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Optimal Reporting Cell Planning with Binary Differential Evolution Algorithm for Location Management Problem

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***Abstract*—**This paper presents binary differential evolution based optimal reporting cell planning (RCP) for location management in wireless cellular networks. The significance of mobile location management (MLM) in wireless communication has evolved drastically due to tremendous rise in the number of mobile users with the constraint of limited bandwidth. The total location management cost involves signaling cost due to location registration and location search and a trade-off between these two gives optimal location management cost. The proposed binary differential evolution (BDE) algorithm is used to determine the optimal reporting cell planning configuration such that the overall mobility management cost is minimized. Evidently, from the simulation result the proposed technique works well for the reference networks in terms of optimal cost and convergence speed. Further the applicability of the BDE is also validated for the realistic network of BSNL (Bharat Sanchar Nigam Limited), Odisha.

Index Terms—Binary Differential Evolution (BDE), location management, location registration, location search, reporting cell planning (RCP).

I. INTRODUCTION

The significance of mobile location management in wireless communication has evolved drastically because of tremendous rise in the number of mobile users with the constraint of limited bandwidth. In order to accommodate more subscribers in a wireless network, mobility management accounts as an important factor in designing the infrastructure of the cellular wireless communication network. In a wireless communication, the sphere of mobility management is a complex and intricate challenge with the goal to track the current location of the users so as to route a call or message to the mobile user within the limited resources [1]. The bandwidth is used for the registration of the mobile user as well in searching the user in a network. However, there is a trade-off between location update and location searching (paging) and mobility management tries to balance between these two, so as to minimize the total cost incurred during the mobile location operation.

Location area [2, 3] and reporting cell planning (RCP) [4] are the two main strategies for solving location management problem, however the paper proposes optimal location management using RCP strategy. For solving the complex optimization problems the differential evolution algorithm has been used in various engineering applications and many works are also carried out to enhance the performance of this algorithm by introducing variants or by modifying it [5-7]. Literatures have been reported on nature inspired algorithms for mobility management [8, 9]. A comparison of three artificial intelligence techniques namely Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Tabu Search (TS) for RCP problem has been studied [4]. The location management in mobile networks is efficiently dealt using evolving cellular automata [10]. Recently, the performance of Binary Particle Swarm Optimization (BPSO) algorithm for optimal design of RCP configuration has been reported [11]. The application of Differential Evolution algorithm for cost optimization in location area, reporting cell and realistic networks is proposed in [12-15]. The best parametric values for Differential Evolution algorithm for mobile location management are studied [16, 17] which are taken into consideration in the present work. A combined genetic-neural and Hybrid GA-PSO algorithms reports optimal mobility management [18, 19]. The location management is also addressed using simulated annealing and modified Hopfield approach [20, 21]. A hybrid swarm intelligence approach involving artificial bee colony is proposed for registration area planning problem [22].

With the objective of testing our approaches we have used reference networks and realistic networks using the collected real data from (Bharat Sanchar Nigam Limited) BSNL, Odisha. The research proposes the use of Binary Differential Evolution (BDE) algorithm for solving the important location management problems to find the optimal or near optimal solutions, comparing with the results of the existing works.

The paper organization is as follows. In the section 2 the problem formulation is discussed where the mobile location management is developed as an optimization problem. Section 3 introduces the implementation details of BDE approach for location mobility management. Section 4 provides a number of detailed simulations for reference network configurations as well as realistic networks that shows the applicability of the proposed approach and compared with the results of other authors. Finally, the conclusion and future scope is outlined in section 5.

II. Problem Formulation

The objective of this work is to develop an optimal reporting cell planning (RCP) configuration such that the total location management cost pertaining to location update and paging is minimum. Thus in this section the system model is demonstrated and the cost formulation analysis is presented.

A. System Model

The Fig. 1 shows the reporting cell planning (RCP) configuration where the 6x6 cellular networks is divided into reporting cells and non-reporting cells. The reporting cells are given the value 1 (represented in grey color) and non-reporting cells as 0 (represented in white color). The location updating takes place only when a mobile user enters the reporting cell and thus the location update cost involves the sum of the location update weights (frequency of movement into the cell) associated with the reporting cells. In the example shown in Fig. 1(a) there are 14 number of reporting cells out of 36 cells which is a test benchmark RCP configuration [24]. The RCP problem includes determining the optimal number as well as the position of the reporting cells such that the location management cost is minimum.

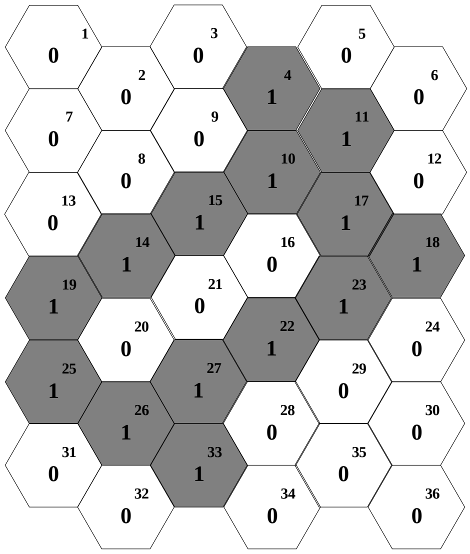


Fig.1. (a) Reporting Cell Planning (RCP) configuration problem

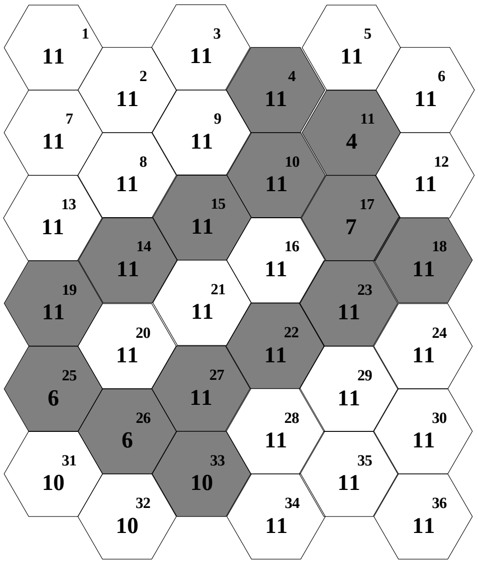


Fig.1. (b) Vicinity factor values in RCP.

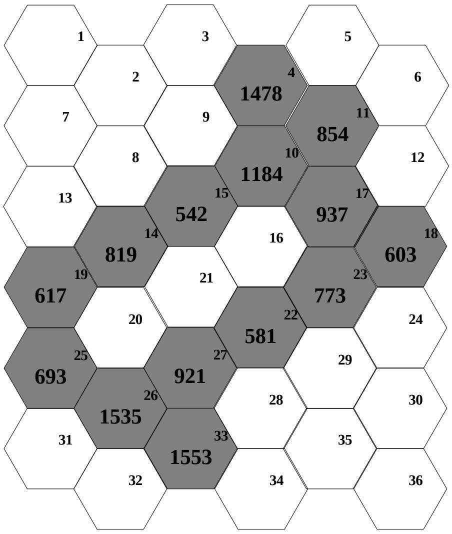


Fig.1. (c) Location updates in RCP problem

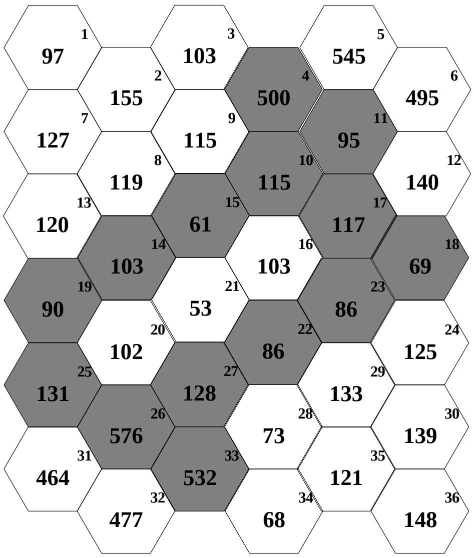


Fig.1. (d) Call arrivals in RCP problem

The tracking of the exact location of the mobile terminal is managed by two operations namely location update (registration) and location inquiry (paging). Location update is done by the mobile terminal to let the network know its current location. Paging is performed by the cellular network to locate the cell in which a mobile user is located so the incoming call for the mobile terminal can be routed to the corresponding base station.

In this paper we have considered the RCP approach in solving the location management issue where the cellular wireless mobile network is divided into reporting cells and non-reporting cells. The reporting cells are those where a location update is performed when a mobile user enters them. So, when a search operation is performed it is restricted only to the last reporting cell as well as its neighbors which are non-reporting cells. The maximum number of cells that are searched (paged) when an incoming call is to be forwarded is termed as vicinity factor. The vicinity factor for a reporting cell is calculated as sum of the number of neighboring non-reporting cells which can be reached without crossing other reporting cells plus the reporting cell itself. Whereas, the vicinity factor corresponding to a non-reporting cell is the maximum vicinity factor among the reporting cells from where this particular cell can be accessed. Fig. 1 (b) presents the vicinity factor values for the reporting cells as well as the non-reporting cells for the given RCP problem. For example, the vicinity factor for cell number 4 which is a reporting cell is calculated by considering the neighbors that are non-reporting cells plus the reporting cell itself(1,2,3,7,8,9,13,5,6,12) which corresponds to the vicinity value of 11. Similarly while calculating the vicinity factor for a non-reporting cell we have to consider the maximum vicinity factor value among the reporting cells from where this cell can be reached. Thus after computing the vicinity values of all the reporting cells the vicinity values of non-reporting cells can be evaluated. For example, the vicinity value of cell number 32 which is a non-reporting cell is calculated by considering the maximum of vicinity factors of reporting cells from where this cell can be reached i.e. cell 25, 26, 33 whose vicinity factors are 6,6,10 respectively. Since the maximum value is 10 it represents the vicinity factor for cell 32.

B. Cost Formulation

Location management cost comprises of weighted sum of location update cost and location paging cost given as:

$$Cost = C \times N_{LU} + N_P \tag{1}$$

Where N_{LU} represents the location update cost and N_P represents the location paging cost over a period of time. The location update cost is generally higher than the location search cost by a factor represented as C which is usually taken as a constant set to 10[11].

Each cell i in the cellular wireless network is associated with two types of weight namely the movement weight (w_{mi}) and the call arrival weight (w_{ci}) where the movement weight represents the number of movements of the mobile terminal into a cell and call arrival weight represents the number of call arrivals within a cell. The location update cost is directly related to the movement weight associated with the reporting cells in a network configuration and given as:

$$N_{LU} = \sum_{i \varepsilon R} w_{mi} \tag{2}$$

Where R is the set of reporting cells in the cellular wireless communication network and w_{mi} represents the movement weight associated with cell i .

The paging cost constitutes the total number of call transactions and is computed as the product of call arrival weight and vicinity factor attributed for that cell and is given as:

$$N_P = \sum_{j=0}^{N} w_{cj} \times v(j) \tag{3}$$

Where N is the total number of cells in a cellular network configuration. The total location mobility management cost is the sum of these two costs i.e. location update cost and location search cost and is given by:

$$Cost = C \times \sum_{i \varepsilon R} w_{mi} + \sum_{j=0}^{N} w_{cj} \times v\left(j\right) \tag{4}$$

In order to explain the evaluation of location management cost consider the Fig. 1(c) and (d) where the location update cost and call arrivals are shown corresponding to test data for 6x6 benchmark RCP problem[24]. For this example considering the location update weights presented in Fig. 1(c) the location update cost can be formulated using Eq.(2) N_{LU}=13087

Similarly, the paging cost is evaluated using Eq. (3)

N_P= 97X11+155X11+103X11+…….+148X11=65680

Hence, the total cost is determined from the Eq. (4)

Cost=10x13087+65680=198,550

Though the location mobility management cost involves other parameters, they are considered same for all strategies and thus do not affect when comparing the results obtained by several approaches.

The total cost divided by total number of call arrivals gives the cost per call arrival which is given by:

$$Cost\ \ per\ \ call\ \ arrival = \frac{Cost}{\sum_{j=0}^{N} w_{cj}} \tag{5}$$

For the given example Cost per call arrival=198,550/6711=29.58

The cost per call arrival is the objective function which is to be minimized to obtain best cellular wireless communication network configuration. Thus the reporting cell planning problem involves determination of optimal topology calculating the number of reporting cells and their position in a cellular network configuration.

III. Binary Differential Evolution Algorithm

First proposed by Storn and Price [23] Differential Evolution (DE) belonging to the category of bio-inspired algorithms is a simple, stochastic and effective tool for global numerical optimization. The BDE technique involves four steps namely: initialization, differential mutation, crossover and selection.In this novel BDE algorithm a probability estimation operator is introduced in mutation stage which increases the diversity of the population. On the other hand the standard DE operates in continuous space which is not fit for solving binary coded combinational optimizations. Hence BDE offers an effective way for location cost optimization in RCP which is a discrete binary optimization problem.

A. Steps involved in BDE

1) Initialization:

Initialisation step involves the generation of N random potential solutions where N denotes the size of the population.The potential solution (individual) refers to each Reporting cell configuration (RCC) as $X_{i,\ j}$where j refers to jth RCC solution. Here $X_{i,j}$ denotesi^{th} cell (i^{th} bit) of j^{th} RCC solution in the solution set.Thus$X_{i,\ j}$ is a binary vector of length equal to the number of cells in the cellular network.

2) Mutation:

After the initialization phase unlike Genetic Algorithm, here differential mutation is performed. Resultant vector namely noisy vector/mutant results using the equation (6):

$$MV = X^{t}_{best,j} + F^{*}(X^{t}_{r2,j} - X^{t}_{r3,j}) \tag{6}$$

Where $X_{best}$is the best RCC solution which corresponds to minimum location management cost in the RCC solution set X.$X_{r2}$and $X_{r3}$are the solutions selected randomly from RCC solution set X. Here DE/best/1/exp variant of DE strategy is used. Scalar factor F controls the amount of variation introduced and its value lies in the range [0, 1].

Probability Estimation Vector (PEV): The PEV is computed using the mutant vector as shown in the Eq. (7):

$$PEV(X^{t+1}_{i,j}) = \frac{1}{1+e^{-2b(MV-0.5)/(1+2F)}} \tag{7}$$

where b is the bandwidth factor which is a real positive constant generally taken as 20. The range and the shape of the probability distribution model is determined by this factor. The RCC vector which is calculated bit by bit in the binary space and obtained after probability estimation is called probability estimation vector (PEV). The binary mutant RCC individual (BMI) is generated using this PEV using the Eq.(8):

$$BMI^{t+1}_{i,j} = \begin{cases} 1, \text{if rand } \leq \text{ PEV}\left(X^{t+1}_{i,j}\right) \\ 0, \qquad \qquad otherwise \end{cases} \tag{8}$$

3) Crossover:

After crossover, trial RCC solution is created by using the strategy given in Eq. (9):

$$T^{t+1}_{i,j} = \begin{cases} BMI^{t+1}_{i,j}, \text{if rand } \leq \ C_r \\ X^{t}_{r1,j}, \qquad \qquad otherwise \end{cases} \tag{9}$$

Where C_r denotes crossover ratio whose optimal value is 0.15 [20]. The C_r value is compared with a generated random number and if it's greater than the random value then the corresponding element of binary mutant individual is taken to the trial vector. Whereas, the target vector parameters are reciprocated to the trial vector if value of C_r is less than the random number.

4) Selection:

In the selection process based on the suitability (fitness) of the candidate solutions they are passed on to the next generation. If the location management cost of the trial RCC solution obtained after crossover operation is less as compared to that of the target RCC solution, then the trial vector replaces the target vector otherwise the target vector continues in the next generation which is demonstrated in Eq. (10). The X_{new} is the new RCC solution set given as

$$X^{t+1}_{i,j(new)} = \begin{cases} T^{t+1}_{i,j}, \text{if Cost}\,(T^{t+1}_{i,j}) \;\le\; \text{Cost}\,(X^{t}_{r1,j}) \\ X^{t}_{r1,j}, \qquad\qquad otherwise \end{cases} \tag{10}$$

B. Implementation flowchart

The binary differential evolution algorithm for RCP problem is discussed briefly:

1. Initially the RCC solutions are generated in random.
2. Setting of control parameters like iteration number, F (scaling factor), b (bandwidth factor) and C_r (crossover ratio)is done.
3. The evaluation of fitness of each of the random initial RCC solutions is done using Eq. (5) and the RCC solution whose location management cost is minimum is identified and denoted as X_{best}. Also a target vector X_{r1} and two random RCC solutions X_{r2} and X_{r3} are choosen.
4. Weighted difference vector and mutant/noisy vector is computed followed by probability estimation vector.
5. Using probability estimation vector,binary mutant RCC vectors are generated.
6. The trial RCC vector is evaluated by using parameters from target vector or binary mutant indivisual based on crossover ratio as given in Eq.(9).
7. The selection procedure compares the fitness value of trial vector and target vector and if the cost of trial is less than that of target vector then the target is replaced by the trial and survive to the next generation. In this way a new set of RCC solutions is set for the next generation.
8. This process continues from step 3 till the stop condition is satisfied.

The pseudo code of the BDE algorithm is presented in Table 1 and also illustrated in the flow diagram given in Fig. 2.

Table 1. Pseudo code of bde algorithm

Steps	**Process Involved**
1	Population initialization
2	Evaluate cost of each individual solution
3	While(stop condition not satisfied) {
4	Randomly select two vectors Xr1 and Xr2
5	Find difference vector = Xr1-Xr2
6	Weighted difference vector=F. (Xr1-Xr2)
7	Evaluate Noisy vector= Xbest+ F. (Xr1-Xr2)
8	Generate Probability Estimation Vector using Probability Estimation Operator
9	Determine Binary Mutant Individual (BMI)
10	Evaluate Trial vector by choosing genes from Target vector or BMI
11	Select the target vector or trial vector for next generation population based on lower cost}

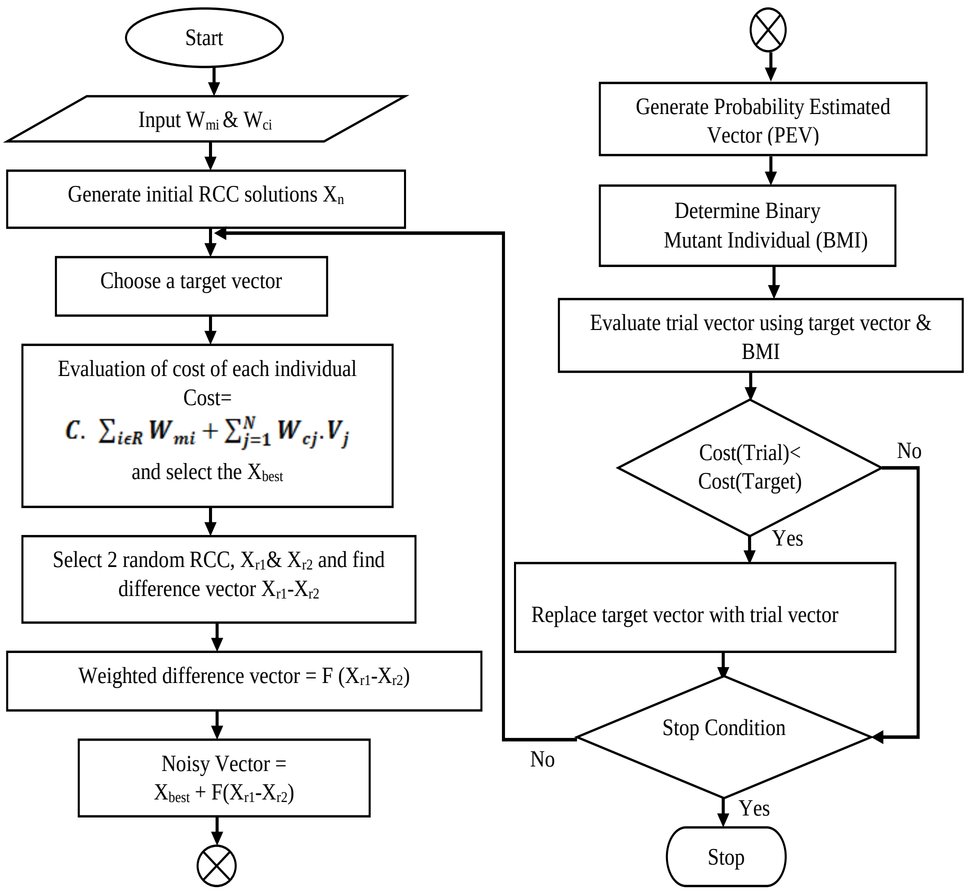


Fig.2. Flowchart implementation of BDE algorithm for RCP problem

IV. Simulation Results and Analysis

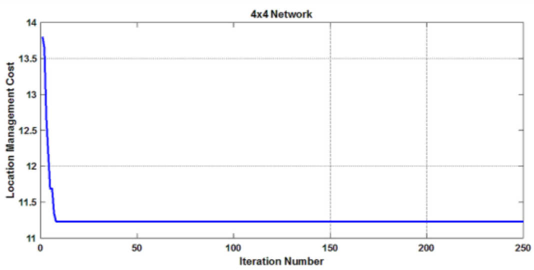
This section presents the simulation results for location management problem through two distinct experiments. First, by using reference data for networks available in literature and second by using realistic networks of BSNL, Odisha. The experimental simulations are conducted taking different networks of size 4x4, 6x6 and 8x8. The optimal parameters that are used for BDE algorithm for solving RCP problem are: Population size= 175, C_r= 0.15, F=0.5, b=20 [17]. We DE/best/1/exp variant is used for optimal results. The simulation results are obtained for 250 iterations. Thedetailed comparision is carried out for demonstrating the performance analysis of different state-of-art techniques reported in the literature for solving RCP problem of location management issue.

Experiment 1- Cost analysis using the reference data available in literature

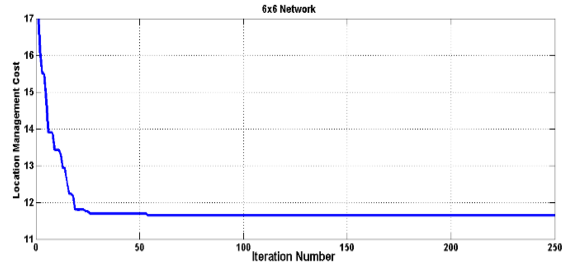
This work presents the simulation analysis taking the weight attributes for reference networks. The weight attributes for call arrival weight and location update weight for 6x6 cells configuration is shown in Table 2 which is available in [4,17]. The column 1 shows the cell number, the column 2 indicates the frequency of location updates in that particular cell and the column 3 corresponds to frequency of arrival of calls. The convergence floor of proposed BDE method for the reference networks of size 4x4, 6x6 and 8x8 is shown in the Fig. 3.

Table 2. Weight attributes for reference data network of size 6x6

Cell	NP	NLU	Cell	NP	NLU	Cell	NP	NLU
1	714	1039	13	238	507	25	328	16
2	120	1476	14	964	603	26	255	332
3	414	262	15	789	1479	27	393	1203
4	639	442	16	457	756	28	370	1342
5	419	1052	17	708	695	29	721	814
6	332	1902	18	825	356	30	769	747
7	494	444	19	462	1945	31	17	146
8	810	1103	20	682	1368	32	265	904
9	546	1829	21	241	1850	33	958	359
10	221	296	22	700	1131	34	191	1729
11	856	793	23	23	236	35	551	190
12	652	317	24	827	1622	36	467	1907



(a)



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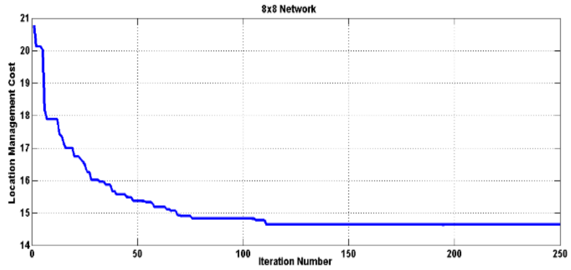


(c)

Fig.3. Trend of cost function convergence for RCP reference networks of size (a) 4x4, (b) 6x6 and (c)8x8

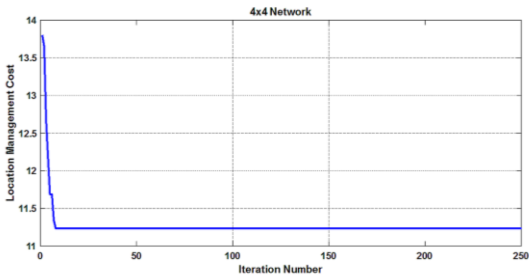
Experiment 2- Cost analysis using realistic network of BSNL, Odisha

Also the results are validated for realistic network of BSNL,Odisha which shows the applicability of BDE based location management in real scenario.

The data sheet for real network with 6x6 attributes is referred in Table 3. A typical run of the proposed BDE approach for cost optimisation in RCP problem taking realistic BSNL, Odisha network is presented in Fig. 4.

Table 3. Weight attributes for bsnl, odisha real network of size 6x6

Cell	**NP**	**NLU**	**Cell**	**NP**	**NLU**	**Cell**	**NP**	**NLU**
1	807	349	13	289	38	25	5003	24
2	700	61	14	236	105	26	2621	154
3	398	321	15	451	193	27	1805	149
4	185	21	16	700	480	28	724	406
5	1197	6	17	1164	486	29	1674	865
6	980	30	18	732	865	30	386	297
7	533	285	19	585	171	31	1177	805
8	1556	324	20	435	301	32	601	173
9	163	36	21	1189	514	33	321	120
10	497	289	22	26	9	34	271	426
11	3567	2045	23	3	7	35	1189	1068
12	1917	187	24	8	25	36	535	794



(a)

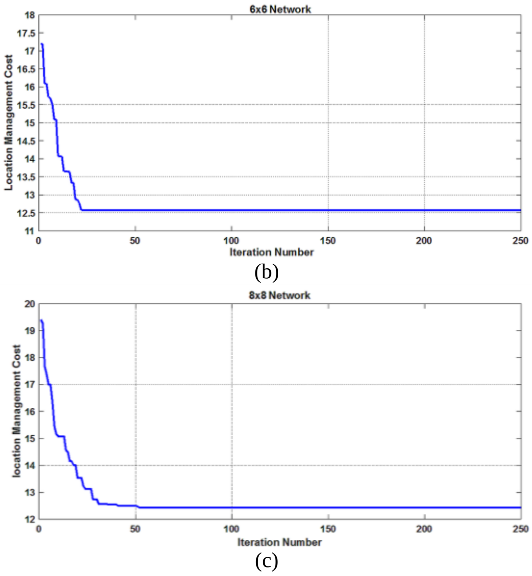


Fig.4. Trend of cost function convergence for realistic BSNL,Odisha networks of size (a)4x4, (b)6x6 and (c) 8x8

Table 4. Cost comparison for different size networks using reference and real networks

Ref. data network	Location update cost	Paging cost	Total cost
6x6	13900	75313	214313
8x8	35260	147357	499957
Real data network	Location update cost	Paging cost	Total Cost
6x6	13900	75313	214313
8x8	33328	125617	458897

Table 5. Call to movement ratio analysis for reference network and real network

Network size (Ref. Network)	**Sum of Call Arrival weights(a)**	**Sum of movement weights(b)**	**Call to Movement Ratio=(a)/(b)**
6x6	18418	33192	0.5548
8x8	31656	64423	0.4913
Network size (Realistic Network)			
6x6	12429	34625	0.3589
8x8	44834	98765	0.4539

Table 6. Ratio of reporting cells for best rcp solutions for real data and reference data networks

Network Size	**Ratio of Reporting Cells**
Service Data(Real Data)	
6 x 6	31/36=0.861
8 x 8	55/64=0.859
Network Size	**Ratio of Reporting Cells**
Service Data(Reference Data)	
6 x 6	23/36=0.638
8 x 8	43/64=0.671

Table 7. No. of iterations to attain the convergence

Reference network	No. of iterations Using BDE	No. of iterations Using BPSO [11]
6x6	55	90
8x8	110	600

Table 8. Comparison of the cost per call arrival using bde with earlier studies

Network Size		4x4	6x6	8x8
Proposed algorithm BDE	Reference	11.234	11.636	14.634
	Realistic	11.234	12.510	12.743
BPSO [11]		NA	11.471	13.782
DE [17]		NA	11.471	13.782
MHN [21]		NA	11.471	N/A
ACO [4]		12.252	11.471	13.801
TS [4]		12.252	11.471	13.782
GA [4]		12.252	12.464	13.782

From the convergence graphs it is observed that the location management cost decreases with the iterations and the optimal solution settles down around 50-100 iterations. The simulation is run for 20 independent runs inorder to validate the proposed BDE for RCP problem. The cost per call arrival which is the cost function reaches to 11.234 for 4x4 network, 11.636 for 6x6 network and 14.634 for 8x8 reference networks which is evident from the Fig. 3. Similarly, the optimal cost per call arrival values for realistic 4x4, 6x6 and 8x8 networks are 11.234, 12.510 and 12.743 shown in Fig. 4. Table 4 depicts the location update cost, paging cost and total location update cost for reference and real data using different network sizes. It is seen that for 6x6 reference network the total cost is 214313 and for 8x8 it is 499957 which shows that it increases as the network size increases. Similar is the case for realistic network. The call arrival to movement ratio for different networks is presented in Table 5. The call arrival to movement ratio depicts the ratio of the number of calls for locating a mobile station over the number of cell boundary crossings. For 6x6 and 8x8 reference network, the obtained values are 0.5548 and 0.4913 and for the real networks the results are 0.3589 and 0.4539 respectively which is comparatively lower. Lower call to movement ratio implies location update cost dominates over paging cost. Table 6 shows the ratio of reporting cells for best RCP solutions for real data and reference data networks. For reference networks of sizes 6x6 and 8x8, the ratio of reporting cells are 0.638 and 0.671 and for real networks the values obtained are 0.861 and 0.859. Higher the ratio of reporting cells more is the location update cost which compensates for the low call to movement ratio in case of realistic network. Table 7 shows the number of iterations to attain convergence compared with that of BPSO. For 6x6 reference network, the no. of iterations before the solution settles down to optimal result using BDE is 55 whereas it is 90 using BPSO. Similarly, for 8x8 reference network the no. of iterations for obtaining the optimal result using BDE is 110 whereas it is 600 using BPSO.

The statistical quality evaluation of the proposed BDE approach for RCP location management issue is evaluated using cost per call arrival comparision with other state-of-art techniques shown in Table 8. It is seen that the proposed BDE performs as good as the other algorithms like standard DE, BPSO, ACO, TS, GA and MHN in case of networks of different sizes 4x4, 6x6 and 8x8. For 4x4 reference network the cost per call arrival value is 11.234 which is less compared to that of ACO, TS and GA counterpart where the optimal value is 12.252. For 6x6 and 8x8 reference networks the optimal cost per call arrival values are 11.636 and 14.634 respectively which do not vary much compared to other algorithms. From the simulation results, the performance of the proposed BDE is statistically similar to the state-of-the-art optimization algorithms in terms of optimality of solution because of its consistency in finding the global optima. Moreover, owing to the convergence speed the complexity of the algorithm is less as the optimal solution settles down around 50-100 iterations.

V. Conclusions and Scope for Further Research

This paper gives a novel approach based on BDE algorithm considering the RCP strategy for cost optimization in location management in cellular wireless network. Since the proposed RCP problem can be modeled as a binary coded optimization problem the research implements the use of a novel BDE for location management issue in cellular networks. This proposed BDE inherits the concept of estimation of distribution algorithm and the standard Differential Evolution algorithm.

The applicability of the BDE for the reporting cells is concisely specified for the proposed problem for reference networks as well as the realistic networks such as BSNL, Odisha. The implementation results are encouraging as it gives equal or better performance when compared with the results of other author works. This work has future scope in terms of applicability and performance comparison aspect of recently developed bio-inspired techniques for cost optimization in location management problem. The work can be extended to other schemes such as location area strategy in mobile location management. The present work opens up new dimension for further research in real world scenario.

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References

[1] Wong V, Leung V. Location Management for Next Generation Personal Communication Networks. IEEE Network, 2000, 14 (5): 18–24.

[2] Subrata R, Zomaya A. Dynamic Location Area Scheme for Location Management. Telecommunication Systems, 2003, 22 (1–4): 169–187.

[3] Demestichas P, Georgantas N, Tzifa E, Demesticha V, Striki M, Kilanioti M, Theologou M. Computationally Efficient Algorithms for Location Area Planning in Future Cellular Systems. Computer Communications, 2000, 23(13):1263–1280.

[4] Subrata R, Zomaya A. A Comparison of Three Artificial Life Techniques for Reporting Cell Planning in Mobile Computing. IEEE Transactions on Parallel and Distributed Systems, 2003, 14(2): 142–153.

[5] Wang L, Fu X, Mao Y, Menhas M I, Fei M. A novel modified binary differential evolution algorithm and its applications. Neurocomputing, 2012, 98: 55–75

[6] Swayamsiddha S, Mondal S, Thethi H P. Identification of Nonlinear Dynamic Systems using Differential Evolution based Update Algorithms and Chebyshev Functional Link Artificial Neural Network. IET Proceedings of the Third International Conference on Computational Intelligence and Information Technology, 2013:508-513

[7] Swayamsiddha S, Behera S, Thethi H P. Blind Identification of Nonlinear MIMO system using Differential Evolution Techniques and Performance Analysis of its variants. IEEE Proceedings of the International Conference on Computational Intelligence and Networks, 2015:63-67

[8] Alba E, Garca-Nieto J, Taheri J, Zomaya A Y. New research in nature inspired algorithms for mobility management in GSM networks. Evo Workshops, Springer, 2008, LNCS 4974: 1–10.

[9] Taheri J, Zomaya A. Bio-inspired algorithms for mobility management. Proceeding of ISPAN'08 – The International Symposium on Parallel Architectures, Algorithms, and Networks, IEEE Computer Society, 2008: 216–223.

[10] Subrata R, Zomaya A. Evolving Cellular Automata for Location Management in Mobile Computing Networks. IEEE Transactions on Parallel and Distributed Systems, 2003, 14(1): 13–26.

[11] Kim S-S, Kim G, Byeon J-H, Taheri J. Particle Swarm Optimization for Location Mobility Management. International. Journal of Innovative Computing, Information and Control, 2012, 8(12): 8387-8398.

[12] Almeida-Luz S, Vega-Rodríguez M A, Gómez-Pulido J A, Sánchez-Pérez J M. A differential evolution algorithm for location area problem in mobile networks. Proceedings of the SoftCOM 2007 – 15th International Conference on Software, Telecommunications and Computer Networks, 2007:1–5.

[13] Parija S R, Sahu P K, Singh S S. Evolutionary Algorithm for Cost Reduction in Cellular network. Proceedings of the Annual India Conference (INDICON), 2014:1-6.

[14] Parija S R, Nanda S, Sahu P K, Singh S S. Novel Intelligent Soft Computing Techniques for Location Prediction in Mobility Management. Proceedings of the IEEE Students Conference on Engineering and Systems (SCES), 2013:1-4.

[15] Almeida-Luz S, Vega-Rodríguez M A, Gómez-Pulido J A, Sánchez-Pérez J M. Applying differential evolution to a realistic location area problem using SUMATRA. Proceedings of the Second International Conference on Advanced Engineering Computing and Applications in Sciences (ADVCOMP'08), IEEE Computer Society, 2008:170–175.

[16] Almeida-Luz S, Vega-Rodríguez M A, Gómez-Pulido J A, Sánchez-Pérez J M. Defining the Best parameters in a differential evolution algorithm for location area problem in mobile networks. New Trends in Artificial Intelligence

APPIA, Associacao Portuguesa para Inteligencia Artificial, J.J.M. Neves (Ed.), 2007:219–230.

[17] Almeida-Luza S M, Vega-Rodríguezb M A, Gómez-Púlidob J A, Sánchez-Pérez J M. Differential evolution for solving the mobile location management. Applied Soft Computing, 2011, 11:410–427

[18] Taheri J, Zomaya A. A combined genetic-neural algorithm for mobility management. Journal of Mathematical Modelling and Algorithms (Springer Netherlands), 2007, 6 (3): 481–507.

[19] Wang L, Si G. Optimal Location Management in Mobile Computing with Hybrid Genetic Algorithm and Particle Swarm Optimization. ICECS,2010: 1160-1163

[20] Taheri J, Zomaya A. A simulated annealing approach for mobile location management. IPDPS'05: Proceedings of the 19th IEEE International Parallel and Distributed Processing Symposium, IEEE Computer Society, 2005: 194–201.

[21] Taheri J, Zomaya A. A modified Hopfield network for mobility management. Wireless Communications and Mobile Computing, John Wiley and Sons Ltd., 2008, 8(3):355–367.

[22] Chaurasia S N, Singh A. A hybrid swarm intelligence approach to the registration area planning problem. Information Sciences, 2015, 302: 50–69

[23] Storn R, Price K, Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces. Journal of Global Optimization, 1997, 11: 341–359.

[24] Test Networks Benchmark: http://oplink.lcc.uma.es/problems/mmp.html (accessed January 2017).

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