Self-Configuration and Self-Optimization for LTE Networks

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ABSTRACT

With the rapid growth of mobile communications, deployment and maintenance of cellular mobile networks are becoming more and more complex, time consuming, and expensive. In order to meet the requirements of network operators and service providers, the telecommunication industry and international standardization bodies have recently paid intensive attention to the research and development of self-organizing networks. In this article we first introduce both the market and technological perspectives for SONs. Then we focus on the self-configuration procedure and illustrate a self-booting mechanism for a newly added evolved NodeB without a dedicated backhaul interface. Finally, mobility load balancing as one of the most important self-optimization issues for Long Term Evolution networks is discussed, and a distributed MLB algorithm with low handover cost is proposed and evaluated.

INTRODUCTION

Future mobile communication systems will construct a flexible service environment, including network operator, vendor, access provider, service provider, software developer, content provider, and customer. It can be foreseen that the business models in Long Term Evolution (LTE) systems will be cross-linked abundantly and provide a wider range of market. On one hand, with the usage of advanced access and transmission techniques, both the transmission bandwidth and quality of service (QoS) of mobile networks have been greatly improved. New wireless service models and applications have been developed with increasing spectrum band and data rate. On the other hand, future mobile networks are also required to be cost effective and easy to deploy. The expectations of customers on coverage and QoS increase continuously. Thus, the requirements on future LTE networks will be high from the early stage of their deployment. More efficient strategies and algorithms have to be integrated in the future mobile networks to further reduce capital expenditures (CAPEX) and operational expenditures (OPEX).

Network optimization is one of the key parts in the life cycle of mobile systems. For second-generation (2G) mobile networks, a series of standardized procedures have been defined for wireless network planning and optimization, while for third-generation (3G) mobile networks, researchers, and engineers are testing and improving the network planning and optimization methods/tools. For example, China Mobile is improving their optimization suite for time-division synchronous code-division multiple access (TD-SCDMA) networks during the ongoing commercial deployment. For both 2G and 3G mobile systems, network optimization should involve base station maintenance, signaling, testing, adjustment, data collection, and analysis functions to improve coverage and reduce interference. However, the deployment and optimization of mobile networks are very complicated and challenging engineering tasks that require a comprehensive systematic approach; conventional procedures usually cost a long time, and a lot of resources and manpower to achieve the goal. In future mobile networks, wherein multiple types of cells (e.g., macro, micro, pico, and even femto) will coexist, an increasing number of parameters need to be taken into account in network optimization, so the challenges become much more intensive.

The revenue from a mobile network highly depends on its operational efficiency; hence, operators are seeking advanced technologies and proper strategies to reduce the OPEX of LTE networks. This motivates the research and development of more efficient network architecture and new technologies, such as mobility load balancing (MLB), for LTE networks [1, 2]. Driven by both the market perspective and the technological potentials, self-organizing network (SON) technology is promoted by the international standardization body Third Generation Partnership Project (3GPP) [3] and operators' lobby Next Generation Mobile Net-

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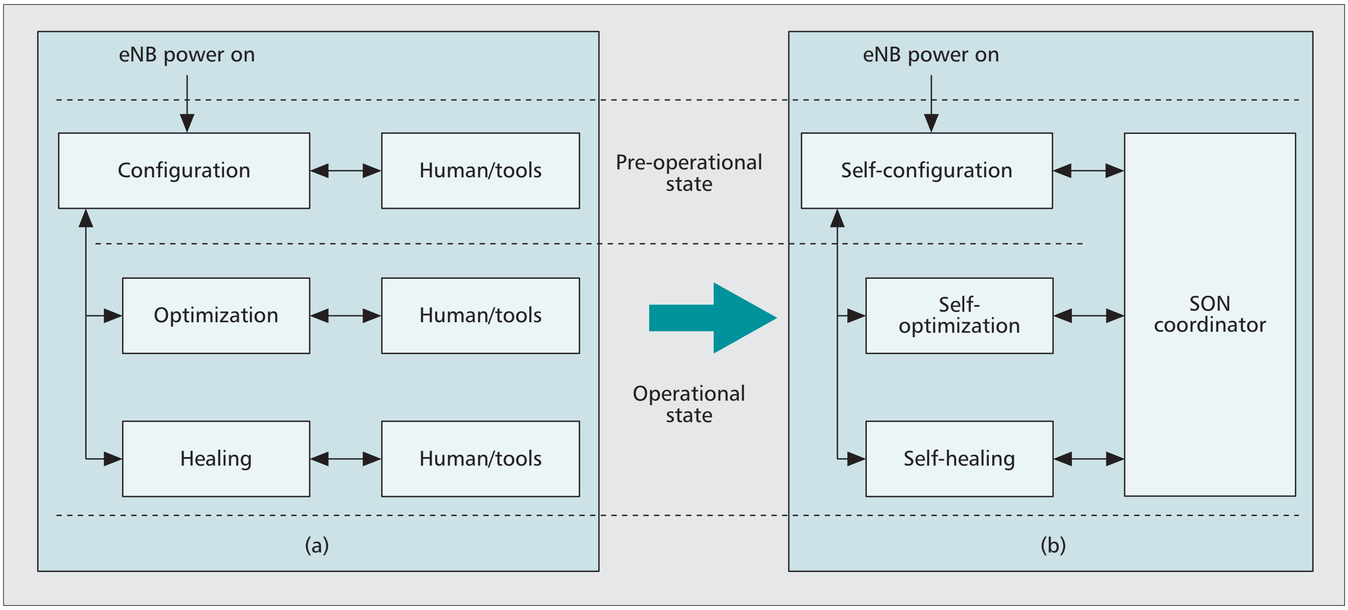

Figure 1. *Network operation a) without; b) with SON functions.*

works (NGMN) [4]. For example, 3GPP has set up an ad hoc SON group in System Architecture Working Group 5 (SA5) and has standardized some SON-related techniques for LTE networks in Radio Access Network Working Group 3 (RAN3) and RAN2. Worldwide, many research projects have been funded to develop key SON technologies, such as the SOCRATES project in Europe [5].

The self-organization capability of a mobile network mainly includes three aspects: self-configuration, self-optimization, and self-healing. Figure 1 gives a comparison between network operation with SON functions and the conventional mechanism, which relies on human intervention or service tools. The self-configuration capability enables fast installation and deployment of future evolved NodeBs (eNBs), which reduces human involvement and deployment time. Moreover, the newly added eNBs can be integrated in a plug-and-play approach. Thus, self-configuration is especially useful at the pre-operational stage of a wireless mobile network. Comparably, self-optimization techniques such as MLB enable a mobile network to automatically select and adjust proper algorithms and system parameters, to achieve optimal system capacity and service coverage. Therefore, self-optimization techniques are crucial for the operational state of mobile networks. Finally, self-healing assists operators in recovering a network when it collapses due to some unexpected reason. It can be seen as an event-driven process, which is necessary at emergent system failures.

In this article we mainly consider the self-configuration and self-optimization of mobile networks. Specifically, we first illustrate a self-configuration mechanism for newly added eNBs without dedicated backhaul interfaces in the next section. Then we propose and evaluate a distributed MLB algorithm with low handover cost for LTE networks. Finally, we conclude this article in the final section.

Self-Configuration Mechanisms

Overview

In the LTE overall description specification [6], the self-configuration process is defined as the process where the newly deployed eNBs are configured by automatic installation procedures to get basic parameters and download necessary software for operation. On the other side, self-configuration will also be applied in failure cases in combination with fast failure detection mechanisms to provide automatic failure recovery or compensation mechanisms (e.g., in cell outage cases).

The self-configuration process takes place at the pre-operational state. First, an eNB gets the IP addresses of itself and the operation, administration, and maintenance (OAM) center. Then the eNB associates with an access gateway (aGW) after it is authenticated to the network. After that, the eNB downloads the required software and the operational parameters. Finally, the eNB configures the neighbor list and the coverage/capacity related parameters according to the downloaded information, and then enters the operational state.

In conventional cellular systems an eNB (or base station) has at least two interfaces, the air interface to user equipment (UE), and the backhaul interface to the core network. Obviously, the self-configuration process uses the backhaul interface. The main point of implementing the self-configuration function is how the eNB gets its IP address and connects to the configuration server. There are several solutions to this issue. Simply, the eNB can use Dynamic Host Configuration Protocol (DHCP) or Bootstrap Protocol (BOOTP) agent to get its IP address. The DHCP or BOOTP broadcast packets can only be transmitted in the same subnet.

If the routers in the backhaul link do not support DHCP or BOOTP , other schemes should be used. For example, as in [7], an eNB is added into a multicast group of routers and a configuration

The self-configuration methods introduced above all assume that the eNB has a dedicated backhaul interface, and the eNB uses this interface connecting to the configuration server. Currently, the physical backhaul interface can be a TDM interface or an Ethernet interface.

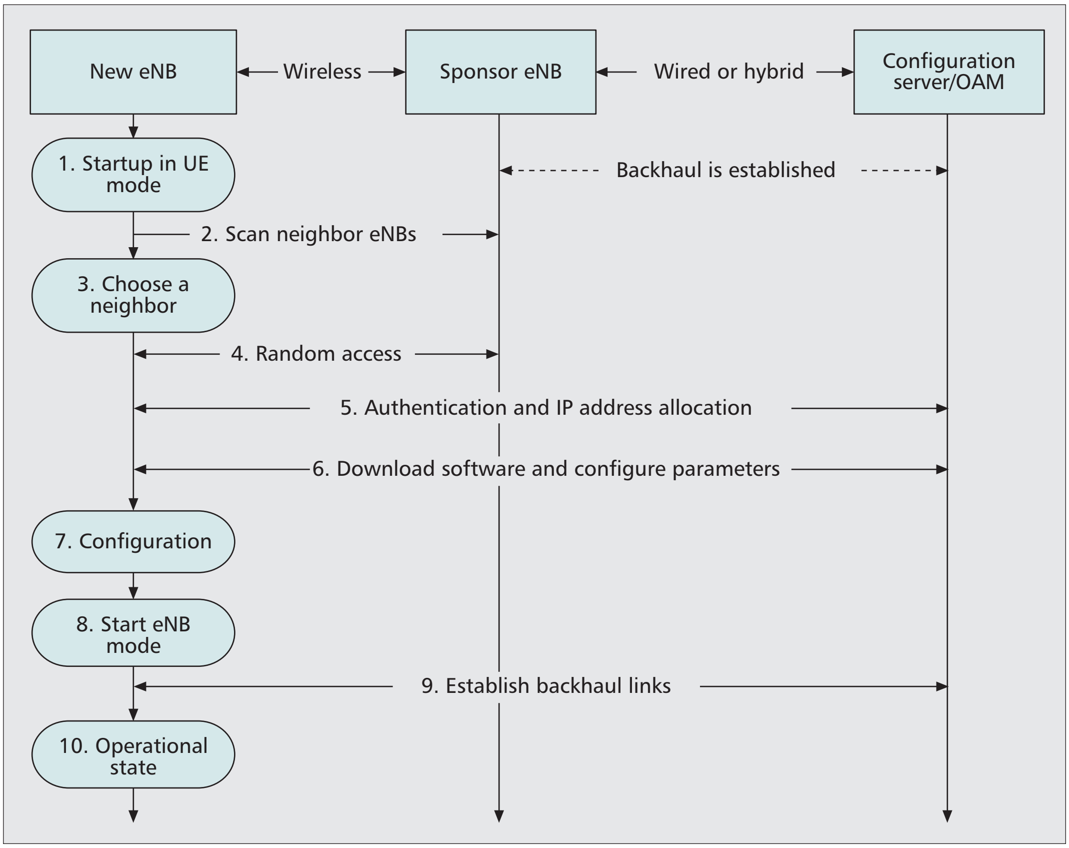

Figure 2. *Neighbor eNB assisted self-configuration procedure.*

server using the Internet Group Management Protocol (IGMP), and the configuration information is received in the multicast IP packet.

CHALLENGES AND SOLUTIONS

The self-configuration methods introduced above all assume that the eNB has a dedicated backhaul interface, and the eNB uses this interface connecting to the configuration server. Currently, the physical backhaul interface can be a time-division multiplexing (TDM) or Ethernet interface. However, in the following cases the eNBs may not communicate through the dedicated backhaul interface:

- When an eNB has a physical backhaul interface, but it is deployed for temporal coverage, there may be no matching interfaces at the place where the eNB is located.
- An eNB may not have a dedicated backhaul interface. Along with the revolution in broadband mobile networks, both the data rate achieved by the cellular system and the density of eNBs are increasing. Thus, the cost of the backhaul network becomes a main burden of operators, and the requirement of reducing the backhaul cost is raised in both 3GPP and NGMN. To reduce the backhaul cost, backhaul transmission protocols of eNBs are proposed to be built on the radio access technology [8].

Moreover, as the operational frequency might be higher in the next-generation cellular system, the density of eNBs will be higher as well. Thus, the probability of an eNB without a dedicated backhaul interface will also increase. In such cases the traditional self-configuration solutions cannot work, and a more flexible mechanism is needed. To start the self-configuration process in these cases, we propose that a newly deployed eNB shall boot up in UE mode first, and then connect to a neighbor eNB in operational state (i.e., already configured) to download the configuration parameters and eNB software. Then the newly added eNB can easily be configured and smoothly enter the operational state.

Figure 2 shows the proposed neighbor assisted self-configuration procedure. The detailed steps are described as follows:

1. When a new eNB is powered on, it starts up in UE mode. The UE mode does not need to be configured.
2. The new eNB scans the neighbor cells.
3. The new eNB chooses one of the neighbor eNBs that already has a backhaul link as its sponsor eNB. The backhaul link can be either wired or hybrid.
4. The new eNB gets access to the sponsor eNB by a random access procedure. To differentiate the new eNB from normal UE and reduce the access time, some dedicated random access channels/codes can be used for the new eNB.
5. The new eNB sends the authentication information to the sponsor eNB. If the new eNB uses the same random access procedure as the UE, a flag should be sent along with the authentication message to indicate that it is different from UE. The sponsor eNB forwards the authentication request to the OAM if it finds that the authentication

is from a new eNB. After the new eNB is authorized, OAM sends the IP addresses of the new eNB, the aGW, and the configuration server to the sponsor eNB. Finally, the sponsor eNB forwards the IP addresses to the new eNB.

6 The new eNB connects to the configuration server, and then downloads the software and operational parameters. This step can be replaced by other alternatives. For example, the new eNB can also use lower-layer signaling to request the sponsor eNB to download the eNB software and operational parameters, and then the sponsor eNB sends these data to the new eNB.

7 After having received the eNB software and operational parameters, the new eNB installs the software and configures itself.

8 The new eNB terminates the UE mode and switches to the eNB mode.

9 The new eNB establishes backhaul connection with both the neighbor eNBs and the core network.

10 The self-configuration procedure completes, and the new eNB enters the operational state.

The above proposed procedure is a more general solution to the eNB self-configuration issue, since this mechanism is independent of the core network type. As long as a neighbor eNB is configured and connected to the core network, the newly deployed eNB can easily be self-configured. Obviously, the proposed approach can also be used for a newly added relay station if needed.

Mobility Load Balancing with Low Handover Cost

Overview

In cellular networks the arrivals of mobile users and the resulting traffic load are random, time-varying, and often unbalanced, which make cell loads in a system unequal. There might be a huge amount of UE in some cells, which are overloaded; while, there is much less UE in other cells where resources are not fully utilized. The inefficient resource utilization may be mitigated by optimal network management and planning. However, the current network planning strategies are far from solving the load balancing problem in LTE systems completely.

There are several facts that make the MLB problem a critical challenge faced by LTE networks. First, network applications and services develop rapidly, and the demand for resources increases very fast, which make resource shortage in cellular networks very common. Second, the traffic is time-varying and unpredictable. Therefore, static and pre-fixed network planning cannot make the network adapt to the varying load dynamically in a timely fashion. Third, remaining competitive at a reduced cost by utilizing resources efficiently is the driver of studying the MLB problem from the market side.

One possible way to balance load is to shift some UE at the border of overlapping or adjacent cells from more congested cells to less congested cells, which is often referred to as handover or handoff. By changing the assigned eNBs for UE, the load is balanced and system performance is improved at the cost of system overhead caused by handovers. The handover procedure consumes substantial system resources, and the involved UE may experience significant system delay and performance degradation. Hence, handovers cannot happen arbitrarily often; otherwise, the performance improvement gained by the more balanced traffic load cannot compensate for the performance loss caused by the handovers.

In the following, we aim to balance the unequal traffic load, improve the system performance, and minimize the number of handovers needed to achieve load balancing. A new MLB algorithm is proposed, which has performance bounds on both the average system delay and the average number of handovers that have taken place. In contrast, the primary interest of traditional load balancing studies is to optimize system performance in terms of throughput, fairness, and system delay. Hence, they do not intend to restrict the occurrence of handovers and might result in a solution with too frequent handovers.

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MLB Algorithm with Penalized Handovers

Consider a downlink constrained packet-switched multicell network. Let U denote the set of UE. Each UE unit, $u \in U$, is assigned to a cell as its serving cell. Let us denote $DataRate(u, c)$ the achieved data transmission rate if serving cell c transmits data to UE u. The transmission rates from cells to UE are determined by instant channel conditions, power allocation, and the resulting interference. The channel conditions, power allocation, and interference level can be sensed and known by UE and eNBs. Hence we assume the instant transmission rates are determined by eNBs and are known. For each UE unit u, we assume its data packets arrive at the backbone network randomly and are buffered at the serving eNB. At each eNB, the queues are UE differentiated. Let us denote the backlog of the queue for u by $QueueBacklog(u)$.

It is reasonable to assign u to a cell providing the largest $QueueBacklog(u) \times DataRate(u, c)$, which helps to maintain system stability and achieve the largest capacity region. In contrast, since the procedure of handovers is costly and cannot happen arbitrarily often, it might be beneficial to keep UE associated with the current serving cell c even if a neighbor cell c' can provide a bit larger $QueueBacklog(u) \times DataRate(u, c')$. By considering the two conflicting motivations together, we propose to assign a penalty to a pair of UE u and cell c if a handover is required to make u assigned to c. Let $PenaltyFactor(u, c) \in [0, 1]$ be a penalty factor if a handover toward cell c is required for UE u. Now we propose to assign u to the cell with the largest $QueueBacklog(u) \times DataRate(u, c) \times (1 - PenaltyFactor(u, c))$, which is denoted $W(u, c)$.

Furthermore, in order to reduce the system overhead caused by handovers, for each cell we only allow at most one UE unit to hand over toward the cell at a time; that is, the UE can hand over toward at most one cell, and a cell can accept at most one UE from other cells. At the same time, we wish to maximize $\sum_{u \in U} W(u, c)$. Hence, the problem of selecting a subset of UE for handovers reduces to a Maximum Weighted Matching (MWM) problem, where UE u is matched to cell c and $W(u, c)$ is the associated weight. We use the greedy distributed algorithm with low complexity and system overhead proposed in [9] to solve the MWM problem in our proposed MLB algorithm.

The proposed MLB procedure stabilizes the system and makes a trade-off between the average queue backlog and the number of handovers. For a larger penalty factor, the algorithm chooses to reduce the number of handovers at the cost of the larger average queue backlog (i.e., the larger average system delay); on the other hand, with the smaller penalty factor, it prefers to have the shorter system delay with an increased number of handovers. The detailed steps of the algorithm are illustrated as follows:

1 Each UE u computes the weight $W(u, c)$ for each cell c with which it is able to communicate.
2 The greedy algorithm [9] is run to solve the MWM problem approximately based on the weights computed in step 1.
3 If UE u is assigned to cell c, which is not the current serving cell of u, UE u hands over toward cell c.

The proposed algorithm can be run repeatedly at different frequency, varying from several time slots to several minutes, which balances various aspects of the algorithm (e.g., performance and system overhead). In the simulation we did experiments with the algorithm running at different frequencies.

Network topology	
Number of cells	19
Number of sectors per cell	3
Distance between origins	1.732 km
Channel model	
Frequency reuse factor	3
Path loss model	$pl(d) = -35.63 - 35 \log_{10}(d)$
Log-normal shadowing	Standard deviation = 8.9 dB
Channel conditions	Good, median, poor
Probability in each condition	1/3
System bandwidth	10 MHz
UE distribution	
Number of UE units	1197
Distribution in each sector	Uniform distribution
No. of sectors (9 UEunits/sector)	19
No. of sectors (18 UE units/sector)	19
No. of ectors (36 UE units/sector)	19
Miscellaneous	
Data arrival	Poisson process
Time slot length	1 ms
Simulation time	40,000 time slots

Table 1. *Simulation setup.*

NUMERICAL EXAMPLES

We did experiments on a two-tier multicell network, and the detailed simulation setup is described in Table 1. Each UE is initially allocated to its eNB based on signal-to-interference-plus-noise ratio (SINR). The UE units are assumed to be static during the simulation. When generating the channel gains, the path loss model in Table 1 and the log-normal shadowing are considered. We use channel conditions to model other factors that can impact the link transmission rate, such as environmental effects or wireless fading. We assume that under a better channel condition, a more efficient physical layer modulation and coding strategy is used to support a higher data rate for the channel. The condition of each channel is generated randomly and independently at each time slot.

Performance Evaluation Metrics — For intra-cell scheduling there are two well-known policies adopted in practice, SINR-based and Proportional Fair (PF). The SINR based policy aims to maximize the system throughput, while the PF policy maintains proportional fairness among UEs [10]. Both policies are used in our simulation.

We have run four tests. In tests 1 and 2, handovers are absolutely not allowed. The SINR-based and PF intra-cell scheduling policies are adopted, respectively. The system throughput of test 1 and the worst case queue backlog of test 2 serve as the benchmarks of system performance. In both tests 3 and 4, the PF policy is used for intra-cell scheduling. In test 3, in each time slot we run the proposed algorithm once to balance the traffic load. Meanwhile, we only run the algorithm once every 1000 time slots in test 4. Since the load balancing procedure runs at a higher frequency in test 3, it causes higher system overhead. In both tests 3 and 4, the penalty factors used are 0.1 for the reassignment of UE involving handovers.

We summarize all the tests in the following.
- Test 1: SINR-based intra-cell scheduling. No handovers are allowed.
- Test 2: PF intra-cell scheduling. No handovers are allowed.
- Test 3: PF intra-cell scheduling. The algorithm runs in each time slot.
- Test 4: PF intra-cell scheduling. The algorithm runs every 1000 time slots.

Results Analysis — In Fig. 3 we show the results of tests 1 to 4 in terms of system throughput and the worst case queue backlog of UE. The throughput is normalized with respect to test 1, and the worst case queue backlog is normalized with respect to test 2. Regarding the maximum system throughput, tests 3 and 4 (with load balancing) improve system throughput by 12 to 13 percent, which will be even larger if compared to test 2. Consider the worst case queue backlog, which is proportionally related to the worst case system delay UE experiences. The worst case backlogs achieved by tests 3 and 4 are smaller than what test 2 obtains, which means tests 3 and 4 maintain good fairness. The number of handovers that have taken place in tests 3 and 4 are 904 and 516, respectively. In test 4 the proposed algorithm runs at a much lower frequency and requires about 40 percent fewer handovers than test 3. Meanwhile, we see that the system performance of tests 3 and 4 is comparable from Fig. 3. Hence, the proposed algorithm can run at a relatively low frequency and still achieve good performance. We summarize that the proposed MLB algorithm achieves a significant improvement at the cost of affordable complexity and system overhead.

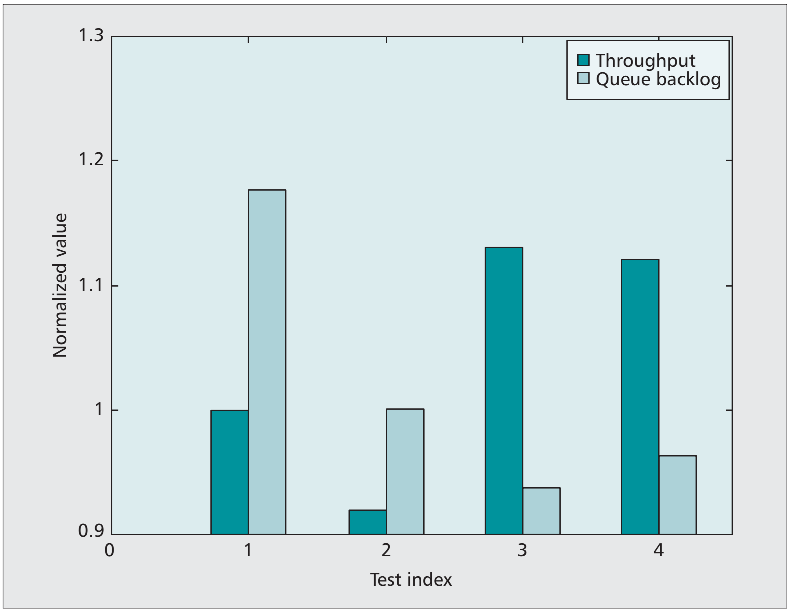

Figure 3. *Comparison of normalized throughput and worst-case queue backlog.*

Next we test the proposed MLB algorithm with different penalty factors. The larger the penalty factor, the more penalties a handover will receive. In Fig. 4a the worst case queue backlogs are normalized with respect to the test where the penalty factor is 0.05. Note that handovers are more heavily penalized when the penalty factor becomes larger. Intuitively, as the penalty factor becomes larger, fewer handovers take place and the worst case queue backlog becomes larger. Figure 4 shows that the number of handovers drops while the worst case queue backlog increases as the penalty factor increases, which verifies the intuition and can be justified as the trade-off between the number of handovers and the worst case queue backlog. With the largest penalty factor we tested (i.e., 0.8), the worst case queue backlog increases by 15 percent, compared to the test with the penalty factor 0.05. Meanwhile, the number of handovers that have taken place drops dramatically from 1600 to about 200. Hence, by selecting different penalty factors, the algorithm prefers different system performance metrics, either the experienced system delay or the handover overhead.

CONCLUSIONS

SON technologies possess a clear and predominant perspective for LTE mobile networks, and thus have attracted much attention from both industry and academia. Meanwhile, many challenges still remain in the R&D of feasible self-configuration and self-optimization techniques for LTE networks, which require more efficient algorithms and network architectures. As the density of eNBs increases in future mobile networks, the proposed self-configuration mechanism can be widely used for the newly added

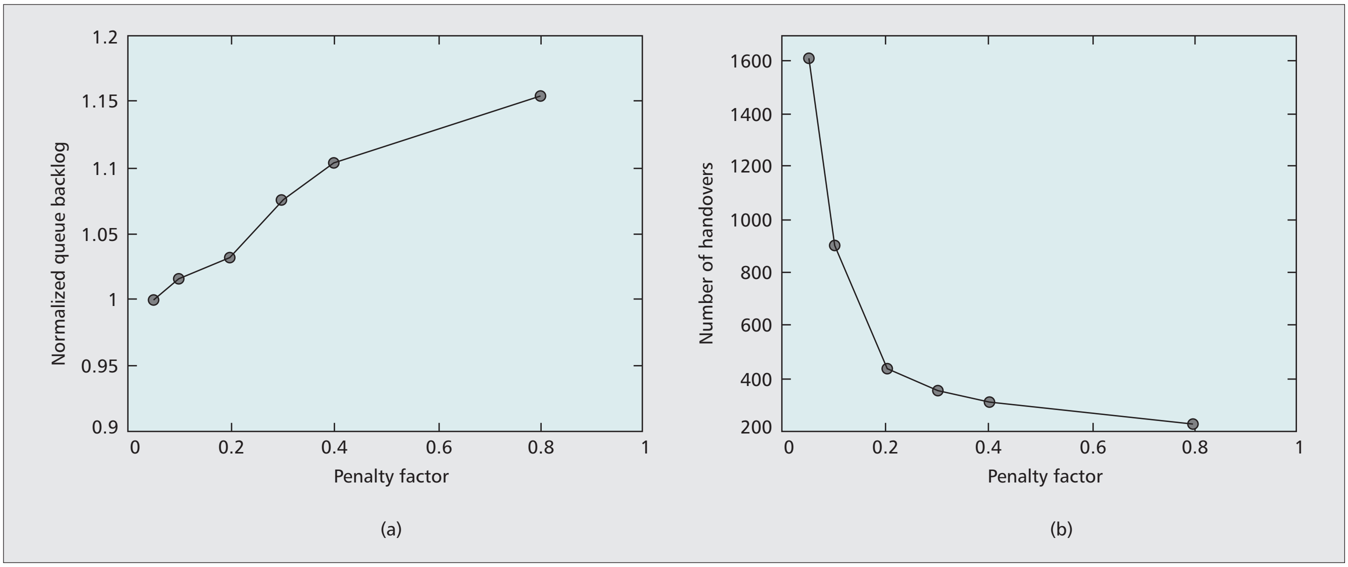

Figure 4. *Comparisons of different penalty factors: a) normalized worst-case queue backlog; b) number of handovers that took place.*

As the density of eNBs increases in future mobile networks, the proposed self-configuration mechanism can be widely used for the newly added eNBs without dedicated backhaul interfaces.

eNBs without dedicated backhaul interfaces. Moreover, numerical results show that by taking into account handover penalty, our proposed MLB self-optimization algorithm can significantly improve system performance.

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BIOGRAPHIES

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