Uplink Power Control Based on an Evolutionary Algorithm with Associative Memory

Vladislav Vasilev[1], Vladimir Poulkov[2], Georgi Iliev[3]
Department of Telecommunications
Technical University of Sofia
Sofia, Bulgaria
E-mail: [1]doublevvinged@gmail.com;[2]vkp;[3]gli@tu-sofia.bg

***Abstract*—In the present paper, a new approach for uplink power control is proposed. The developed method is based on dividing the cell into sectors and applying an evolutionary algorithm approach of controlling the transmitted uplink power. Simulation experiments are presented demonstrating the control of transmitted power from the active cell sectors as the overall neighboring cells interference is kept below a predefined threshold. The major advantage of this approach is the random power allocation over active sectors which results in increased throughput and fair resource management.**

Keywords-evolutionary algorithms; long term evolution (LTE); dynamic uplink power control

I. INTRODUCTION

Over the years, Evolutionary Algorithms (EA) have attracted a lot of attention from different research areas because of their ability to solve complex optimization problems by imitating some aspects of natural evolution. In the context of biology, the evolution is considered as the change of one or several individual characteristics which are then transferred to the offspring. EA make use of different biological processes as reproduction, mutation, recombination and selection to find the optimal solution in a particular application. The solution candidates are considered as individuals belonging to a particular population while the environment is defined as a set of constraints to the optimization problem. As a rule, considerable computational resources are needed for EA simulation as the problem solution time is very sensitive to the specific model and its parameters.

Basically, two groups of optimization problems are solved using EA. First one is formed by a variety of Stationary Optimization Problems (SOPs) where the problem is precisely defined in advance and remains fix over the time [1]. The second group is related to the field of dynamic optimization problems (DOPs) which are characterized with ever-changing environment [2]. Usually for SOPs the aim is to find quickly and precisely the optimal solution in the search space. However, for DOPs, where the environment is dynamic, in addition to the above mentioned aims an ability to track and adapt to the changing conditions is crucial and often is in conflict with the requirement for fastness and preciseness.

Following the existing examples of application areas for EA, in the present paper, we propose an EA to solve the problem of uplink power control in Long Term Evolution (LTE) wireless mobile networks. We consider this problem as DOP and utilize the intrinsic ability of EA to solve such kind of problems. At present, several methods for uplink power control are practically considered.

First one is a 3GPP specification and provides slow Open Loop Power Control (OLPC). The method is known as Fractional Power Control (FPC) that allows for full or partial compensation of slow path gain (path loss) and shadowing variations. The performance of FPC has been investigated intensively in [3] and [4]. The basic conclusion is that there is a trade-off between the overall cell throughput (overall spectral efficiency) and the outage cell throughput.

Second method is named Interference Based PC (IBPC) [5] and [6]. It is based on Closed Loop PC (CLPC) to adjust the user equipment (UE) power thus improving the system performance both from the overall and outage cell throughput perspective. The basic idea is that the power should be controlled to compensate for the generated interference to the system rather than the path gain (path loss). The result is that each user generates the same amount of interference. IBPC is very promising but still keeping the average cell throughput of the outage cell gain is less than 30 %.

Other methods are also suggested in the literature based on combining the above ones or applying game theoretical or cognitive approaches [7].

Despite all of the above mentioned approaches, the problem of uplink power control is still open in the context of throughput gain and fair resource allocation for users in the central and outage cell areas. Moreover in most of the cases these methods are analyzed assuming static conditions such as fixed bandwidth, balanced loads, evenly distributed users in the cell, etc. This is the motivation to try the application of EA to solve uplink power control problem considered as a typical DOP.

The reminder of the paper is organized as follows. Section II introduces details about some basic characteristics of EA. Section III presents the proposed EA for uplink power control (EA-UPC). The main results are presented in Section IV, and finally, the conclusions are summarized in Section V.

II. EVOLUTIONARY ALGORITHM WITH ASSOCIATIVE MEMORY

An EA can be divided into three major phases. First phase: a number of individuals exist in the environmental

 ISBN: 978-1-61208-166-3

plane. They interact between each other and with the environment. In the second phase, using a fitness function estimation, the most successful individuals are chosen. Their characteristics are combined, processed and transformed according to specific predefined rules. In the third phase (selected evolved individuals), the most successful individuals are taken back to the environment. This process of evolution is illustrated in Fig. 1.

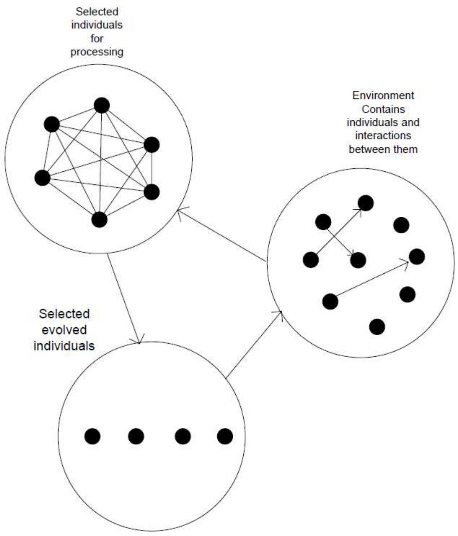

Figure 1. The main phases of an EA.

If we consider the evolutionary process from the perspective of one individual (G) its behavior can be characterized by several specific features:

1. Random behavior in the process of finding solutions and nondeterministic state;
2. Every interaction, even self-interaction, generates reaction which can not always be estimated or measured;
3. Each evolved individual G has found at least one solution as a result of the interaction;
4. There are a finite number of individual states;
5. There are an infinite number of interactions with the environment but their intensiveness is finite.

An example of evolutionary process and solution finding is illustrated in Fig. 2 for one individual (G). In order to prevent information loss for the EA, it is necessary the state "S", which is responsible for solution finding, to have access to the results from each generation "G" on the evolutionary path. In addition to the decision which available tools (filters) to be used, S generates also a set of possible states (T) which can be tested along the path. Therefore the process of solution finding evolves by evolving the states (T).

The following three equations represent the main features of an evolutionary process and solution finding.

$$S = \sum\{G\} + \sum\{T\} \tag{1}$$

$$\deg(S) = |\{G\}| + |\{T\}| \tag{2}$$

where $\deg(S)$ is the degree of vertex S, $|\{G\}|$ is the number of tested generations and $|\{T\}|$ is the number of evolved tools.

$$f(S(T)) = extremum\ (f) \tag{3}$$

Eq. 3 means that using a particular tool T, EA finds a local extremum for the environmental fitness/cost function.

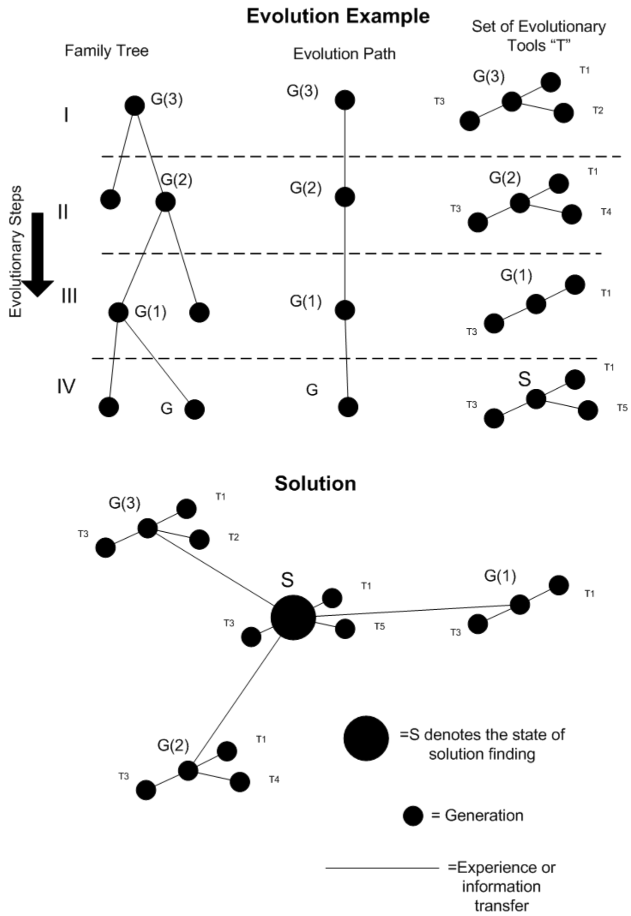

Figure 2. Example of evolutionary process and solution finding.

Usually, during the implementation of an EA, Eqs. 1 and 2 are solved, the current solutions are temporary buffered, and the best are placed in an associative memory. As seen in Fig. 2, state S provides information or attempts to describe the environment using the tools of the individual. The final solution is random and the probability to find a better individual/generation depends entirely on the ability of state S to deduct information from the previous generations.

III. UPLINK POWER CONTROL USING EA

In order to develop an EA for uplink power control, formulating the optimization problem is necessary first. We consider an example situation as presented in Fig. 3. A LTE cell with base station (BS) "B" is given. The neighboring cells are presented by their BSs – B1, B2, B3, B4, B5, B6. The cell is divided into sectors. The users located in each sector can transmit a signal with a total power of $p(i, j)$ and thus for every neighboring cell a maximum overall level of the interference, measured at its BS, is defined.

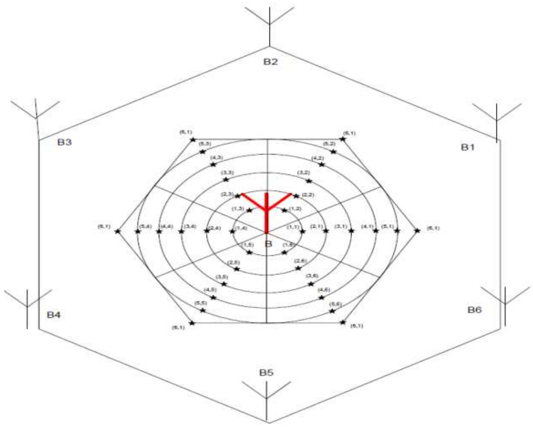

Figure 3. Cell division into sectors.

The interference vector $\vec{V}_{\Sigma}^{k}$ is a sum of the interference caused by each active (transmitting at that time) sector as shown in Fig.4. A sector is considered as active if the transmitted power is above a predefined threshold.

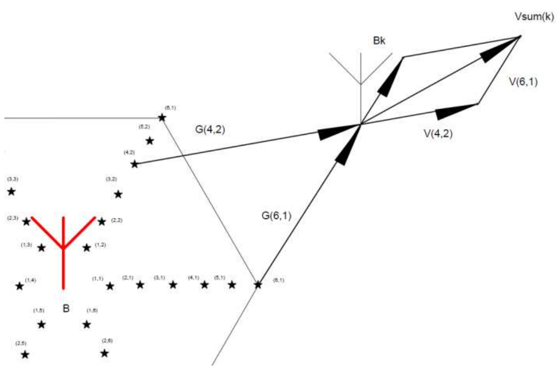

Figure 4. Interference at BS "B$_k$" caused by active sectors G(4,2) and G(6,1).

Having this arrangement for the cell and the interference vector, we formulate the optimization problem as follows. First, the interference measured at BS "B$_k$" is represented by $\vec{V}_{\Sigma}^{k}$. Second, $\vec{T}_m=[\vec{X}_m(i,j),\vec{p}_m(i,j)]$ contains the current generation. Third, $\vec{X}_m(i,j)=[\vec{a}_m(i),\vec{b}_m(j)]$ represents the coordinates of the sectors belonging to generation $\vec{T}_m$.

The intensity of the interference can be found using Eq.4.

$$E=\frac{\sqrt{p_m(i,j)}}{\left|\vec{X}_m-\vec{B}_k\right|} \tag{4}$$

where $\vec{B}_k$ represents the coordinates of BS "B$_k$".

The interference vector $\vec{V}_m^k$ for the active sector with coordinates (i, j) transmitting a signal with power $p_m(i,j)$ is defined as

$$\vec{V}_m^k=\frac{\vec{X}_m}{\left|\vec{X}_m\right|}E \tag{5}$$

Substituting E in Eq. 5 we find

$$\vec{V}_m^k=\frac{\vec{X}_m}{\left|\vec{X}_m\right|}\cdot\frac{\sqrt{p_m(i,j)}}{\left|\vec{X}_m-\vec{B}_k\right|} \tag{6}$$

Finally, the overall interference vector for BS "B$_k$" is represented by

$$\vec{V}_{sum}(k)=\vec{V}_{\Sigma}^{k}=\sum_{m=1}^{n}\vec{V}_m^k \tag{7}$$

The objective is maximizing the throughput under the constraint that the interference level is below a given limit. Then, if a set $\{\vec{X}_m\}$ is given, the aim is to find $\{p_m\}$ for which Eq.8 holds, subject to the constrains presented in Eq.9:

$$\max\sum_{k=1}^{6}\left|\vec{V}_{\Sigma}^{k}\right| \tag{8}$$

$$\left|\vec{V}_{\Sigma}^{k}\right|\leq P_{\max}, k=1,2,3,4,5,6 \tag{9}$$

As seen from Eqs. 8 and 9, during the uplink power control optimization process we try to increase the signal power of the active sectors, thus increasing the throughput, while keeping for each neighboring cell the interference below a predefined threshold (P_{max}).

To solve the uplink power control optimization problem we develop an EA implemented in the following steps.

Evolution Step 1: First, let the total number sectors is "J", and the number of active sectors is "N" (N<J). We choose one set consisting of "n" (n<N) active sectors in a random manner. The transmitted signal power for each of these

ISBN: 978-1-61208-166-3

sectors is allocated randomly. We check if the requirements in Eq. 8, and the constrains in Eq. 9 are fulfilled. If the check is positive, then the solution is considered as suboptimal and the current generation $\vec{T}_m$ is memorized. This is performed for a number of "I" iterations. Then we perform this experiment for another set of active sectors. This is done for all possible sets of n active sectors - R. As a result from step 1 we have memorized a number of suboptimal solutions, including the sets of active sectors with their corresponding allocated transmitted signal power.

Evolution Step 2: The allocated signal power found in step 1 of each of the "R" set of active sectors is transformed as follows. We increase by a random factor the transmitted power for all sectors belonging to the set. This goes for another "I" iterations. Then we check if the constrains in Eq.9 are fulfilled. If the check is positive then the solution is considered as suboptimal and it is memorized.

Evolution Step 3: We again randomize the sector combinations, but this time using (n+1) active sectors. Then we look for combination match in the memory of sector indexes for each permutation of randomized combination. If there is one or more matches we use one of them as base for step 3. We chose randomly one active sector belonging to the set and increase its power with 1 unit. Then we check if the constrains in Eq.9 are fulfilled. If the check is positive then the solution is considered as suboptimal and it is memorized.

The flow chart of the proposed EA for uplink power control (EA-UPC) is presented in Figs. 5, 6, 7 and 8.

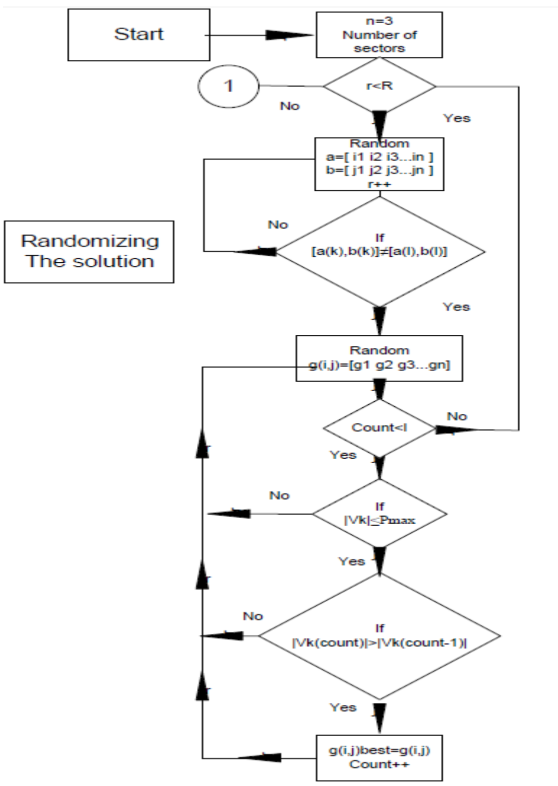

Figure 5. EA-UPC chart diagram (EA step 1).

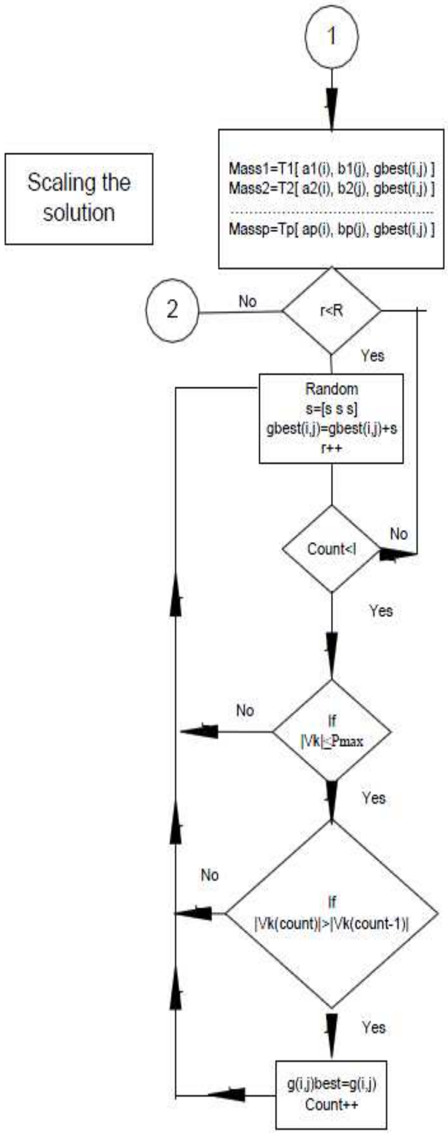

Figure 6. EA-UPC chart diagram (EA step 2).

As a result from EA-UPC we build a look-up table consisting of different combinations of active sectors with their signal power. These combinations represent the suboptimal solutions found in the optimization process.

Evolution Step 4: Each solution is compared to others using the sector coordinates and if the difference vector for two solutions is below a given threshold an associative link is created between them. This process develops an associative memory as shown in Fig. 9. Here, the elements MASS(m,n) represent the combination set of active sectors and STR[(m,n),(p,q)] the associative links between them. During uplink power control if a particular solution comes out not to be appropriate, because of specific sector or cell throughput requirements, or some QoS issues [8], then one of its associates could be used. The STR links could be also used for further evolutionary processing.

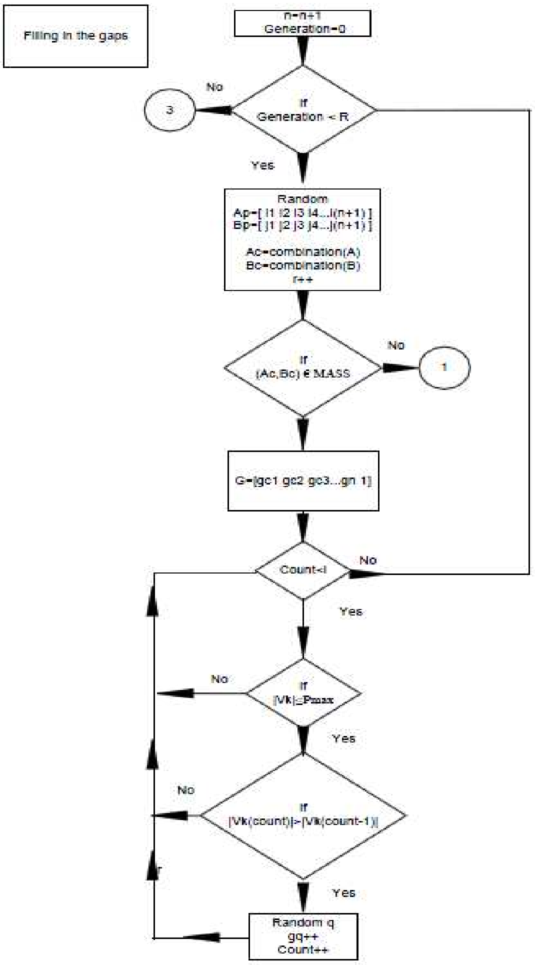

Figure 7. EA-UPC chart diagram (EA step 3).

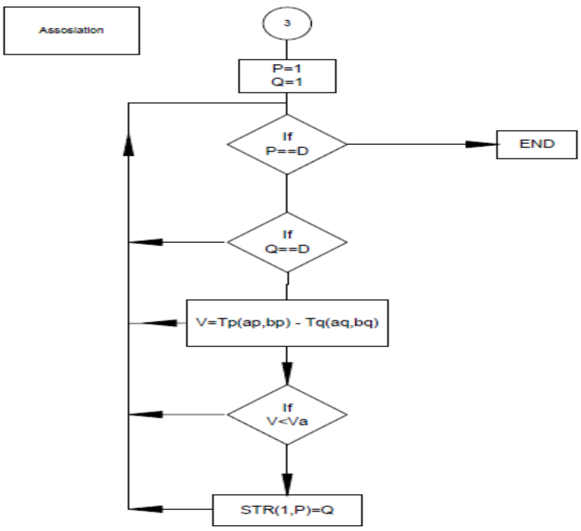

Figure 8. EA-UPC chart diagram (EA step 4).

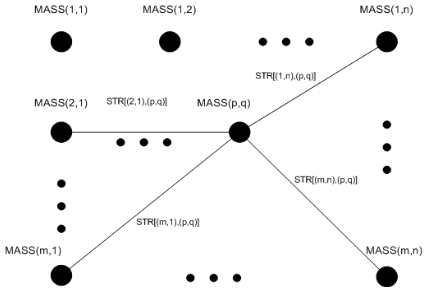

Figure 9. Associative memory.

IV. SIMULATION RESULTS

As a simplified example for EA-UPC we consider the cell presented in Fig. 10, and assume that the number of active sectors is four. The cell is divided into six sectors and in the process of initial set up BS "B", applying the EA a "look-up table" is created in which the suboptimal solutions are memorized. For our case of four active sectors the look up table is illustrated in Table 1. During the operation the BS locates the set of active sectors. Then using the look up table, the BS limits the corresponding uplink signal power level for each one of the active sectors. If some of the sectors needs power above the assigned limit, because of throughput or QoS requirements, then the BS can use one of the associated combinations. The fourth column of Table 1 represents the associative combinations.

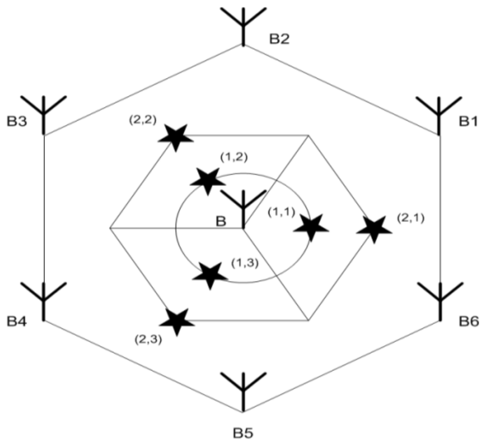

Figure 10. A simplified example for EA-UPC UPC.

To evaluate the performance of EA-UCP we simulate each evolutionary step during the initial set-up procedure of the BS. The results are presented in Fig. 11. During the experiments, the maximum allowed for each neighboring cell interference is set at an absolute value of 20. We run 150 independent simulations of the EA-UCP and each one undertakes 300 iterations. The results for the overall neighboring cells interference are averaged over all 150 simulations. Combinations of different active sectors are investigated to evaluate the influence of the sectors location on the performance of EA-UPC.

TABLE I. LOOK-UP TABLE FOR EA-UPC

Active sector combination MASS (m,n)	Sector coordinates	Corresponding power $p_m(i,j)$ (absolute value)	Associate combinations STR([(..),(..)]
1	(2,3), (1,1), (1,2), (2,2)	1, 6, 6, 1	15, 10
2	(2,2), (2,1), (1,1), (1,2)	5, 2, 5, 1	15, 9
3	(2,3), (1,3), (1,1), (2,1)	1, 8, 4, 1	12, 10, 9
4	(1,3), (2,1), (1,2), (2,2)	9, 6, 1, 1	9, 12
5	(1,2), (1,3), (1,1), (2,3)	2, 2, 1, 1	5, 14
6	(2,1), (2,3), (2,2), (1,3)	10, 9, 2, 1	8
7	(1,1), (1,3), (2,1), (1,2)	8, 1, 3, 1	14
8	(2,1), (2,3), (2,2), (1,2)	10, 9, 2, 1	8, 11, 6
9	(1,3), (2,2), (1,1), (2,1)	5, 2, 2, 1	4, 3, 2
10	(1,3), (2,2), (1,1), (2,3)	5, 2, 2, 1	13, 3, 1
11	(2,2), (2,1), (1,1), (2,3)	5, 2, 5, 1	11, 8
12	(1,3), (2,1), (2,3), (1,2)	8, 8, 7, 1	13, 4, 3
13	(2,2), (2,3), (1,3), (1,2)	2, 3, 5, 1	12, 10
14	(1,3), (1,2), (2,2), (1,1)	7, 8, 3, 1	7, 5
15	(2,3), (1,1), (1,2), (2,1)	1, 6, 6, 1	3, 2, 1

The simulation results demonstrate that in each of the evolutionary steps, the EA-UPC algorithm tends to maximize the overall neighboring cells interference, thus maximizing the overall cell throughput, but at the same time keeping the interference below the predefined allowable threshold. All steps in EA show, as expected, a logarithmic increase in overall neighboring cell interference. While the algorithm goes thought steps 1, 2, and 3, the second derivative decreases and the graphics straighten, as the difference in power allocated between steps differs.

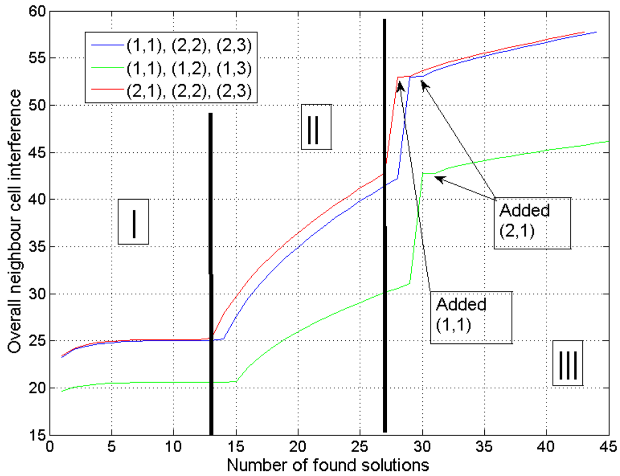

Figure 11. Combined evolutionary steps.

It could also be seen from this simple example, that after the 10th suboptimal solution of the first evolutionary step, most probable is each following suboptimal solution to give very little contribution to the increase of the overall neighboring cells interference and thus to the throughput. This justifies the application of the next step of EA. The simulation results show, that in the third evolution step (Fig.11), the rise of the interference level reaches the maximum allowable limit. For the chosen set of sectors the algorithm stops to evolve, as it has reached the constraints of maximum interference of the absolute value of 20 for one of the neighboring BS stations.

V. CONCLUSIONS

The proposed, in this contribution, evolutionary algorithm can be used effectively for uplink power control in LTE networks. Assuming an interference limited approach to power control, based on the division of the cell into sectors and estimating, via the proposed EA algorithm, the maximum allowable overall interference generated for different combinations of active sectors, a maximum of average cell throughput could be achieved. The EA-UPC demonstrates good performance characteristics for a broad range of active sector combinations. Compared to the now-existing methods for uplink power control the presented approach reveals several major advantages. First, EA-UPC is CLPC method because we keep the interference below a predefined maximum. Second, because of the random manner of power allocation for the active sectors, EA-UPC provides fair resource management independent of the sector location in the cell (central or outage zone). Besides these the look up table could be cell specific depending on the number of sectors in the cells, dimension and type of the area (rural or non-rural) QoS requirements and other cell parameters or conditions.

ACKNOWLEDGMENT

This work was supported by the Bulgarian National Science Fund – Grant No. DDVU 02/131.

REFERENCES

[1] P. Larranaga and J. Lozano, Estimation of Distribution Algorithms: A New Tool for Evolutionary Computation, MA: Kluwer, 2002.

[2] S. Yang and X. Yao, Population-Based Incremental Learning with Associative Memory for Dynamic Environments, IEEE Trans. on Evolutionary Computation, vol.12, Oct. 2008, pp. 542–561.

[3] C. Castellanos, D. Villa, C. Rosa, K. Pedersen, F. Calabrese, P. Michaelsen, and J. Michel, Performance of uplink fractional power control in UTRAN LTE, Proc. VTC Spring 2008, 11-14 May 2008, Singapore, pp. 2517–2521.

[4] D. Astely, E. Dahlman, A. Furuskar, Y. Jading, M. Lindstrom, and S. Parkvall, LTE: the evolution of mobile broadband, IEEE Communications Magazine, Apr. 2009, pp. 44-51.

[5] M. Boussif, N. Quintero, F. Calabrese, C. Rosa, and J. Wigard, Interference based power control performance in LTE uplink, Proc. IEEE International Symposium on Wireless Communication Systems, 21-44 Oct. 2008, Reykjavik, pp. 698–702.

[6] B. Muhammad and A. Mohammed, Performance evaluation of closed loop power control for LTE system, Proc VTC Fall 2009, 20-23 Sept. 2009, Anchorage, pp. 1-5.

[7] H. Gochev, V. Poulkov, and G. Iliev, Improving Cell Edge Throughput for LTE Using Combined Uplink Power Control, Proc. TSP 2010, Vienna, 2010, pp. 465-467.

[8] E. Pencheva and I. Atanasov, book chapter Web Services for Quality of Service Based Charging, in „Developing Advanced Web Services through P2P Computing and Autonomous Agents: Trends and Innovation", IGI Global, 2010, pp. 219-236.