A Heuristics Based Approach for Cellular Mobile Network Planning

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ABSTRACT

Designing and planning of the switching, signaling and support network is a fairly complex process in cellular mobile network. In this paper, the problem of assigning cells to switches in cellular mobile network, which is considered a planning problem, is addressed. The cell to switch assignment problem which falls under the category of the Quadratic Assignment Problem (QAP) is a proven NP–hard problem. Further, the problem is modelled to include an additional constraint in the formulation. The additional constraint is of the maximum number of switch ports that are used for a cell's Base Station Transceiver System (BTS) connectivity to the switch. The addition of the constraint on the number of ports on a switch has immense practical significance. This paper presents a non–deterministic heuristic based on Simulated Evolution (SimE) iterative algorithm to provide solutions. The methods adopted in this paper are a completely innovative formulation of the problem and involve application of Evolutionary Computing for this complex problem that may be extended to solutions of similar problems in VLSI design, distributed computing and many other applications.

1. INTRODUCTION

Mobile telephones are used extensively in the world today. A tremendous growth was observed in the last decade and the trend is expected to exponentially improve in the near future. This continuous growth is possible because the cellular concept makes it possible for users to have freedom with respect to mobility and ease of use, while still receiving a good quality of service [1].

A large subscriber base, scarcely available network resources and intensive competition in the telecommunication market makes efficient and demand adaptive network design a key factor for survival of cellular mobile network providers. Besides, the upcoming applications of cellular mobile network systems for data communication (3G, 4G and UMTS) [2] require more optimum and flexible network structure.

Network planning in mobile telephony entails planning of the supporting, switching, signaling and interconnection networks. This is a particularly complex process, partly because of the numerous intervening factors and partly because there are variable environmental conditions which must be taken into account in order to provide the user with a specified quality of service at any time.

One of the most important problems of network planning, the problem of assigning cells to switches in cellular mobile network, is considered. The problem is further modified to include additional constraints on the switch with respect to the maximum number of available ports. This modification has immense practical significance in real life cellular mobile network design scenarios. It should be noted that the cell to switch assignment problem is an NP (Non Polynomial time) hard problem since the problem falls under the category of the Quadratic Assignment Problem (QAP) which is a proven NP–hard problem [3]. As such, no deterministic algorithm which can find an optimal solution for the above problem in polynomial time exists. Thus the problem is solved using iterative heuristics, like Simulated Annealing (SA) and Simulated Evolution (SimE) [4], to provide solutions which are based on different heuristics and compare them with existing methods. These methods are completely innovative formulation of the problem and involve application of evolutionary computing for this complex problem that may be extended to solutions of similar problems in VLSI design [5], distributed computing and many other applications.

The conventional layout of a cellular network follows a honey comb structure [6]. The basic geographic unit of a cellular system is called a "cell". The geographical area of coverage is divided into hexagonal cells which are arranged in a hierarchical manner to reduce link costs. Each cell has an antenna called base station which is used to communicate with the subscriber mobile unit over some preassigned frequencies. A certain number of cells are chosen to install switches that communicate with one another and serve as relays for communication between any pair of cells. Because of the subscriber mobility, switches serving as relays could change if the subscriber moves from its current cell. The operation that consists of detecting that a user has changed a cell and carrying out the required updates constitutes a hand-off.

The hand–off that occurs between two cells linked to the same switch is called a simple hand–off and a hand–off that occurs between two cells connected to different switches is called a complex hand–off. In a simple hand–off there are few necessary updates in the switches, while in a complex hand–off, update procedures consume more resources than in the case of a simple hand–off.

The problem of cell assignment could be summarized as follows: for a set of cells and switches (whose positions are known), assign the cells to the switches in a way that minimizes the cost function. The cost function integrates a component of link cost and a component of hand–off cost. The assignment must take into account the switches capacity constraints that make them capable to host only a limited number of calls. Also, the constraint on the maximum number of available ports on a switch must be taken into account.

First, a brief review of the related work is presented in Section 2. Then, a simple mathematical formulation for the problem is suggested based on the so called conventional methods in cell to switch assignment problem. Only the complex handover cost and link cost between cells and switches with respect to the maximum switch capacity constraints is considered in this formulation. With this assumption the mathematical formulation is presented in Section 3. The problem is further modified to include additional constraint with respect to the maximum number of ports. Section 4 provides an overview of SA and SimE based approaches to solve the problem. The details of the computational results and the comparisons between SA and SimE are presented in 5. Finally, section 6 presents conclusions.

2. RELATED WORK

A substantial amount of work has been done in the field of computer network design in general. Comparatively very little work has been undertaken for solving the problem of designing cellular networks (assigning cells to switches) in particular. Few papers related to this work were found in the literature.

Merchant and Sengupta [7] tried to solve the problem using deterministic algorithms and provided the basic formulation of the problem. They considered a scenario of assigning cells to the switches of a Personal Communication Services (PCS) network in an optimum manner. The problem is formulated as an integer programming problem. Their work also proposed three heuristic solutions and showed that two of them perform extremely well.

S. Pierre and F. Houeto [6] extended the work of Merchant and Sengupta [7]. They solved the problem using tabu search, a non–deterministic iterative algorithm, and provided results for problems of varying sizes (in terms of number of cells and switches). Their approach defines a series of moves applicable to an initial solution in order to improve the cost and establish the feasibility of the solution. For this purpose, they identified a gain structure with update procedures to efficiently choose the best solution in the current neighborhood. The implementation was tested with different parameters of tabu search. They also compared these against the results obtained from simulated annealing, another non-deterministic iterative algorithm.

S. Menon and R. Gupta [8] improved upon the work of S. Pierre and F. Houeto [6] and provided results which were obtained in lesser durations. According to their paper, in the presence of capacity constraints at the switches, the problem of assigning cells to switches becomes a difficult one to solve, with all effective solution approaches being based on heuristic techniques. Their paper presents a hybrid heuristic, named Price Influenced Simulated Annealing (PISA), which integrates ideas from linear programming into a simulated annealing framework. Extensive computational results are presented comparing the performance of the heuristic with the lower bound obtained from the linear programming relaxation. These results indicate that the PISA procedure is extremely efficient, usually providing solutions with gaps around 1% in less than 1 second.

A memetic algorithm (MA) was recently proposed by Quintero and Pierre [9] for assigning cells to switches in cellular mobile networks. The implementation of this algorithm has been subject to extensive tests. The results obtained confirm the efficiency and the effectiveness of MA to provide good solutions for moderate- and large-sized cellular mobile networks, in comparison with tabu search and Merchant and Sengupta's heuristics.

Shyu et al. [10] implemented an algorithm based on the ant colony optimization (ACO) for solving the problem of cell assignment in PCS networks. It is a metaheuristic inspired by the foraging behaviors of ant colonies. The problem is modeled as a form of matching problem in a complete bipartite graph. Experimental results show that the proposed algorithm is an effective and promising approach with practically reasonable run times. Similarly, a lot of work related to the problem of cellular mobile network design has been carried out and the details are available in the literature [11, 12, 13].

3. PROBLEM FORMULATION

A brief description of the variables used in the problem formulation is provided here. We follow the same problem formulation as presented in [6, 7].

Let n be the number of cells to be assigned to m switches. Assume that the location of cells and switches are fixed and known. Let H_{ij} be the cost per unit of time for a simple handover between cells i and j involving only one switch, and H'_{ij} the cost per time unit for a complex handover between cells i and j $(i, j = 1, 2 \ldots, n \quad with \quad i \neq j)$ involving two switches. H_{ij} and H'_{ij} are proportional to the handover frequency between cells i and j that could be measured or estimated. Let c_{ik} be the amortization cost of the link between cell i and switch k $(i = 1, 2 \ldots, n \quad and \quad k = 1, 2, \ldots, m)$ and λ_i the number of calls per time unit destined to cell i. The capacity of a switch k is denoted by M_k.

The cost function to be optimized is formulated as given below:

$$f = \sum_{i=1}^{n} \sum_{k=1}^{m} c_{ik} x_{ik} + \sum_{i=1}^{n} \sum_{j=1, i \neq j}^{n} h_{ij}(1 - y_{ij}) \qquad (1)$$

The description and cost function presented in [6, 7] covers all the basic aspects for the formulation of the problem. Although this formulation is complete, one important constraint is left out. Therefore, the problem is modeled to include an additional constraint in the formulation. This additional constraint is of the maximum number of ports, that are used for a cell's BTS connectivity, on each switch. The addition of a constraint on the number of available ports on a switch has immense practical significance. This is because in a real life cellular mobile network scenario, the MSC is not only limited by its call processing capability, but also by the number of ports present in each switch or MSC.

In certain scenarios, the number of ports present may be less and the switch may still have enough call processing capacity left. But in certain other scenarios, the processing capacity may have been exhausted but a certain number of ports would still be available on the switch. Thus the inclusion of port constraints to the original problem formulation has immense practical significance.

If P_k denotes the number of ports available on each switch k, then the constraint on the number of ports may be represented as follows:

$$\sum_{i=1}^{n} x_{ik} \leq P_k \qquad for \quad k = 1, 2 \ldots, m \qquad (2)$$

Where x_{ik} is defined as:

$$x_{ik} = \begin{cases} 1 & \textit{if cell i is related to switch k} \\ 0 & \textit{otherwise} \end{cases}$$

For this modified model, the problem then is to solve (1) subject to the original constraints in [6] as well as the constraint in equation (2).

4. PROPOSED APPROACHES

This section provides a brief overview of the algorithms used to solve the cell to switch assignment problem.

4.1 Simulated Annealing (SA)

Simulated annealing is one of the most popular and general *adaptive* heuristic which belongs to the class of *non-deterministic* algorithms [14]. SA has been successfully applied for solving a vast number of combinatorial optimization problems. It is relatively easy to implement and also produces high quality solutions regardless of the choice of the initial configuration. The main components of the algorithm are the initial temperature T_0, the cooling rate α, constant β, and M which represents the time until the next parameter update. The core procedure of the algorithm is the *Metropolis* procedure, which simulates the annealing process. The complete details of the general simulated annealing algorithm can be found in [4]. In our implementation, the values chosen for the main parameters are M=10, T_0=10000, β=1.0095, and α=0.963. The values for these parameters were assigned after carrying out a number of trial runs for different parameter values and extensive tuning of parameters. The ultimate factor for decision making was the final solution result. A simple cooling schedule was followed for the SA implementation. A decrement function is used to reduce the initial temperature T_0 in a geometric progression.

4.2 Simulated Evolution (SimE)

Simulated Evolution is a non-deterministic iterative heuristic which is based on an analogy of principles of natural selection thought to be followed by various species in their biological environments. The algorithm was proposed by Kling and Banerjee in 1987 [15]. It has been designed to exhibit superior performance to that of simulated annealing with respect to run time requirements and/or quality of solution.

According to the theory of evolution, it is a well known concept that the more an organism adapts to its environment, the better are its chances of survival. In other words, by adapting, an organism optimizes its chances of surviving in its environment. Hence, adaptation is seen as a form of optimization. This similarity has given rise to a new class of randomized iterative algorithms which consists of *Genetic Algorithms, Simulated Evolution*, and *Stochastic Evolution*. For all three algorithms, the cost function is an estimation of the degree of adaptation of a particular solution to the target objective. For a maximization problem, the higher the value of the objective function is, the more that particular solution is adapted to its environment. The complete details of the SimE algorithm can be found in [4].

4.3 Modified Implementation

The algorithms considered so far were implemented such that the solutions produced were only validated to check the switch processing capacity constraint violation. The algorithms need modification to include the additional constraint on the number of ports present in a switch. The validity function thus changes for this implementation. The solution produced in every iteration is passed to the validity function for checking both the processing capacity and number of ports constraints. The solution is termed valid only if both the constraints are not violated. The solution is termed invalid even if one of the two constraints is violated.

5. EXPERIMENTAL RESULTS

The problem described in section 3 is solved using Simulated Annealing (SA) and Simulated Evolution (SimE) algorithms. These algorithms were coded in C language and the results obtained are compared with those obtained by Pierre and Houeto [6] using SA (which will be termed as SA-P for the purpose of distinction with SA in this paper) and Tabu Search (TS) algorithms in [6]. The data sets are generated as in [6, 7]. Readers are referred to these papers for the details of the data generation process. The data generated comprised of problem sets with number of cells varying between 15 and 500 and the number of switches varying between 2 and 12. Twenty data sets were generated of each type.

The programs were executed on a Red Hat Linux system. A series of test runs were conducted on the generated data sets using the proposed algorithms to determine their efficiency in terms of percentage of feasible solutions generated and the minimization of cost value. Test runs were also conducted to determine the timing efficiency of these algorithms. The performance of the proposed algorithms, when applied to the problem with the inclusion of additional constraints on the number of ports, is analyzed.

Table 1: Comparison between SimE and SA with port constraint for both.

Problem	SimE	Time(sec)	SA	Time(sec)
15–2	97.8072	0.005928	102.4707	0.284906
30–3	265.5235	0.013466	260.9837	1.025724
50–4	505.3431	0.687048	548.1965	3.066327
100–5	1162.0067	0.133096	1198.347	14.801109
150–6	1991.3575	0.348633	2116.6357	34.149955
200–7	3639.9645	0.729478	3540.3312	68.433888
250–8	4240.2983	1.193978	4242.4876	118.91105
300–9	6119.7368	1.869187	6042.9186	187.41385
350–10	7179.7658	2.73929	7099.5593	274.69034
500–12	13203.5318	6.40145	12600.5318	643.32823

Table 1 provides the comparison of the final solution costs and run times for the SA and SimE with port constraints, while Table 2 provides the comparison of the final solution costs and run times for the SA (without port constraint) and SA with the inclusion of port constraint. Comparison between SimE without port constraint and SimE with port constraint is provided in Table 3.

Figure 1 shows the comparison between the run times of SA and SimE. It can be observed that the run time for SA almost increases exponentially with increasing problem size, where as the run time for SimE shows a linear increase with increasing problem size. SimE is much faster than SA, particularly, for large sized problems.

Figure 2 shows the comparison of solution costs between SimE, SA, TS, and SA-P for different problem instances. Figure 3 provides the comparison of the final solution costs between SA without port constraint and SA with the inclusion of port constraint.

Table 2: Comparison between SA without port constraint and SA(WPC) with port constraint.

Problem	SA	Time(sec)	SA (WPC)	Time(sec)
15–2	97.8072	0.272592	102.4707	0.284906
30–3	257.1508	0.99541	260.9837	1.025724
50–4	486.8911	2.934759	548.1965	3.066327
100–5	1157.1383	12.909532	1198.347	14.801109
150–6	1943.6049	33.71893	2116.6357	34.149955
200–7	2966.2921	67.753639	3540.3312	68.433888
250–8	3852.7231	116.987371	4242.4876	118.91105
300–9	5190.4683	184.92604	6042.9186	187.413846
350–10	6574.7308	272.424261	7099.5593	274.690336
500–12	11550.5805	640.933072	12600.5318	643.328232

Table 3: Comparison between SimE without port constraint and SimE (WPC) with port constraint.

Problem	SimE	Time(sec)	SimE (WPC)	Time(sec)
15–2	86.8706	0.005987	97.8072	0.005928
30–3	229.1357	0.013404	265.5235	0.013466
50–4	432.3942	0.033028	505.3431	0.687048
100–5	1055.906	0.133496	1162.0067	0.133096
150–6	1701.811	0.348627	1991.3575	0.348633
200–7	2453.9762	0.719335	3639.9645	0.729478
250–8	3329.5575	1.184121	4240.2983	1.193978
300–9	4004.1733	1.86348	6119.7368	1.869187
350–10	4624.6573	2.740815	7179.7658	2.73929
500–12	7812.2196	6.392662	13203.5318	6.40145

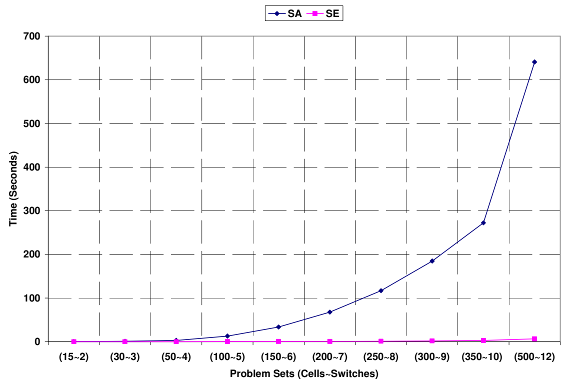

Figure 1: Comparison of CPU times for SA with SimE.

Comparison of the final solution costs between SimE without port constraint and SimE with the inclusion of port constraint is provided in Figure 4.

From Figure 2 it can be observed that SA and SimE perform better when compared to SA-P for all problem sizes. The results for SA and SimE are similar when compared to TS, except for the problem size (200–7).

The SA (WPC) produces higher cost solutions when compared to SA, as shown in Figure 3. This is because SA (WPC) is restricted by the additional constraint on the number of ports on a switch, whereas SA is not. Similarly, SimE (WPC) produces higher cost solutions when compared to SimE. If Figures 3 and 4 are compared, it can be observed that results obtained by SA(WPC) and SimE(WPC) are similar. This shows that the SA algorithm is

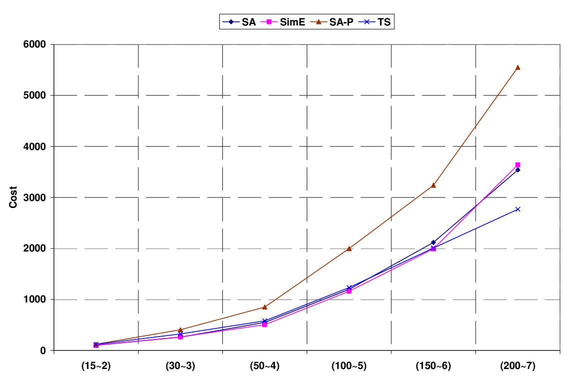

Figure 2: Comparison of solution cost between SimE(WPC), SA(WPC),SA-P, and TS.

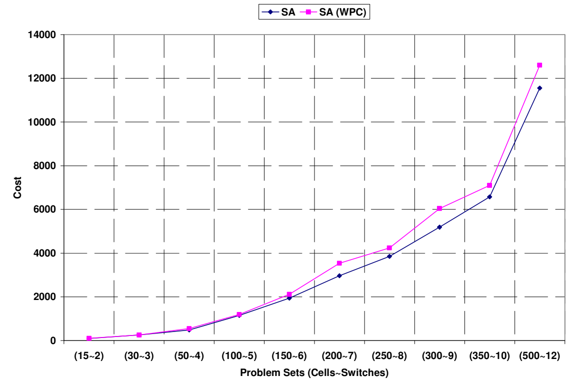

Figure 3: Comparison of solution cost between SA and SA(WPC).

able to perform well even when more number of constraints are included, whereas SimE performance degrades with the inclusion of additional constraints compared to its performance without port constraints.

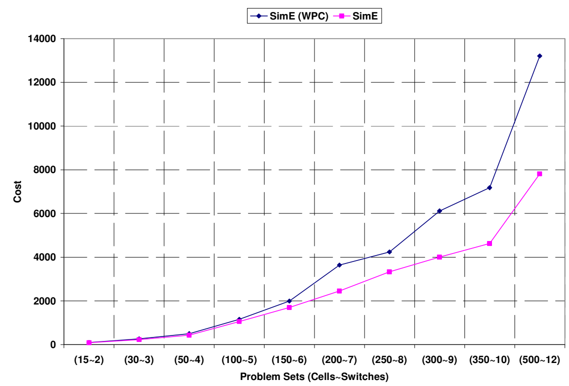

Figure 4: Comparison of solution cost between SimE and SimE(WPC).

In general it can be observed that the non–deterministic algorithms like SA and SimE find higher cost solutions when they are restricted by additional constraint. This is because the algorithm us unable to accept the lower cost solutions which may be satisfying the switch call processing capacity constraint but violating the port constraint.

6. CONCLUSIONS

In this paper, a modification to the cellular network design problem of assigning cells to switches is presented. The modified problem formulation takes into consideration the constraint on the maximum number of available ports on the switch. A heuristic called Simulated Evolution (SimE), based on evolutionary computation, and Simulated Annealing (SA) are implemented as solutions to the cell to switch assignment problem. Implementation of SA required tuning of several parameters, while the implementation of SimE approach consisted of defining a goodness function to compute the goodness value of each individual cell for every iteration. The goodness value provides a direction to proceed when trying to identify new solutions, thereby increasing the probability of improving upon the cost of solution. This criteria is the main driving force for obtaining speed up in SimE when compared to SA which can be extremely slow for large–sized problems. Extensive computational tests are conducted and the SimE algorithm is observed to perform reasonably better when compared to the results provided by other heuristics, from the literature, without the inclusion of port constraints.

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