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An Effective Load Balancing In Long Term Evaluation Self Optimization Network Using Multi Objective Optimized Algorithm

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Abstract— A self-optimizing network is an effective method for network management and maintenance in Long Term Evolution, which supports the co channel deployed heterogeneous networks and significantly increases the quality of service. The Zone based Load Balancing uses several game theoretic approaches to carry out load balancing but it results in uncoordinated load distribution among multiple cells. It may cause the problem of hidden cell case and slow convergence issues. Along with this problem the Nash Equilibrium used in game theory algorithm cannot be obtained, it may continuously finding solution for long duration. It can be solved by introducing the innovative method of meta heuristic search algorithm called Multi objective Bat Algorithm. It is very promising and could outperform the existing algorithms. The Multi Objective Bat algorithm combined with the priori expert knowledge reduces search space and computational time required for designing the MLB controller. The Multi Objective Algorithm provides the best optimization solution in short period of time and the problem of slow convergence time gets eliminated.

.Index Terms—Multi Objective Bat algorithm, long-term evaluation (LTE),Handover optimization, self-optimizing networks (SONs).

INTRODUCTION

A SELF-OPTIMIZING NETWORK is an efficient way to facilitate future network management and maintenance in long-term evaluation (LTE) systems, which fully supports the cochannel-deployed heterogeneous networks and significantly increases the quality of service. More importantly, it sharply decreases the cost of network operation . As an important use case of the SON, load balancing (LB) can release the traffic unbalance of multiple eNBs (E-UTRAN NodeBs) to improve network-wide capacity .

LB is a mechanism whereby highly loaded cells offload some of their traffic to their lightly loaded neighbor cells to make more efficient use of resources. In an LTE SON, LB is usually referred to as mobility load balancing (MLB)which is automatically performed to optimally use overall network resources by setting the cell individual offset (CIO) value and is applied between the overloaded cell and a possible target cell if an omnidirectional antenna is used to achieve optimal system performance.

The sensor nodes have the capability to collect (sense) data from the environment, and cooperate with other sensor nodes to relay the data to a central processing center, known as the sink, using multi-hop wireless communication. WSNs are used in a wide range of agricultural, environmental, industrial, manufacturing, military, and security monitoring applications.

In 3GPP TS 36.331, handovers (HOs) can be triggered by a number of events . In this paper, we are concerned with one particular event known as event A3, which defines the entering and leaving conditions of HOs. Note that the event is reached and reported only when the entering criterion is kept fulfilled and the leaving condition is not reached within the interval time-to-trigger. MLB is based on the entering condition. When the inequality of the entering condition is held for a particular user equipment (UE), the UE will be handed over from its currently serving cell to a spe-cific neighbor target cell, which is mathematically represented .

Several related works have been done for MLB in LTE sys-tems, most of which are with extensive simulations In detailed system-level simulation results of a self-optimizing load-balancing algorithm in LTE mobile communication sys-tems are presented. A method for load estimation based on signal-to-interference-plus-noise ratio (SINR) prediction and UE measurements after HO occurs is presented in [6] by optimizing the offset value to make the users be handed over to the target cell. An autonomic flowing water balancing method is proposed in [7], and new modules are added in eNBs to detect the overload conditions and trigger HO actions..

All of the aforementioned approaches balance the traffic load between a pair of cells, i.e., a highly loaded cell offloads some traffic to one of its lightly loaded neighboring cells. Due to the insufficient load information of other cells (hidden cells, the details of which can be found), irrational LB might be triggered, causing a "ping-pong" LB problem. This means that the offloading will be returned to the source cell again in a short period of time. Meanwhile, the huge diversity of load distribution easily triggers a series of MLBs among multiple cells, causing another slow-convergence problem

Differing from these cell-to-cell ways, a multicell-to-multicell LB method is proposed in this paper, the rationale of which is motivated by the theoretical conclusion in [15]: "Assume that the total traffic in an n-cell system is T Erlangs, then the (system wide) call blocking probability is minimized when the traffic in each cell is T/n Erlangs." This is to say always, a low blocking probability will be achieved when each cell carries the similar load. More specifically, the problem of slow convergence is solved, and the system average blocking probability decreases, which are pointed out as serious issues in [15]. The main contributions of this paper are fivefold.

- To deal with potential risks of ping-pong and slow-convergence problems in the conventional MLB schemes, we propose a cluster based load balancing algotithm, which implements multicell-to-multicell LB to achieve an optimal load redis-tributions and low blocking probability.
- In the multi objective BAT algorithm system, an innovative technique is introduced which is called multi objective bat algorithm for combines a priori expert knowledge with Multi-Objective BAT algorithm, which allows to considerable reduce the search space and the computational time required for designing the MLB SON controller. After that, the dynamicity of the optimization phase is addressed.

This paper is organized as follows. In Section II, the network model and some preliminaries are given. In Section III, the existing algorithm of zone based load balancing is described,in section IV Multi Objective Bat algorithm is described. The load-balancing in multi objective in bat algorithm is given in Section V. Finally, the simulation results and a comparative analysis are presented in Section VI.

II. Network Model and Preliminaries

To combat the potential ping-pong load transfer and low-convergence issues, we propose an Multi Objective Bat algorithm which considerably reduces the search space and provides optimal solution in a short period of time.

The goal of using bat algorithm in this research is to produce balance. Bat algorithm is a type of Metaheuristic algorithm and functions based on probability.

A. Network Model

Bat algorithm was presented by yang in 2010 who was inspired by the natural behavior of bats. Bats use a type of sonar, called echolocation, to detect prey, avoid obstacles, and locate their roosting crevices in the dark. These bats emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects.

The Multi Objective bat algorithm can be instructed as follows:

1.All bats use echolocation to sense distance, and they also „know" the difference between food/prey and background barriers in some magical way.

2. Bats fly randomly with velocity vi at position xi with a fixed frequency f_{min}, varying wavelength and loudness A_0 to search for prey. They can automatically adjust the wavelength λ (or frequency) of their emitted pulses and adjust the rate of pulse emission r 2 [0, 1], depending on the proximity of their target.

3. Although the loudness can vary in many ways, it is assumed that the loudness varies from a large (positive) A0 to a minimum constant value A_{min}

B. Hidden Cell

In traditional MLB, source eNBs exchange load information with their adjacent eNBs using an X2 interface. A specific cell just knows the load state about its neighbor eNBs [16]. Therefore, the hidden-cell problem arises. Given a specific cell i, the cells that are two hops away are its potential hidden cells.

The detailed effects and description of the hidden-cell phenomenon are shown in Fig. 1, where we concentrate on the hidden-cell phenomenon within the two overloaded cells termed cells 6 and 11. Cell 7 will be first involved in the game circle of cell 6. At the same time, it may also be one component for cell 11's circle, so that if certain UE devices of cell 6 are offloaded to cell 7 while certain UE devices from cell 11 are also offloaded to cell 7, then cell 7 will become the new overloaded cell. This phenomenon happens due to the hidden-cell phenomenon, where cells 6 and 11 are the mutual hidden cells with respect to cell 7 since there is no direct interaction between eNB2 and eNB4. If cell 6 knows the load information about cell 11 in advance, then cell 6 may reduce the expectation of its own MLB by offloading less traffic to its target cell (e.g., cell 4). In our load-balancing scheme, the hidden-cell problem is solved, which will be discussed as follows.

C. Adjustment of Mobility Parameters

In MLB, each cell will adjust the HO regions by biasing the HO measurements. More specifically, for A3 event, the HO condition can be expressed as [4]

$$M_j - M_i > O_i^{(cs)} - O_{i,j}^{(cn)} + Hys + off \qquad (1)$$

where M_i and M_j correspond to the UE measurement result of cells i and j, respectively, which can be in the form of reference signal received power (dBm) or reference signal received quality (dB) [4]. $O_i^{(cs)}$ is the cell-specific offset of the serving cell i, and $O_{i,j}^{(cn)}$ is the cell-specific offset of the neighbor cell j with respect to cell i. Hys is a hysteresis term, and off is a fixed offset. By increasing the offset $O_{i,j}^{(cn)}$, it is possible to cause a mobile user served by cell i to be handed over to the neighbor cell j, thereby reducing the load in cell i. In our paper, each cell will automatically adjust the value of mobility parameter $O_{i,j}^{(cn)}$ based on cell load measurements to perform LB.

III. PROPOSED APPROACH OF ZONE BASED MOBILITY LOAD BALANCING GAME MODEL

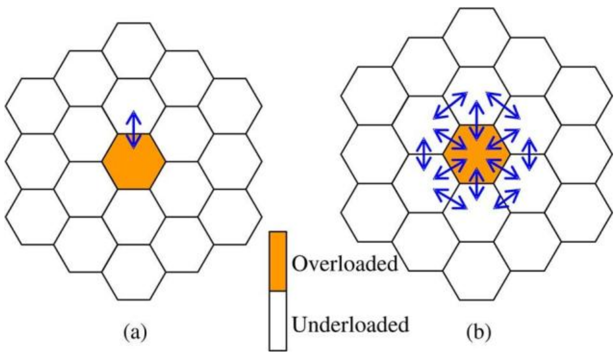
It is well known that a multioligopoly Cournot model can well depict the commodity exchange process among a limited number of monopoly companies involving several parameters of price and production of a specific commodity [9]–[12]. If we regard the traffic load bearing of a cell in the investigated cell set as the commodity, then we can observe the similarity between ZLB implementations and the multioligopoly Cournot game model. Hence, we formulate the multicell-to-multicell ZLB problem as a Cournot game model G_{ZLB} to capture the dynamic behaviors and strategic interactions between different cells. Using this game model, we can get the optimal load distribution of each cell.

Definition 1: The ZLB game model is defined as $G_{ZLB} = \{N, L, U\}$, where

- N is the cell set of ZLB associated cells in a specific zone, where each cell is one of the players in the ZLB game;
- L is the LB strategy space, which contains all the load distribution strategies L_i of each cell $i \in N$. In addition, each choice of load of cell $i \in N$ is $l_i \in L_i$, so that set

To compare the proposed ZLB scheme with the conven-tional MLB, we depict their basic implementation principles, as shown in Fig. 2. Here, to simply illustrate the rationale behind them, we only depict “Overloaded” and “Underloaded” cells in Fig. 2. In Fig. 2(a), the overloaded cell will offload the traffic just to one of the underloaded neighbor cells.

However, in Fig. 2(b), the ZLB scheme utilizes a totally different algorithm, where the offloading requirement of the overloaded cell will further trigger the load redistribution of a series of neighbor cells. The design of our ZLB strategy consists of two parts as follows.



- We design the utility function of each game player as a function of load distribution (l_i, l_{-i}), where l_i and l_{-i} represent the load of cell i and other cells except cell i, respectively. We solve this game to find out the optimum load distribution (l_i^*, l_{-i}^*) in the zone.
- After deriving the optimum load distribution (l_i^*, l_{-i}^*), each cell can calculate the difference between its current load and the optimal load value. Then, a detailed load-balancing algorithm based on a utility-metric function has been presented to redistribute the load to multiple cells.

IV MULTI OBJECTIVE BAT ALGORITHM

In the multi objective BAT algorithm system, an innovative technique is introduced which is called multi objective bat algorithm for combines a priori expert knowledge with Multi-Objective BAT algorithm, which allows to considerable reduce the search space and the computational time required for designing the MLB SON controller. After that, the dynamicity of the optimization phase is addressed. In the second phase, the controller is pushed into the base stations to implement the MLB SON. The method is applied to dynamically adapt Handover Margin parameters of a large scale LTE network in order to balance traffic of the network eNodeBs.

This algorithm consists of some procedures:

Step1: In the first step the value of velocity ,pulse emission ratio ri,and loudness A0 is obtained.

Step 2:In this step the position,velocity is measured and obtained.

Step 3: Fitness function of each bat, will be determined. Fitness function is a function which determines ability of each element.

Step 4: According to fitness function of each bat, the best position of bat is determined.

Step 5:By (1) ,(2) and (3) equations, frequency, velocity and position of each bat will be update.

Step 6: If pulse emission is less than the accidental value, random walk will be applied for that bat.

Step 7: If the new fitness function is less than the old fitness function, the value of the best solution is replaced with the new solution, and the value of pulse emission ratio and the loudness must be update.

Step 8: The algorithm will frequency from 5 to 7 steps, until the frequencies end in implementation of this algorithm. Here Random walk refers to the accidental path way to find the best solution In every iteration, the new solutions are generated by adjusting frequency and update the velocity and position of bats. Select the best solution based on the fitness value. Rank the bats and find the current best.

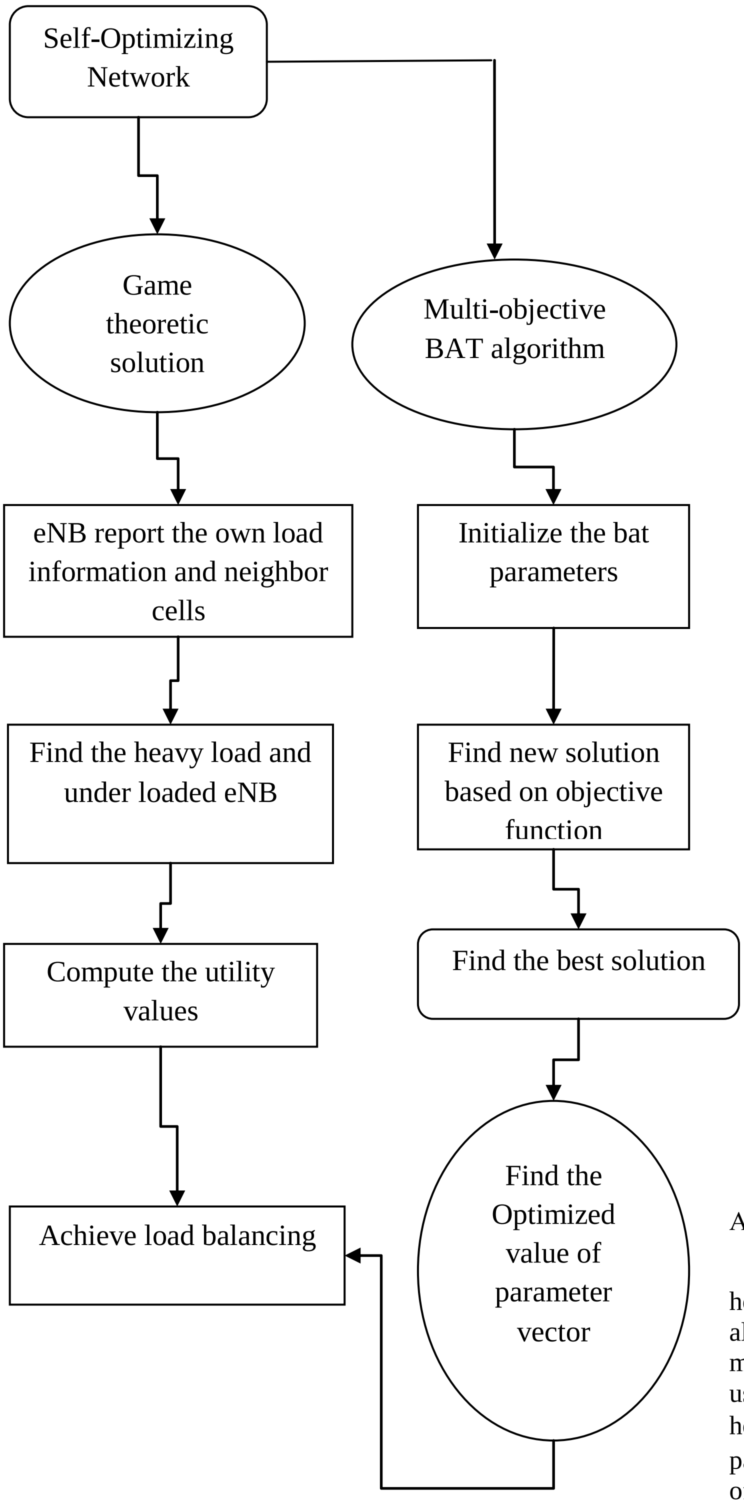


Figure 1 System flow diagrm

VI Load Balncing in Multi Objective Bat Algorithm.

MLB controller is designed using Multi-Objective BAT which incorporates a priori expert knowledge to considerably reduce the search space and optimization time. Expert knowledge refers to a priori knowledge on the optimization problem.

It gives rough information (or tendency) on the type of parameter modification that will improve the system performance in different states of the system. Expert knowledge can be used to guide the optimization process and to reduce the search space. In the general case, the parameter x is a function of the vector $\vec{u}$.

For example the parameter x stands for the Handover Margin (HM), and the vector $\vec{u}$ for the load vector $(L_i L_j)$. To write x as where surf stands for a multi-dimensional surface.

Experience in HM optimization shows that the parameter function x varies smoothly with $\vec{u}$. The expert knowledge given by a set of rules is used to guess a simple form for the function surf. The aim is to find a parametric representation of surf, namely to write it as a function of a parameter vector .

$$\vec{p} = (p_1, .. p_m) \quad (1)$$

$$x = surf(\vec{u}; \vec{p}) \quad (2)$$

Hence the form of the function surf is fully defined by the vector $\vec{\mathbf{p}}$ that is determined via an optimization process. The function surf is denoted hereafter as the parameterization surface. Denote by

$\hat{F}(x) = (f_1(x), .. f_n(x))$ the objective function to be optimized where $f_i(x)$ represents a KPI which depends on the parameter x. It is recalled that the parameter x has a parametric representation, hence $\vec{F}$ can be written as a function of $\vec{\mathbf{p}}$**.**

A.*Performance of BAT Algorithm*

The BAT algorithm is used here to optimize the parameter vector $\vec{p}$that defines the parameterization surface. It utilizes a population of bats, each of which represents a solution, namely a parameter vector defining the parameterization surface. In the BAT notation, the position of a bat i, $\vec{p}_i$ stands for the parameter seek to optimize (i.e. the parameter vector defining the parameterization surface in the present work).

TABLE I
BASIC SETTINGS OF SIMULATION SCENARIO

Bandwidth	10MHz (50 PRBs)
Simulation time	120 min
Cell layout	19 regular hexagonal cells
ISD	1732 m
Transmitted power	46dBm
Antenna pattern (horizontal)	$A(\theta) = -\min(12(\frac{\theta}{\theta_{3dB}})^2, A_m)$, where $\theta_{3dB} = 70\,\mathrm{deg}, A_m = 20dB$
UE noise figure	7 dB
MLB threshold	0.9, 0.7 (normalization load)
Scheduler	max CIR
Traffic model	512Kbps CBR
UE speed	3 Km/h random walk
HO hysteresis	3dB

Initialization of the bat population is performed randomly. Generating the new solutions is performed by moving virtual bats according the following equations:

$$Q_i^{(t)} = Q_{min} + (Q_{max} - Q_{min})U(0,1),$$
$$v_i^{(t+1)} = v_i^{(t)} + (X_i^{(t)} - best)Q_i^{(t)},$$
$$X_i^{(t+1)} = X_i^{(t)} + v_i^{(t)} \qquad (3)$$

Where U(0,1) is a uniform distribution. A random walk with direct exploitation is used for local search that modifies the current best solution according to equation:

$$X^{(t)} = best + \epsilon A_i^{(t)}(2U(0,1) - 1), \qquad (4)$$

Where ϵ is the scaling factor, and $A_i^{(t)}$ the loudness. The local search is launched with the proximity depending on the pulse rate r_i.

The term in line 13 is similar to the simulated annealing behavior, where the new solution is accepted with some proximity depending on parameter A_i .

In line with this, the rate of pulse emission r_i increases and the loudness A_i decreases. Both characteristics imitate natural bats, where the rate of pulse emission increases and the loudness decreases when a bat finds a prey. Mathematically, these characteristics are captured with following equations:

$$A_i^{(t+1)} = \alpha A_i^{(t)}, r_i^{(t)} = r_i^{(0)}[1 - \exp(-\gamma\epsilon)],$$

. Actually, the α parameter plays a similar role as the cooling factor in simulated annealing algorithm that controls the convergence rate of this algorithm.

Simulation Results

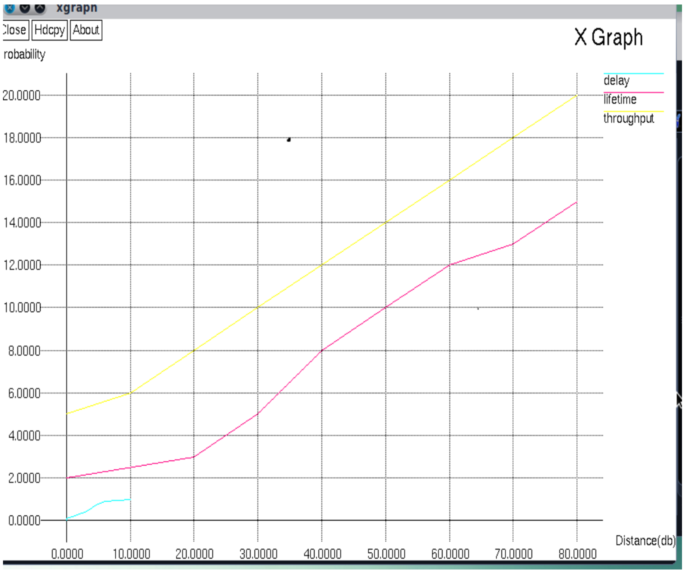


Figure 2 System Throughput

System Throughput: Fig. 2 is the statistical results of sys-tem throughput with the user arrival rate. The average through-put of the system is gradually increased as the user arrival rate increases. We can see that the system throughput of the three compared schemes is in the sequence of MOBA > ZLB > Without LB. When the user is uniformly generated within the system, the proposed ZLB algorithm achieves a slightly higher throughput than the other two cases. When the user is not uniformly distributed, the gain of the ZLB algorithm is relatively close to the MLB algorithm, which is due to the fact that the average blocking rate of both algorithms is closer to each other.

Conclusion And Future Work

The proposed ZLB carries out the LB action from the perspective of the multicell region, which means that the participants of the LB process are extended from a pair of cells to a zone of cells. Under the strategic game theory framework, analyze the existence, uniqueness, and optimality of NES, which direct us to implement the newly proposed ZLB algorithm. The consideration of hidden cells and the optimal load redistribution can effectively overcome irrational load transferring and, hence, efficiently mitigate ping-pong effects. In addition, the parallel LB behavior of multiple cells shortens the convergence time of LB. But the disadvantage in this method in the game theory algorithm some time Nash equilibrium cannot be obtained, it may continuously finding solution for long duration. So, in the proposed system an innovative technique is introduced which is called multiobjective bat algorithm for combines a priori expert knowledge with Multi-Objective BAT algorithm, which allows to considerable reduce the search space and the computational time required for designing the MLB SON controller.

FUTURE WORK

Providing secure communication in the vehicular adhoc networks is an important concern. Majority of nodes in VANETs dependent on batteries for their energy. So the most important parameter for optimization is energy conservation. The another consideration is that the load balancing is done based optimization it can be done for cluster of nodes thus the performance gets increased and the time complexity gets even more reduced.

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