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Performance Analysis of Particle Swarm Optimization Approach for Location Area Planning in Cellular Network

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Abstract— **Location Area (LA) planning has critical impact on the quality of service objectives. The goal of LA planning is to partition the network into a given number of location areas such that the total paging cost and handoff (update) cost is minimized. The problem is characterized by the tradeoff between the updates overhead and the paging cost. Accordingly, the tradeoff between these two factors must be optimized in such a way that the total cost of paging and updating can be minimized along with the link cost. This paper addresses the LA planning problem by developing Particle Swarm Optimization based approach for solving it. The proposed approach is implemented and evaluated with other meta-heuristic approaches.The performance of the approach is investigated and evaluated with respect to the solution quality on different data sets and network sizes. Experimental work demonstrated the performance evaluation in terms of different degree of mobility and paging loads. Potential improvement is achieved over other meta-heuristic based approaches. Moreover, the approach is applied to an existing network layout with real data, and the potential improvement is achieved in terms of paging and location update costs.**

Index Terms— **Location Management in Cellular Networks, Particle Swarm Optimization, Simulated Annealing Optimization, Ant Colony Optimization, Swarm Intelligence.**

I. Introduction

The aim of many existing techniques for solving the location area planning and cell-to-switch assignment problem is to design, organize, and manage the mobile cellular networks to reduce the cost of operation and meet the quality of service requirements required by the subscribers. The efficiency of these techniques is influenced by the location management of mobile cellular networks, which is pivotal and is defined as the Location Management (LM). LM deals with how to keep track of an active mobile station. There are two basic operations involved with location management; location update and paging [4]. One of the strategies used in LM is to partition the network area into Location Areas (LAs). Each LA has one or more number of cells. The goal of LA management is to partition the network into a given number of location areas such that the total paging cost and location update cost is maintained at its minimum. In such partitioning approach, a balance between the location update cost and paging cost is done with the objective of minimizing the cost of tracking the location of mobile stations [7]. In particular, upon the arrival of a mobile-terminated call, the system tries to find the mobile terminal by searching for it among a set of Base Transceiver Stations (BTSs) over the current region of the mobile terminal. This search is called paging, and the set of cells in which a mobile is paged is LA. At each LA boundary crossing, mobile terminals register (i.e., update) their new locations through signalling in order to update the location management databases. Therefore, the size of the LA is important for reducing the cost of paging and location updates (LUs) signalling.

Finding the optimal number of location areas and the corresponding configuration of the partitioned network has motivated many researchers as it is a difficult combinatorial optimization problem which is classified as an NP- hard problem [8]. The previously reported studies divided the whole problem into two sub-problems, the cell-to-switch assignment problem [3], and the LA planning problem [8]. Many approaches have been introduced to solve the cell-to-switch assignment problem in the literature, such as Genetic Algorithm [6], an Evolutionary Algorithm [5], Ant Colony System [12], and Particle Swarm Optimization [10]. These approaches are based on the static LM scheme, where the service area is divided into fixed LAs sizes, and the users in a given region are assigned to the same LA regardless of their characteristics. For the economic feasibility of any communication system, the good design method should optimize cost, while considering some factors such as traffic, bandwidth, and capacity. The weakness of the above approaches is that the paging cost is not considered in the implementation. Moreover, it is assumed that each switch manages only one LA that is equal the size of the cells belonging to that MSC, which further degrades the quality of the service. It is also assumed for some approaches that there is only one link cost between a cell and its switch, whereas in wireless cellular networks such as in Global System for Mobile (GSM) system, the connection between the BTS, the Base Station Controllers(BSCs), and Mobile Service Switching Centres (MSCs) are not identical. These facts have left much room to improve.

Due to high mobility and increase of subscribers, most of recent mobile network systems, including the GSM system, are employing the zone based scheme [4]. In this scheme, the service area is divided into groups of cells forming LAs. The mobile terminals update their locations only when they leave their current LAs and enter new ones. The optimization of the size of the LA of this scheme has not been widely studied, unlike that of other schemes. Only few studies have addressed the LA planning problem for the zone based scheme such as in

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[1] and [8]. In [8], the authors have addressed the LA planning problem for the zone based scheme using Simulated Annealing Algorithm. In their approach, LU overhead and paging cost are considered, but ignored the cabling cost. In [1], the Ant Colony System (ACS) is applied to the LA planning problem based on zone scheme, location update, paging, and cabling costs are included in this work. In this paper the Particle Swarm Optimization (PSO) algorithm is adapted to provide a solution to the LA planning problem for the zone based scheme, since most of the existing personal mobile networks use the zone based scheme in practice and include all its realistic objectives and constraints.

The rest of the paper is organized as follows: Section II provides the mathematical problem formulation of the problem. Section III presents the adaptation of the PSO algorithm to the LA planning problem. Section IV provides a set of computational experiments for the analysis and performance comparison. Finally, some concluding remarks are provided in Section V.

II. PROBLEM FORMULATION

Typically, the GSM system model consists of BTSs, BSCs, and MSCs. LA planning problem is defined as follows.

The service area is divided into a number of Location Area (LAs) and each LA consists of a number of BTSs. The problem arises from the trade-off between the location update and the paging costs, along with the consideration of the link cost which represents the distance between BTSs, BSCs, and MSCs.

The total cost can be represented by

$$C_{total} = M.C_P + P.C_{LU} + R.C_{link} \qquad (1)$$

Where, C_p is the paging cost, $C_{LU}$is LU cost (or registration cost),$C_{link}$is the link cost.M, P and $R$are relative factors. The paging cost of a cell is the total paging rates of the cells that belong to the same LA which is calculated by

$$C_P = \sum_i \lambda(1-d_{is}), \qquad (2)$$

Where λ is the paging rate per unit time for each BTS in the network, and d is a function that returns 1 if i BTS and sBTS reside in a different LA, and is 0, otherwise. The LU cost is calculated by

$$C_{LU} = \sum_i \sum_s d_{is} h_{is} , \qquad (3)$$

Where h is the rate of crossing the LA boundary (handover rate) from the i BTS to the sBTS.

The amortized cabling cost which consists of the cabling cost from i BTS to j BSC and that from j BSC to kMSC can be calculated as follows:

$$C_{link} = \sum_i (\sum_j \sum_k w_{ij}.x_{ij} y_{jk} + \sum_j \sum_k w_{jk} y_{jk}) \qquad (4)$$

where $w$is the link cost between BTS_i and BSC_j. $w$is the link cost between $BSC_j$and MSC_k. is decision variable, is defined as 1 if BTS_i is connected to BSC_j, and 0 otherwise. $y$is decision variable, is defined as 1 if $BSC_j$is connected to MSC_k, and 0 otherwise.

The objective is to minimize the total costin Equation 1subject to the following constraints:

1. Each BTS should be assigned to only one BSC. In this case, the i^{th}cell in the BTS-BSC topology matrix should have only one entry in thei^{th} row that is equal to 1 and the others must be equal to 0.

Since each cell must be assigned to only one BSC, the constraint is:

$$\sum_j x_{ij} = 1, \forall i \quad (5)$$

2. Each BSC must be assigned to only one MSC. For j^{th} BSC, the BSC-MSC topology matrix should have only one entry in the j^{th}row that is 1, and the others are 0 such that:

$$\sum_k y_{jk} = 1, \forall j \qquad (6)$$

3. Each BTS should belong to only one LA. For thei^{th}cell, BTS-LA topology matrix must have only one entry in thei^{th}row that is 1 and the others are 0 such that:

$$\sum_n l_{in} = 1, \forall i \quad (7)$$

Where: l_{in}decision variable, is defined as 1 if BTS_i resides in LA n , and 0 otherwise.

4. Each LA must reside within only one MSC. For each cell pair i and s ,if they belong to the same LA, they are also connected to the same MSC. If: $\sum_n l_{in} l_{sn} = 1$, then

$$\sum_k (\sum_j x_{ij} y_{jk} \sum_r x_{sr} y_{rk}) = 1, \forall (i,s) \qquad (8)$$

5. The maximum number of paging for any BTS in a one time slot must not exceed the paging capacity of the BTS.

$$\lambda \le P_i^{BTS}, \forall i \quad (9)$$

6. Regarding the paging capacity of any BSC, the maximum number of paging for one BSC must not exceed the maximum capacity of the BSC, which is formulated as: $\sum_i x_{ij} \lambda_i < P_j^{BSC}, \forall j$ (10)x_{ij}=1, if i^{th}cell is a member of j^{th}BSC; 0, otherwise. P_j^{BSC}, is the paging capacity of each BSC.

7. The call traffic capacity of the BSC is the maximum number of the calls for one BSC in one time unit that must not exceed the traffic capacity limit of the BSC, which is expressed as:

$$\sum_i x_{ij} c_i < C_j^{BSC}, \forall j \quad (11)$$

whereC_i is the call traffic rate for BTS i , and C_j^{BSC} is the maximum call traffic capacity of BSC_j.

8. The call traffic capacity of MSC is the maximum number of the calls for one MSC in one time unit that must maintain the constraint below:

$$\sum_j \sum_i x_{ij} y_{jk} c_i < C_k^{MSC}, \forall k \quad (12)$$

$y_{jk} = 1$, if j^{th} BSC belongs to k^{th} MSC; otherwise, 0. C_k^{MSC} is the maximum call traffic capacity of each MSC.

9. The BHCA capacity of the BSC, where BHCA stands for the busy hour call attempt rate, can be computed by

$$\sum_i x_{ij} d_i < D_j^{BSC}, \forall j \qquad (13)$$

Where d_i is the peak call attempt rate of cell i per unit time, and D_j^{Bsc} is the busy hour call attempt capacity of each BSC.

10. The BHCA capacity of any MSC is the maximum call processing capability of the MSC that can create a limit on the peak call arrival rate. So, BHCA capacity must not be exceeded and is calculated as:

$$\sum_j \sum_i x_{ij} y_{jk} d_i < D_k^{MSC}, \forall k \; (14)$$

Where D_k^{MSC} is the busy hour call attempt capacity of eachMSC.

11. The TRX capacity of the BTS, where each BSC has a finite number of transmitters is:

$$\sum_i x_{ij} r_i < R_j^{BSC}, \forall j \qquad (15)$$

r_i is the number of TRXs in each BTS ^{i} , and R_j^{BSC} is the number of TRXs in each BSC_j.

12. The TRX capacity of the MSC, where each MSC has a finite number of TRXs, which define the number of channels that used by each cell, can be expressed as:

$$\sum_j \sum_i x_{ij} y_{jk} r_i < R_k^{MSC}, \forall k \qquad (16)$$

Where R_k^{MSC} is the maximum number of TRXs for each MSC.

The challenge is to assign BTSs to BSCs, BSCs to MSCs, and BTSs to LAs considering the assignment costs such that the total cost represented by Equation 1 should be minimized and the set of constraints represented by Equation 5 to Equation 16 must be satisfied.

III. Particle Swarm OptimizationApproach

A. PSO algorithm

Particle Swarm Optimization (PSO) is a population based search algorithm inspired by bird flocking and fish schooling originally designed and introduced by Kennedy et al. [9]. In contrast to evolutionary computation paradigms such as Genetic Algorithm, a swarm is similar to a population, while a particle is similar to an individual. Typically, the particles fly through a multidimensional search space in which the position of each particle is adjusted according to its own experience and the experience of its neighbours. In binary (discrete) version, each particle is composed of *D* elements which indicate a potential solution [9]. The appropriateness of the solution is evaluated by a fitness function. Each particle is considered as a position in a *D*-dimensional space and each element of a particle position can take the binary value of 0 or 1 in which 1 means "included" and 0 means "not included". Each element can change from 0 to 1 and vice versa. Also, each particle has a *D*-dimensional velocity vector, the elements of which are in range [V_{min}, V_{max}]. Velocities are defined in terms of probabilities that a bit will be in one state or the other. At the beginning of the algorithm, a number of particles and their velocity vectors are generated randomly. Then, the velocity (*V*) and position vector (*X*) are updated iteratively using Equation 17 and Equation 18, respectively,

$$V_i^{t+1}(j) = W\, V_i^t(j) + C_1 r_1 \left(pbest_i^t(j) - X_i^t(j)\right) + C_2 r_2 \left(nbest_i^t(j) - X_i^t(j)\right) \qquad (17)$$

$$X_i^{t+1}(j) = \begin{cases} 1 & if\ sig(V_i^{t+1}(j)) > r_{ij} \\ 0 & otherwise \end{cases} \qquad (18)$$

$$sig\left(V_i^{t+1}(j)\right) = \frac{1}{1+exp(-V_i^{t+1}(j))} \qquad (19)$$

X_i^t is the position of j^{th} element of i^{th} particle in t^{th} iteration. V_i^t is the velocity of j^{th} element of the i^{th} particle in t^{th} iteration. The *pbest* is the current best position of the particle, and *nbest* is the best position found so far. C_1 and C_2 are positive acceleration constants which control the influence of *pbest* and *nbest* on the search process. r_1 and r_2 are random values in the range [0, 1] that are sampled from a uniform distribution. *W* is called inertia weight, which is introduced to control the exploration and exploitation abilities of the swarm. r_{ij} of Equation 2 is random number on the range [0, 1]. Equation 19 represents the sigmoid function. The advantage of the PSO algorithm is the combination of local search methods (through self-experience) with global search methods (through neighbouring experience). However, the set of parameters in Equation 1 need to be tuned sensibly in order to balance exploration and exploitation for the search of high quality solution. For more details on the PSO algorithm, the reader may refer to [9] and [11].

B. Adaption of PSO algorithm

In order to adapt PSO algorithm for solving the LA planning problem, we represent the problem in the form of three following connections: the BTS-BSC connection, BSC-MSC connection, and BTS-LA connection such that each particle can be encoded as three $m \times n$ matrices, which called the position matrices of the particle. *m* represents the number of BTSs in the matrix of BTS-BSC connection and BTS-LA connection, and the number of BSCs in the matrix of BSC-MSC connection. *n* represents the number of BSCs in the matrix of BTS-BSC connection, the number of MSCs in the matrix of BSC-MSC connection, and the number of LAs in BTS-LA connection. Each position matrix of each particle has the following properties:

- All the elements of the matrices have either the value of 0 or 1.
- In each row of these matrices only one element is 1 and others are 0.

In position matrix 1, each column represents a BSC and each row represents allocated BTS in a particular BSC. In position matrix 2 each column represents MSC and each row represents BCS allocated in a particular MSC. In position matrix 3 each column represents LA and each row represents BTS allocated in a particular LA. For instance, Table I illustrates the position matrix 1 (BTS-BSC connection) for one particle; the position matrix 1 illustrates that BTS1 is assigned to BSC1, BTS2 is assigned to BSC2, BTS3 is assigned to BSC2, etc. The same interpretation is applied for the other matrices.

TABLE I POSITION MATRIX 1 FOR A SINGLE PARTICLE.

	BSC1	BSC2	BSC3	BSC4
BTS1	1	0	0	0
BTS2	0	1	0	0
BTS3	0	1	0	0
BTS4	0	0	1	0
BTS5	0	0	0	1

Velocity of particles is represented by a ***m*×*n*** *velocity* matrix whose elements are in the range [V_{min},V_{max}]. p*best*and *nbest*are ***m*×*n***position matrices and their elements are 0 or 1. p$best_k$represents the best position that k particle has visited since the first iteration and$nbest_k$representsthe best position that k particle and its neighbors have visited from the beginning of the algorithm. For updating *nbest* in each iteration, *pbests* are used so that if the fitness value of *pbest* is greater than *nbest*, then*nbest* is replaced with *pbest*. Equation 20 is applied for updating the velocity matrix and Equation 21 is applied to update the position matrix of each particle.

$$V_k^{(t+1)}(i,j) = W.V_k^t(i,j) + c_1 r_1\left(pbest_k^t(i,j) - X_k^t(i,j)\right) + c_2 r_2\left(nbest_k^t(i,j) - X_k^t(i,j)\right) \quad (20)$$

$$X_k^{(t+1)}(i,j) = \begin{cases} 1 & if\ \left(V_k^{(t+1)}(i,j) = \max\{V_k^{(t+1)}(i,j\right. \\ 0 & \text{Otherwise} \end{cases} \quad (21)$$

$V_k^t(i,j)$ denotes the element in i row and j column of the k velocity matrix in t iteration of the algorithm, and $X_k^t(i,j)$ denotes the element in i row and j column of the k position matrix in t iteration. Equation 6 illustrates that in each column of position matrix a value 1 is assigned to the element whose corresponding element in velocity matrix has the maximum valuein its corresponding column. If there is more than one element in the column of velocity matrix with maximum value, then one of these elements is selected randomly and 1 assigned to its corresponding element in the position matrix. Fig. 1 illustrates the basic steps of the adapted structure of the PSO algorithm for solving the LA planning problem.

- Initialize particles with random positions.
- Initialize each particle with random velocity.
- Initialize *pbest* and *nbest*.

While iterations<= Max_of _iterations

For each particle

Calculate the fitness value from the obj. function.

If current fitness value >fitness value of the *pbest*

Then update *pbest*

End for

-Update *nbest* from *pbest*.

-Apply assignment criteria (determine the assignment type).

- For each particle
  - Update the particle velocity (Equation 20)
  - Update the particle position (Equation 21)
- End For

End while

Return the solution from the *nbest*.

Fig. 1 The adapted structure of PSO algorithm.

C. Neighbourhood Structure (Assignment Types)

In this paper, three types of assignments are introduced for the connection of BTSs, BSCs, and MSCs. The feasible solution can be generated by any of the three types of assignment and each assignment affects the network structure in different ways.

1. BTS to BSC Assignment: In this type, the BTS-BSC connection or position matrix of the particle is considered. Equation 20 will be used to update the velocity matrix related to BTS-BSC connection, and the BTS-BSC position matrix is consequently updated by Equation 21. Thereafter the new load on each BSC is updated and all the constraints affected by this BTS-BSC new connection are checked. If these constraints are violated then this particle is marked at the end of the iteration as invalid (infeasible solution) otherwise it is marked as valid. Finally, for each MSC starting with one LA, BTSs are assigned to an LA. If LA capacity (i.e., paging capacity of BTSs) reaches to its limit, then a new LA is created and remaining BTSs started to be assigned to that LA. Here, the aim is to create the minimum number of LAs for each MSC. The reason of marking the particles at the end of each iteration as valid or invalid is that; the infeasible solutions that is found with invalid particles which means they did violate the constraints, may eventually lead to better positions/solutions, or may not. Thus, it is might be better to use some of these invalid particle in each iteration. In order to control the number of invalid particles in each iteration so they will not be the majority and eventually affect the quality of the solution with iterations, a mechanism of accepting a predefined ratio of invalid particle to the valid once in each iteration has been used. Thus, number of invalid particles can be controlled in each iteration.
2. BSC to MSC Assignment: In this assignment type, velocity and position matrices are updated on the BSC-MSC connection without affecting the BTS-BSC connection. First, the BSC-MSC velocity matrix is updated using Equation 20 and then the BSC-MSC position matrix is updated using Equation 6. Due to the new connections caused by Equation 21, the feasibility of the capacity and proximity constraints of that new BSC-MSC connection must be checked. Particles that violate the constraints will be marked as invalid at the end of the iteration for the same purpose illustrated in BTS-BSC assignment type. Finally, for each MSC starting with one LA, BTSs are assigned to an LA. If LA capacity (paging capacity of BTSs) reaches to its limit, then a new LA is created and remaining BTSs started to be assigned to that LA.
3. BTS to LA Assignment: In this assignment type, the particle changes the BTS-LA assignment without affecting the BTS-BSC connection (i.e., the particles search for all the LAs residing within the same BSC). The assignment is done by updating the velocity matrix of BTS-LA connection using Equation 20, then the BTS-LA position matrix is updated using Equation 21.

Subsequently, the capacity constraint of BTS-LA connection is checked, in case this constraint is violated then this particle will be marked as invalid, the position/solution will not be accepted, and the particle will continue with its old connection/position.

IV. COMPUTATIONAL EXPERIMENTS

Several experiments are conducted for parameter setting, effects of network factors on the performance, and evaluation of the proposed approach. Moreover, the proposed approach is compared to the SA and the ACS based approaches and applied to an existing network in order to enhance its performance. The proposed approach and the other two meta-heuristic based approaches are implemented using visual C++ and executed under Windows8 operating system, with Intel® core ™ i5-3210M 2.50 GHz CPU and 12 GB RAM.

A. ParameterSetting

The velocity update equation depends on a number of parameters that need to be determinedin order to provide high quality solution [9]. In this paper, the PSO approach is applied to a typical network that consists of 398 BTSs, 2 BSCs, and 1 MSC for the parameter setting experiments. The preliminary experiments are performed starting with an initial setting of the parameters based on values previously reported in the literature [13].

The PSO tends to have more global search ability at the beginning of the run while having more local search ability near the end of the run in order to refine a candidate solution. The inertia weight (*W)* has some valuable information about previously explored directions. It governs how much of the previous velocity should be retained from the previous time step [13]. The best found starting value of *W* is1.2 and gradually declined towards 0 during the search.

The acceleration parameters *C1* and C_2denote the direction of the particle towards optimal positions. They represent "cognitive" and "social" component, respectively. They affect how much the particle's local best and the global best influence its movement. From the experimental results it found that giving equal chances to exploration and exploitation didn't improve the cost as good as when giving different values for and . It has found that choosing a larger cognitive parameter, than a social parameter, , (*i.e.,*=1.5 , =0.5) gives the best result.

To ensure convergence of the heuristic, every velocity vector is bounded component-wise by minimum and maximum values[V_{min}, V_{max}] as in Equation 4.These parameters are proved to be crucial, because the maximum velocity V_{max} serves as a constraint to control the global exploration and exploitation ability of the particle swarm.The best result is achieved when V_{max} and V_{min} are equal to 50 and 0.05, respectively.

The type of assignment is chosen according to some probabilities assigned for each type of assignment. The best quality solutions were obtained, when the probability assignment of the BTS-BSC is 0.2, BSC-MSC assignment is 0.5, and BTS-LA assignment is 0.3.

The quality of solution is affected by the number of particles participating in the search process. More particles indicate a more cooperative interaction. To determine the appropriate number of particles, the results obtained for different numbers of particles, and it has found that the best number of particle is 30.

The parameters values have been tested and verified with different problem instances in terms of network cost. Fig. 2 depicts the cost of the solution found at different stages of a typical run ofPSO based approach for a sample network.

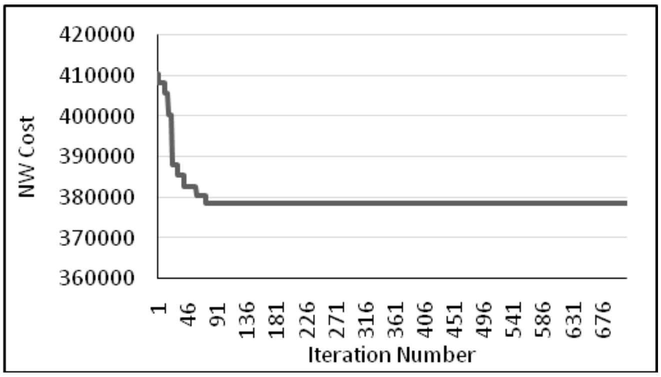

Fig. 1Atypical run of the PSO based approach on a sample network.

B. Performance Evaluation on Different Mobility and Paging loads

An extensive performance study is carried out to evaluate the effectiveness of the proposed approachfor the LA planning problem on different networks and datasets. Four data sets (denoted by 1, 2, 3, and 4) of network I (203 BTSs, 6 BSCs, and 3 MSCs) and four datasets (denoted by 5, 6, 7, and 8) of network II (400 BTSs, 2 BSCs, and 1 MSC) reported in [8] are applied for the performance evaluation.

In this experiment, different patterns of mobility, paging loadsare generated for all data sets.The performance of the approach is investigated and evaluated with low and high mobility and paging load.

To achieve a network with high mobility, the value of the handover rate of the network is scaled up by 70%. For low mobility, the same values of the handover rate is scaled down (divided by two).The other factor values remain unchanged. Fig. 3 demonstrates the performance on eight data sets for high, moderated, and low mobility.

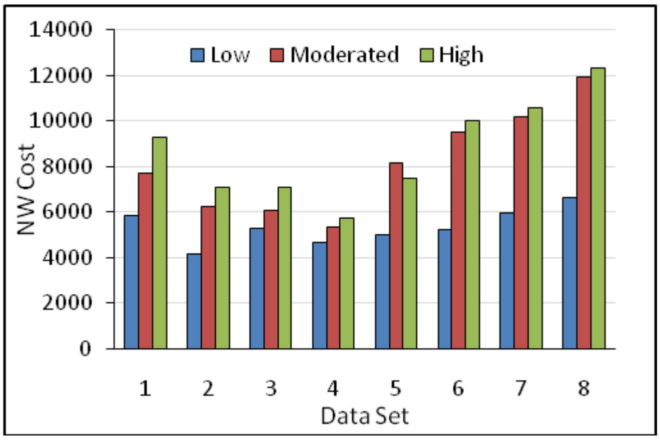

Fig.3 Performance evaluationwith different mobility.

For high mobility, the obtained costs of all data setsareincreased as a result of high crossing rate (i.e., high location update) except for dataset 5. For low mobility, the obtained cost for all data sets is decreased as a result of low crossing rate (i.e., low location update).Practically, the position update equation (Equation 21) is affected by the handover constraints. As a result the obtained costs are slightly higher for high mobility compared with the moderated mobility.

The paging load results from the number of mobile terminated calls, generated in a unit time. A high paging load means the number of mobile terminated calls is high, and a low paging load means the number of mobile terminated calls is low.The network with high and low paging load are generated to examine the performance of the approach.A high paging load is obtained by increasing the values of the paging load for each BTS by 70%. The low paging load is obtained by scaling down the values of the paging load by 50%. The other values remain unchanged. Fig. 4 demonstrates the performance on eight data sets for high, moderated, and low paging load.

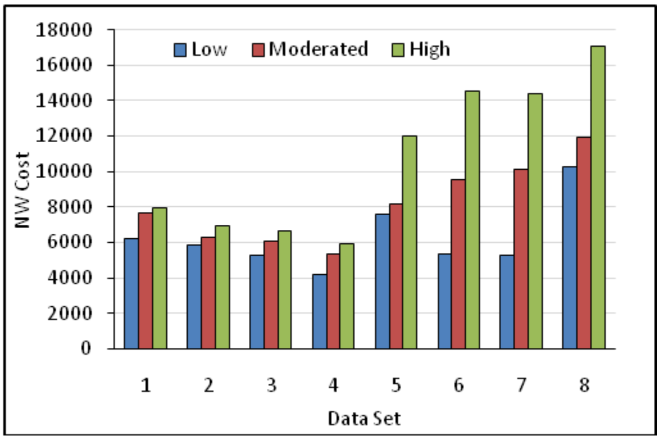

Fig.4 Performance evaluationwith different paging load.

For high paging load, the obtained costs of all data sets are increased as a result of high paging rate. For low paging load, the obtained cost for all data sets is decreased as a result of low paging rate. As result, the solutions are slightly degraded for high paging loads compared with the moderated paging loads for network I. This is due to the fact thatthe paging capacity limit cannot be violated in low paging rate.

C. Performance Comparisonwith other Approaches

To demonstrate the potential of applying the PSO algorithm for solving the LA planning, the PSO approach is compared with other existing meta-heuristic approaches.The PSO is compared with the Simulated Annealing (SA) and Ant Colony System (ACS) algorithms on different networks anddata sets.Four data sets (denoted by 1, 2, 3, and 4) of network I (203 BTSs, 6 BSCs, and 3 MSCs) and four datasets (denoted by 5, 6, 7, and 8) of network II (400 BTSs, 2 BSCs, and 1 MSC) reported in [8] are applied for the performance comparison. The parameters values of the SA and ACS have been chosen as reported in [8] and [1], respectively.For more details on SA and ACS based approaches for solving LA problem, the reader may refer to [8] and [1], respectively.The three approaches are evaluated on the basis of the average of 30 independent runsfor each dataset.

Results denoted by (*) represent the results of SA and ACS as reported in [8] and [1], respectively. As shown in Table II, the PSO obtained the best solution for all datasets.

TABLE II PERFORMANCE COMPARISON BETWEEN DIFFERENT APPROACHES

Data Set	SA	ACS	PSO
1*	9880	9685	**7687**
2	7453	6866	**6256**
3	8951	8148	**6058**
4	6529	5997	**5332**
5	13600	10580	**8180**
6	13630	10667	**9520**
7	14570	12335	**10151**
8	13781	13550	**11922**

D. Network Case Study

To demonstrate the potential of applying the PSO algorithm for solving the LA planning, the PSO approach is applied on AlmadarAljadeed network with its current data. AlmadarAljadeed is one of GSM mobile operators in Libya. The network covered two main geographic regions (eastern and western regions) of the entire country. This study focuses on the westernregion of the country. The current layout of the westernregion consists of 1808 BTSs clustered in a set of sites, controlled by 7 BSCs, and 8 LAs. The proposed approach starts with already planned cellular network, so the approach starts with an initial feasible solution; the borders of the LAs are specified, and the constraints are met. The specifications and capabilities of BSCs are taken from the Almadar network expansion documents [2], and the traffic data taken from the BSCs counters for the busiest hour during one week. Figure 5illustrates borders of the LAs design of the already planned cellular network (i.e., current layout).

The upper bound on the size of an LA is the service area of an MSC. The optimum LA design must minimize the LU on the borders and also reduce the paging since both are inversely proportional. Between this extremes there is one or more partitions of the MSC service area that can minimize the total cost of paging and updating along with link cost.

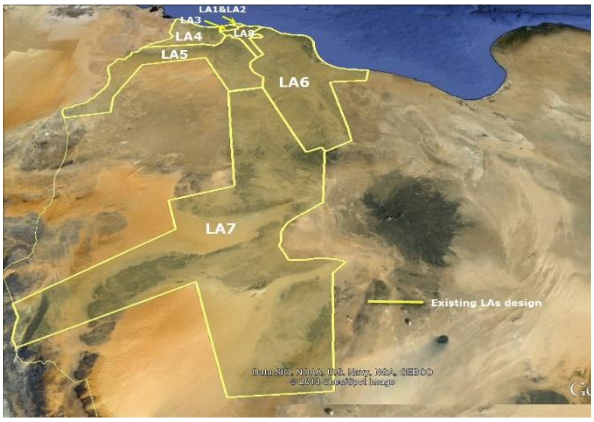

Fig. 5 LAs current design of Almadar-Aljadeed network.

To simplify the search, the paging cost has been preserved to a given threshold. In this regard the paging is kept at 56.59% of its full capacity, then the search for minimum location update cost is performed along with link cost. Upon that, the criteria of the design evaluation is based on how many location update event will be occur at the LAs borders and the less number of LU the better LAs design performance, at the same time the paging should be kept under the given threshold along with minimum link cost. Optimizing the existing LA borders with the site constraints make it more complicated to the particles to find feasible solutions in the early stages of the run, That is the search space is more restricted due to this extra constraints.

The design constraints have been met since there is no capacity over load and it also shows that the paging has been kept under the capacity limits. The best result is obtained from 10 independent runs. The result is compared with the existing design, and analysed by visualizing the data on geographic map as shown in Fig. 6. This Figureillustrates the complete design for the optimized LAs design.

Fig. 6 LAs optimized design of Almadar-Aljadeed network.

Table III illustrates the LU cost for the current and optimized layout of each LA. The most effective reduction is located in BSC1 and BSC2, where BSC1 and BSC2 are controlling LA1 and LA2 in the existing design and the total LU cost caused by these two LAs is 47204. This area actually has the largest LU cost in the existing network. In the optimized LAs design BSC1 and BSC2 control LA1, and the load on these two BSCs has been reduced up to 50.6%.

TABLE III LU COST OF THE CURRENT AND THE OPTIMIZED NETWORK LAYOUT.

Network layout	Las	LU Cost
Current layout	LA1:BSC1	11909
	LA2:BSC2	35295
	LA3:BSC3	4679
	LA4: BSC4	4156
	LA5: BSC5	1267
	LA6: BSC6	2527
	LA7: BSC7	165
	LA8: BSC3	28339
	Total LU Cost	88337
Optimized layout	LA1:BSC1, BSC2	23279
	LA2: BSC3	32206
	LA3: BSC5, BSC6, BSC7	2913
	LA4: BSC4, BSC5	5260
	Total LU cost	63658

Finally, Fig.7illustratethe performance comparison between the existing and the optimized layouts in terms of the total location update cost (LU cost) and the total network cost (NW cost). The reduction rate in LU cost is 27.9% and in the network cost is 7.8%.

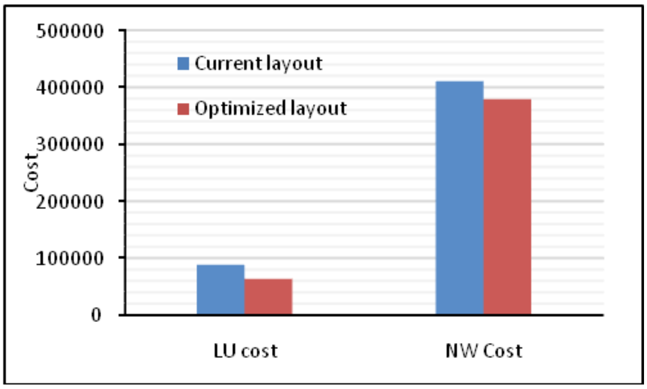

Fig. 7 performance comparison between the current and the optimized network layouts.

V. CONCLUSION

The most important benefit of optimizingthe LA planning is preventing unnecessary radio resource usage that can instead be allocated for the communication of the subscribers. Furthermore, thenetwork resources can be utilized more efficiently and network construction costs can be reduced. The formulation of the problem should include all the constraints related to the capacities of the network resources and the costs related to the location update,the paging loads, and the link.

In this paper, the particle swarm optimization algorithm is adapted to solve the LA planning problem. The aim is to developan approach that can solve the problem more efficiently. The potential improvement has been accomplished through the design and the analysis of PSO approach. The experimental results have shown that the PSO approach outperforms other meta-heuristic approaches on different network sizes and data sets. Moreover, the proposed approach is applied to the AlmadarAljadeed GSM network; all its realistic constraints and objectives are considered. A significant improvement is obtained over the existing design. This improvement can help the planning engineers to enhance the efficiency of the whole network.

However, further improvement to enhance the proposed approach is still needed. Of particular importance is the investigation on the assignment criteria to include clustering of cells based on frequencies. Since the cells need to be clustered in terms of the frequencies pattern, such as in GSM networks, due to a limited frequency bandwidth. Another extension is to investigate on the computation time andthe concept of parallelization of the proposed approach.

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