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Particle swarm optimization for mobile network design

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Abstract: In mobile network design, the challenge is to efficiently determine the locations of base control stations (BSCs), mobile switching centers (MSCs), and their connecting links for given locations of base transceiver stations (BTSs) so that a predefined objective function is satisfied. In this paper, a particle swarm optimization- (PSO-) based optimization engine is used to effectively lay out the network components and their interconnections such that the overall deployment cost is kept as low as possible. The performance of the PSO-based engine is then compared with a genetic algorithm- (GA-) based one. The simulation results show that the PSO-based optimization engine is able to successfully optimize the network deployment cost and significantly outperforms the GA-based optimization engine.

Keywords: mobile network design, PSO, GA, BTS, BSC, MSC

Classification: Wireless circuits and devices

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1 Introduction

The mobile networks enable wireless communications between end-to-end mobile users. It basically consists of four interacting layers; these layers are the mobile users or user equipments (UEs) layer, the base transceiver stations (BTSs) layer, the base station controllers (BSCs) layer and lastly, the mobile switching centers (MSCs) layer. Each layer has its own functions as well as some interactions among each other. Many countries have already established a very good foundation on the mobile network. However, the implementation of such networks is still an open research area focusing on many objectives such as improving the network performance and coverage, reducing the traffic intensity, and minimizing the deployment cost. The last objective is of interest in this research work. The idea is to formulate the mobile network deployment problem using an optimization tool in order to reduce the overall implementation cost by reducing the cabling cost that is the cost of establishing inter- and intra-links between the network layers. Here, the main objective is to develop a PSO-based optimization engine for a generalized mobile network model that can optimally place the BSCs and MSCs at optimum locations for given predefined locations of BTSs such that it gives the shortest interconnection links between the network components.

In cellular mobile communications, multiple BTSs communicate with a single BSC, multiple BSCs then will communicate with a MSC. Finally, each MSC then will communicate with other MSCs. However, this interlink connections are subjected to constraints; a BTS can only be connected to a single BSC and a BSC can only be connected to a single MSC. In addition, a single BSC may be linked to several BTSs while a single MSC can be connected to several BSCs [1, 2, 3].

2 Particle Swarm Optimization

PSO is a population-based stochastic optimization technique inspired by social behavior of bird flocking or bees. The PSO mechanism is initialized with a population of random solutions and searches for optima by updating generations [4, 5, 6]. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (best fitness) it has achieved so far. This value is called *pbest*. Another "best" value tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighbors of the particle. This location is called *lbest*. The best value ever in the whole search space is called as the global best (*gbest*). The particle swarm optimization concept involves, at each time step, changing the velocity (accelerating) of each particle towards its *pbest* and *lbest* locations. This particle movement is governed by the equation of motion given by

$$\begin{aligned} V_{(n+1)} &= w.V_{(n)} + C_1.(lbest - X_{(n)}) + C_2.(gbest - X_{(n)}) \\ X_{(n+1)} &= X_{(n)} + V_{(n+1)} \end{aligned} \tag{1}$$

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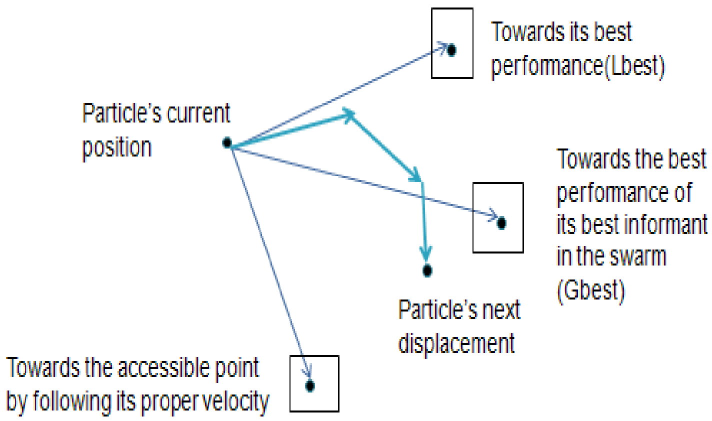

Fig. 1. The next-displacement scenario for a swarm particle.

where w is the weight inertia, C_1 is the self-confident coefficient and C_2 is the confident in other coefficients. These two parameters together with the swarm size are the PSO's intrinsic control parameters that can be analyzed to achieve better performance for a given problem. Fig. 1 shows the next displacement calculation for a particle in the swarm.

3 Problem formulation

In this research work, the PSO technique is invoked to obtain an optimized solution that minimizes the deployment cost objective function. Each possible solution will be mapped to a particle in the PSO framework. Any complete possible solution is composed of two parts; the first part of the solution (particle) is a representation for the possible links between the network components. The assignment of interconnection links between BTS and BSCs and between BSCs and MSCs is realized by employing an encoding scheme of binary digits, 1's and 0's, to indicate the presence and absence of the links between the nodes, respectively. The total number of bits in this part of the solution can be modified from [1] as follows:

$$Total\ number\ of\ bits = (N_{BTS} * N_{BSC}) + (N_{BSC} * N_{MSC}) + \sum_{s=1}^{N_{MSC}-1} s \quad (2)$$

where N_{BTS}, N_{BSC}, and N_{MSC} are the number of BTSs, BSCs, and MSCs, respectively. The multiplication process in Eq. (2) indicates to the maximum possible interconnection links exists between the network components. In this paper, we are using a simplified network model of 19 BTSs, 4 BSCs, and 2 MSCs. Thus, the number of possible links between the BTSs and the BSCs is 76 links, the number of possible links between the BSCs and MSCs is 8 links, and there will be one necessary link between the two MSCs. Thus, the total links in the mobile network is 85 links (binary digits). The network is deployed on an imaginary two dimensional X-Y space of 20 X 20 miles^2.

The second part of the complete possible solution is the coordinate locations of the network components, BSCs and MSCs, for given locations of BTSs on the proposed search space. The coordinate locations of BSCs and

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MSCs are expressed by the 2-D coordinates $\{\mathrm{X}_i, \mathrm{Y}_i\}$, where $i = 1, 2, 3$, or 4 for BSCs and $i = 5$ or 6 for MSCs in this proposed network model.

Now, by combining these two parts together, we can form complete possible solutions for the mobile network design, any complete solution contains 84 bits indicate to the possible links between BTSs and BSCs and between BSCs and MSCs as well as twelve decimal numbers indicate to the six $\{\mathrm{X}_i, \mathrm{Y}_i\}$ pairs that are coordinate locations of 4 BSCs and 2 MSCs. The PSO algorithm has been adapted to simultaneously work with binary digits for the possible links as well as decimal numbers for the coordinate locations.

The total deployment cost, that is the objective function of the PSO, is then designated. It is clear that the cost increases by having more links between the network components and also by having these components far from each other as this will increase the overall cabling cost. The overall deployment cost is formulated by the equation

$$C = \sum_i \sum_j L_{ij} X_{ij} + \sum_j \sum_k L_{jk} Y_{jk} + \sum_k \sum_l L_{kl} Z_{kl} \tag{3}$$

where $i = 1, 2, \ldots, N_{BTS}$, $j = 1, 2, \ldots, N_{BSC}$, $k = 1, 2, \ldots, N_{MSC}$, L_{ij} = the cost of cabling for the link between BTS_i and BSC_j, L_{jk} = the cost of cabling for the link between BSC_j and MSC_k, L_{kl} = the cost of cabling for the link between MSC_k and MSC_l, $X_{ij} = 1$ if $\mathrm{BTS_i}$ is assigned to $\mathrm{BSC_j}$ or $X_{ij} = 0$ otherwise, $Y_{jk} = 1$ if $\mathrm{BSC_j}$ is assigned to $\mathrm{MSC_k}$ or $Y_{jk} = 0$ otherwise, and $Z_{kl} = 1$ if $\mathrm{MSC_k}$ is assigned to $\mathrm{MSC_l}$ or $Z_{kl} = 0$ otherwise. However, this function is governed by the following constraints: $\sum_i X_{ij} = 1$, for $j = 1, 2, \ldots, \mathrm{N_{BSC}}$ (to ensure that each BTS is assigned to exactly one BSC), and $\sum_j Y_{jk} = 1$, for $k = 1, 2, \ldots, \mathrm{N_{MSC}}$ (to ensure that each BSC is assigned to exactly one MSC).

4 Simulation results and discussion

In order to improve the performance of the PSO engine, an intrinsic parameters analysis is carried out to carefully determine the best set of parameters that enhances the convergence speed of the algorithm. Thereafter, the improved PSO is used to solve the mobile network design problem. Finally, the PSO performance is compared with GA-based optimization engine. All Simulations have been done using C++ and their results have been displayed using Microsoft Office Excel.

4.1 Intrinsic PSO parameter analysis

The main parameters that bring significance to the results are the swarm size (s), weight inertia (w), and the confident coefficient (C_1). These three parameters are analyzed in effort to further decrease the implementation cost. Firstly, the swarm size is varied while the other two parameters are held constant at their empirical values as shown in the Fig. 2 (a). Next, the weight inertia will be varied while the swarm size and the confident coefficient are held constant as shown in Fig. 2 (b). Finally the confident coefficient is

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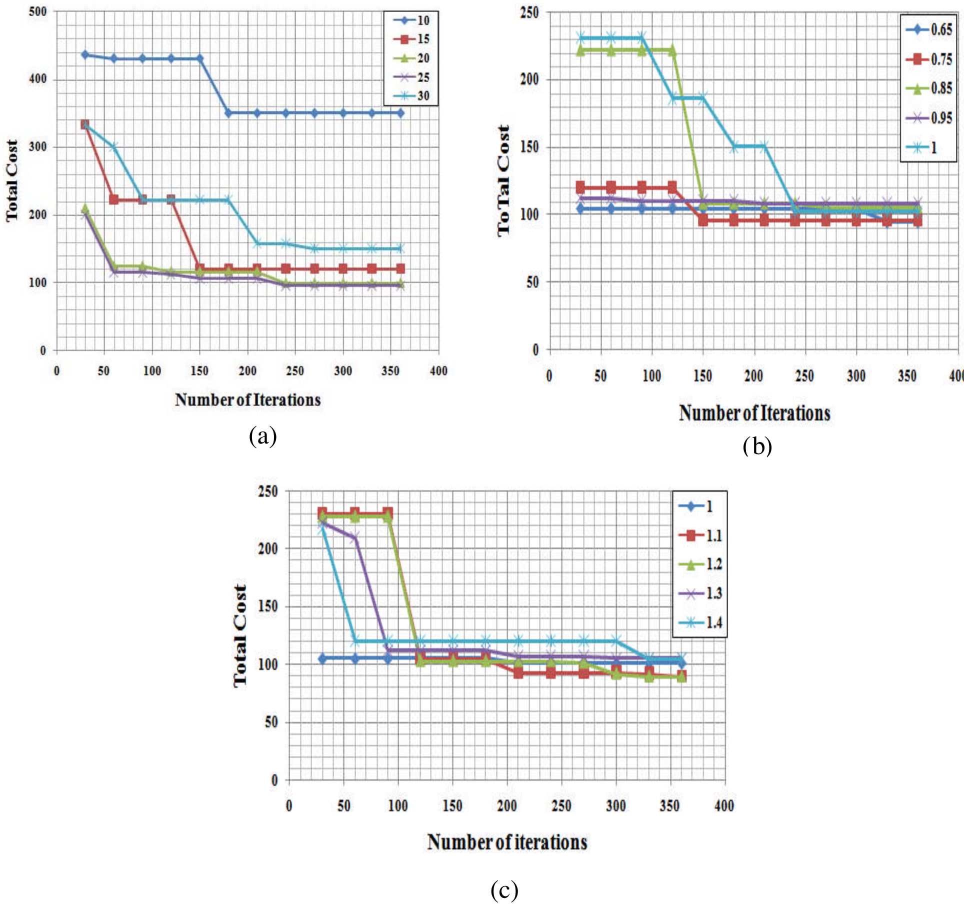

Fig. 2. Optimizing PSO parameters (a) Varying swarm size analysis, (b) Varying weight inertia analysis, and (c) Varying confident coefficient analysis.

varied while the weight inertia and swarm size are held constant as shown in Fig. 2 (c). The simulation results show that the best set of parameters at which the overall deployment cost is minimized are $s = 25$, $w = 0.65$ and $C_1 = 1.2$.

4.2 PSO implementation for mobile network design

In this section, the PSO-based engine with its optimized parameters is used. Fig. 3 (a) shows a sharp drop in the overall deployment cost for the mobile network with increasing the number of generations until it reaches to a minimum cost level (89.7 currency units) at 360 generations after which the deployment cost cannot be minimized anymore. Fig. 3 (b) shows the optimal locations and assignment links of the network components (BSCs and MSCs) at the minimized cost. The placement of each station obeys the constraints whereby there is only one link from any BTS to any BSC and also only one link from any BSC to any MSC.

4.3 Performance comparison with genetic algorithm (GA)

A performance comparison between the PSO-based and GA-based optimization engines is performed as shown in Fig. 3 (c). It is clear that the PSO

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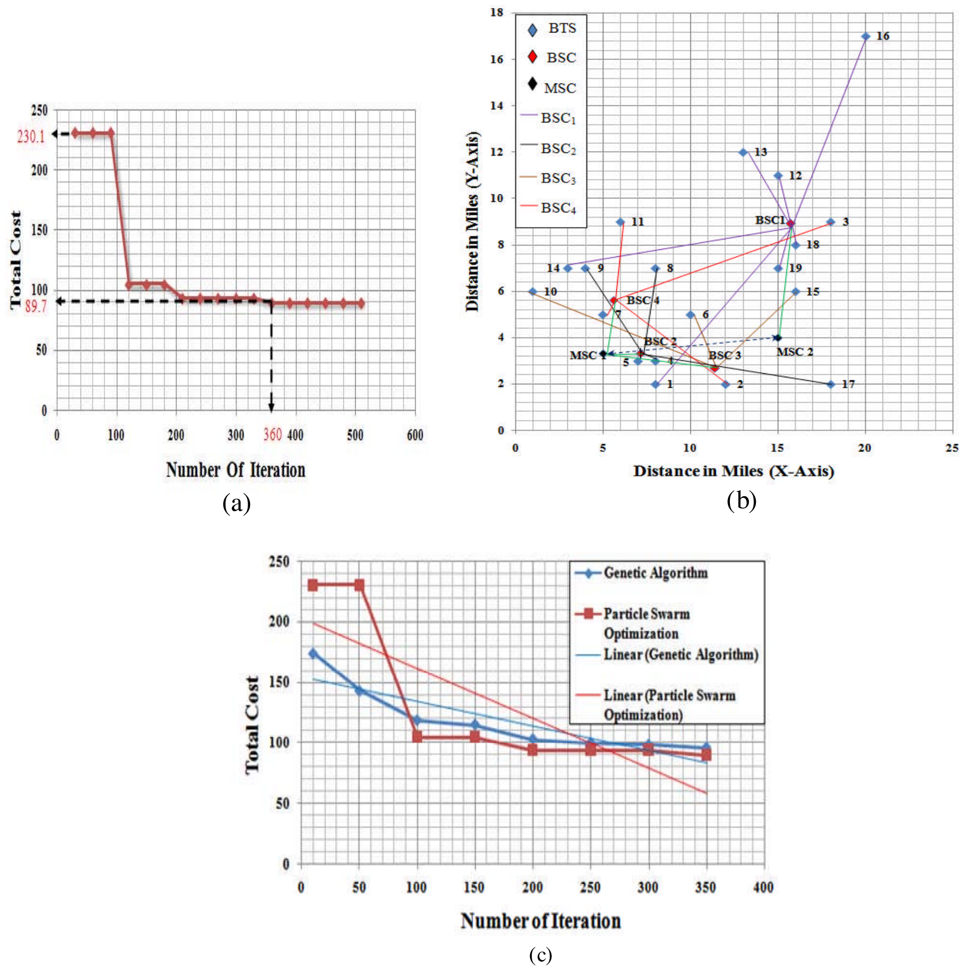

Fig. 3. Mobile network analysis (a) Overall cost using the best set of PSO parameters, (b) Optimized locations of mobile network stations at the minimal cost, and (c) PSO performance comparison with GA.

optimization offers lesser cabling cost than the GA one. Linear (PSO) and linear (GA) are the straight lines that best fit the points of the cost-number of generations relationship found by regression. It is again obviously clear that the PSO converges faster than the GA as the primer has a sharper slope.

5 Conclusion

In this paper, a PSO-based optimization algorithm has been proposed as a key solution for the mobile network design problem. The PSO parameters have been first analyzed to specify their best values that improve algorithm performance for the problem at hand. The enhanced PSO-based algorithm was then used to minimize the deployment cost of a proposed mobile network by efficiently assign links between the network components as well as by carefully placing these components at optimal locations. The performance of the PSO-based engine was finally compared with a GA-based optimization engine and the simulation results showed that the PSO-based engine performs better and it is therefore, more equipped to handle complex design problems.

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