatic zooming capability, where there is an automatic switching from explorative search to exploitative search, as the optimal solution region approaches. Also, the control parameters, such as loudness and pulse rate are varied as the iteration proceeds to alter the search capability from exploration to exploitation, whereas BDE-PEO and BPSO use pre-tuned algorithm dependent fixed control parameters. The application of meta-heuristic algorithms specifically BABA in next-generation wireless networks is a promising area of research (Jiang et al., 2017).

## 5. Conclusion

In this paper, Bat algorithm has been proposed for the first time in the field of location management cost optimization based on RCP strategy in cellular networks. It combines the advantages of other bio-inspired algorithms (specifically PSO and Harmony Search Algorithm) and surpasses its objective in most of the cases. The most visible form of improvement could be observed in terms of the swift rate of convergence combined with the ease of scalability to various sizes of networks. Future work should focus on widening the performance gap between the proposed BABA and the other meta-heuristic algorithms, especially for the larger networks. Adjusting the BABA parameters to obtain even the faster

convergence would be appreciated. This algorithm may be extended to solve the problem of registration area and may be combined with different parameters, such as dwell time distribution to improve its performance further. This work can be further extended for 4G and beyond networks by incorporating the tracking area and tracking area list-TAL and considering the architectural aspects of recent standards.

## Declarations

### Author contribution statement

Swati Swayamsiddha: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Prateek, Sudhansu Singh, Smita Parija: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Dilip Pratihar: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

### Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

### Competing interest statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

## References

Almeida-Luz, S.M., Vega-Rodríguez, M.A., Gómez-Púlido, J.A., Sánchez-Pérez, J.M., 2011. Differential evolution for solving the mobile location management. *Appl. Soft Comput. J.* 11, 410–427.

Bettencourt, S.M.A., 2004. *Lecture Notes in Computer Science*, p. Imp004.

Chaurasia, S.N., Singh, A., 2015. A hybrid swarm intelligence approach to the registration area planning problem. *Inf. Sci.* 302, 50–69.

- Gao, M.L., Shen, J., Yin, L.J., Liu, W., Zou, G.F., Li, H.T., Fu, G.X., 2016. A novel visual tracking method using bat algorithm. *Neurocomputing* 177, 612–619.
- Hossein Gandomi, A., Yang, X., 2012. Bat algorithm: a novel approach for global engineering optimization. *Eng. Comput.* 29, 464–483.
- Jiang, C., Zhang, H., Ren, Y., Han, Z., Chen, K., Hanzo, L., 2017. Machine learning paradigms for next-generation wireless networks. *IEEE Wirel. Commun.* 24, 98–105.
- Kim, S.-S., Kim, G., Byeon, Ji-Hwan, Taheri, J., 2012. Particle swarm optimization for location mobility management. *Int. J. Innov. Comput. Inf. Contr.* 8, 8387–8398.
- Mukherjee, A., De, D., 2016. Location management in mobile network: a survey. *Comput. Sci. Rev.* 19, 1–14.
- Parija, S., Sahu, P.K., 2018. A metaheuristic bat inspired technique for cellular network optimization. In: *Proc. – 2017 2nd Int. Conf. Man Mach. Interfacing, MAMI 2017 2018–March*, 1–6.
- Parija, S., Singh, S., Swayamsiddha, S., 2017a. Particle swarm optimization for cost reduction in mobile location management using reporting cell planning approach. *Rec. Dev. Intell. Nat. Inspired Comput.*
- Parija, S.R., Sahu, P.K., Singh, S.S., 2017b. Cost reduction in location management using reporting cell planning and particle swarm optimization. *Wirel. Pers. Commun.* 96, 1613–1633.
- Prateek, Swayamsiddha, S., Singh, S.S., Parija, S., Sahu, P.K., 2018. Impact of dwell time distribution on location management in cellular networks. *J. Eng. Sci. Technol.* 13, 1330–1344.
- Premkumar, K., Manikandan, B.V., 2015. Speed control of brushless DC motor using bat algorithm optimized adaptive neuro-fuzzy inference system. *Appl. Soft Comput.* 32, 403–419.
- Rahimi, A., Bavafa, F., Aghababaei, S., Khooban, M.H., Naghavi, S.V., 2016. The online parameter identification of chaotic behaviour in permanent magnet synchronous motor by self-adaptive learning bat-inspired algorithm. *Int. J. Electr. Power Energy Syst.* 78, 285–291.
- Subrata, R., Zomaya, A., 2003a. Evolving cellular automata for location management in mobile computing networks. *Parallel Distrib. Syst. IEEE Trans.* 14, 13–26.
- Subrata, R., Zomaya, A.Y., 2003b. Dynamic location management for mobile computing. *Telecommun. Syst.* 22, 169–187.

- Subrata, R., Zomaya, A.Y., 2002. Artificial life techniques for reporting cell planning in mobile computing. In: Proc. — Int. Parallel Distrib. Process. Symp. IPDPS 2002 14, pp. 203–210.
- Svecko, R., Kusic, D., 2015. Feedforward neural network position control of a piezoelectric actuator based on a BAT search algorithm. *Expert Syst. Appl.* 42, 5416–5423.
- Swayamsiddha, S., Parija, S., Sahu, P.K., Singh, S.S., 2017a. Optimal reporting cell planning with binary differential evolution algorithm for location management problem. *Int. J. Intell. Syst. Appl.* 9, 23–31.
- Swayamsiddha, S., Prateek, Singh, S.S., 2017b. Location management cost optimization using normalized percentile dwell time. *J. Eng. Sci. Technol. Rev.* 10, 104–107.
- Taheri, J., Zomaya, A.Y., 2007a. A combined genetic-neural algorithm for mobility management. *J. Math. Model. Algorithms* 6, 481–507.
- Taheri, J., Zomaya, A.Y., 2007b. A modified hopfield network for mobility management. *Wirel. Commun. Mob. Comput.* 8, 355–367.
- Wang, L., Fu, X., Mao, Y., Ilyas Menhas, M., Fei, M., 2012. A novel modified binary differential evolution algorithm and its applications. *Neurocomputing* 98, 55–75.
- Wong, V.-S., Leung, V.C.M., 2000. Location management for next-generation personal communications networks. *IEEE Netw.* 14, 18–24.
- Yang, X.-S., 2010. A new metaheuristic bat-inspired algorithm. *Nat. Inspired Coop. Strateg. Optim.* 65–74.
- Yang, X.S., He, X., 2013. Bat algorithm: literature review and applications. *Int. J. Bio Inspired Comput.* 5, 141.