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Mobility Load Balancing – A Case Study: Simplified vs. Realistic Scenarios

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***Abstract*— The performance of emerging self-organizing network (SON) algorithms is often evaluated based on simplified, regular hexagonal networks. Nevertheless, such algorithms are supposed to exploit the inherent inhomogeneity and therefore need to be tested in realistic network scenarios. For this, a common SON algorithm, namely mobility load balancing (MLB), is evaluated with different degrees of complexity in the simulation scenarios; and the results show a significant impact on the performance of MLB. Moreover performance characteristics for the different scenarios are compiled.**

***Keywords*— hexagon scenario; realistic scenario; SON; self-organizing networks; MLB; mobility load balancing; network management; mobility models;**

I. Introduction

Self-organizing networks (SON) is an emerging topic in the field of radio access networks. More and more SON algorithms are coming up addressing different optimization aspects particularly of UMTS, LTE and LTE-Advanced networks. With SON, the mobile network achieves the ability to react and adapt on changing situations without any (human) interaction. This is done by evaluating network measurements and automatically adjusting the respective (radio) parameters. Use cases which fall under the SON concept are self-configuration, e.g. automatic neighbouring relationship planning (ANR), self-healing, e.g. cell-outage-compensation (COC) and self-optimization, e.g. mobility load balancing (MLB) or handover optimization. In order to evaluate these SON algorithms, system level simulations are conducted. The underling network topology can be reflected in different ways and with different complexity. Starting with rather simple assumptions like regular hexagonal network layout in combination with user mobility that follows no specific directions (e.g. random walk), up to real or realistic network layouts, predicted using ray-optical pathloss prediction models and realistic user mobility models. Each degree of complexity might lead to highly diverse statements about the performance of such SON algorithm.

One prominent example for SON algorithms is, as already indicated, the so-called mobility load balancing (MLB). This algorithm is supposed to reduce the amount of overloaded cells and by that means increase the network throughput and decrease the number of unsatisfied users. The algorithm is commonly simulated and evaluated based on simple simulation assumptions. Recent investigations on the necessary degree of complexity in SON system level simulations have shown that the scenario has a significant impact on the resulting performance [1].

This paper is organized as follows: In Section II the SON algorithm and the purpose of mobility load balancing are described. The underlying implementation is explained in more detail. Additionally, alternative implementations are presented. In Section III the different simulation assumptions considering different environmental aspects are presented in detail. Followed by Section IV where the MLB algorithm is simulated and evaluated with respect to different modelling aspects with a varying degree of complexity. Starting with a simplistic network layout and ending in a realistic scenario by adding more and more complexity in each consecutive step. The results are then presented in a comparison. Finally, Section V provides a conclusion.

II. Mobility Load Balancing

MLB is part of the self-organizing network concept, which was introduced in LTE. By applying MLB in the network, gains in terms of higher network performance and a decreasing number of unsatisfied users are the optimization goal. This is supposed to be achieved by reducing highly loaded cells in the network. Usually the MLB monitors the cell load values and tries to distribute the traffic of highly loaded cells among less loaded neighbouring cells in the network [2]. This can be done by adjusting the (virtual) cell borders, e.g. adding a cell individual offset which will be taken into consideration for handover decisions, or changing the transmit power of the cell. By doing this the area of highly loaded cells will be made smaller, where on the other hand the area of less loaded cells will be enlarged. Figure 1 illustrates this concept.

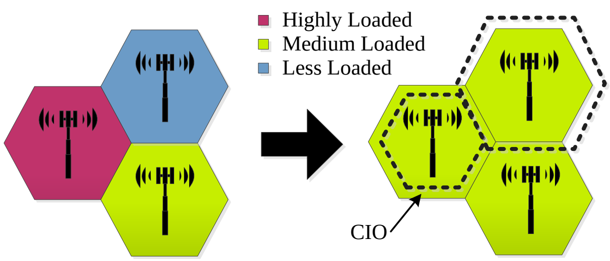

Figure 1: MLB adjusting the (individual) cell offsets to balance the load in the network

The herein used MLB implementation is an outcome of the FP7 SOCRATES project [3]. It is designed for LTE downlink systems. The algorithm uses the cell load values, e.g. coming from LTE X2 interfaces [4], and user equipment (UE) measurements as input parameters. Control parameters are the maximum accepted load in the system (Max_Load) from which the MLB becomes active, the maximum accepted load in the serving eNodeB (SeNB) (Max_Load@SeNB) and the maximum accepted load in the target eNodeB (TeNB) (Max_Load@TeNB). The MLB calculates handover decision and sets cell individual offsets (CIO) to the SeNB and TeNB accordingly. The CIO values can range from 0 dB to a predefined threshold (CIO_Max) in an also predefined step size (CIO_Step) [5]. All input-, output- and control-parameters are illustrated in Figure 2.

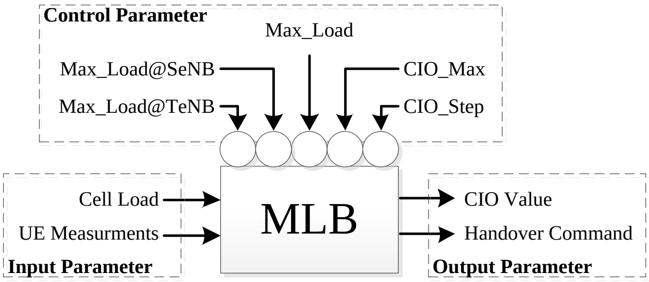

Figure 2: Input-, Output- and Control-Parameters of the mobility load balancing algorithm of [5]

The basic principles of the used MLB are as follows: If MLB is activated because a cell load exceeds the Max_Load threshold UE measurements are evaluated in terms of RSRP values to potential TeNBs. Users are grouped based on the respective RSRP differences between SeNB and TeNB. After that the resulting load in the potential TeNBs are estimated based on SINR measurements. The users are sorted in an ascending order by the required CIO to the regarding TeNB and shifted to the TeNB if the Max_Load@TeNB threshold is not exceeded. This is done until the load in the SeNB is below the Max_Load@SeNB threshold or no users can be moved because no appropriate TeNB has a load value below Max_Load@TeNB or the needed CIO value would exceed the CIO_Step value.

Other load balancing techniques can be found in the literature. For example [6] proposed an MLB algorithm that calculates the cell borders not based on the RSRP differences between SeNB and TeNB but on the load differences. In [7], the authors presented a method which also includes non-adjacent neighbouring cells. The authors of [8] propose a method for self-optimization of pilot powers to perform load balancing. All MLB algorithms were tested in a regular hexagonal environment. Moreover [9] did investigation on the performance of MLB in non-regular networks, but did not consider large scale realistic networks with realistic user mobility.

III. SIMULATION APPROACH AND SCENARIOS

The simulations in this study are based on pre-generated, continuous, microscopic user mobility traces. For each individual user position, pathloss predictions for every cell of the network are made. In order to quantify the influence of the MLB algorithm, a baseline simulation without MLB is performed for every scenario combination of interest. The analysis in Section IV is grouped into two parts: First, geometrical aspects denoting to the network layout (cf. Subsection A) and the users in the scenario (cf. Subsection B). Second, simulation assumptions related to the calculation of the Load and SINR (cf. Subsection C).

A. *Network Layouts*

Two different network layouts are compared in this study, namely a simple hexagonal network layout following the specifications by the 3GPP and the much more realistic but also more complex network layout taken from the "Urban Hannover Scenario" described in [10]. In order to realistically account for interference effects from the outside on the small inner scenario area of 3x5 km², both networks are defined for a large area of 20x24 km². Figure 3 gives an impression of different deployments.

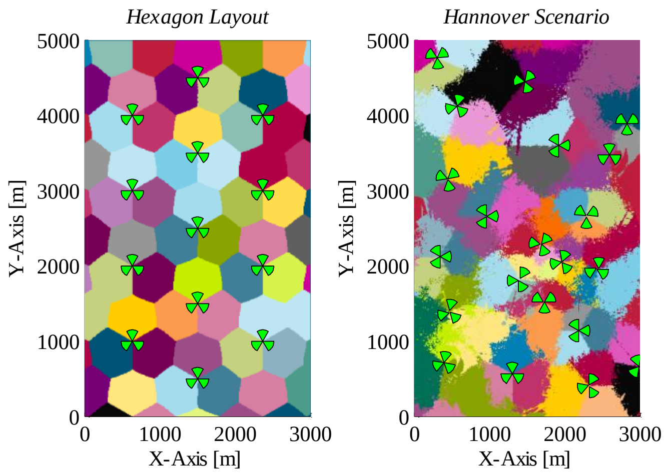

Figure 3: Best-Server-Map of the Simplified Hexagonal Network (left) and the Realistic Urban Hannover Scenario (right)

1) *Hexagonal Network*

The key parameters of this simple scenario are given in Table 1.

Network	**Hexagonal**
Layer	LTE 2000 Macro
Cells (total/inner)	231 / 51
Bandwidth	10 MHz
TX power	46 dBm
Inter-site distance	1000 m
Antenna down tilt	6° (mechanical)
Pathloss model	$128.1 + 37.6 \log_{10}(r/[km])$
Antenna model	3GPP 3D model [11]

Table 1: Hexagonal Network

2) *Realistic Urban Hannover Scenario Network*

The key parameters of the realistic scenario are given in Table 2 and described in much more detail in [10].

Network	Urban Hannover Scenario
Layer	LTE 1800 Macro
Cells (total/inner)	195 / 65
Bandwidth	10 MHz
TX power	46 dBm
Inter-site distance	n/a
Antenna down tilt	4° (mechanical)
Pathloss model	3D Ray-optical
Antenna model	Kathrein 742212 (real)

Table 2: Realistic Urban Hannover Scenario Network

B. *Mobility Models*

Two different mobility models are considered. On the one hand, the "Random Walk" model is used; on the other hand, a compilation of realistic mobility traces is employed. The mobility traces have a temporal resolution of 100 ms, which corresponds to the temporal resolution of the LTE system level simulator used in this study.

1) *Random Walk Mobility*

3000 traces based on random walk mobility are generated for the evaluations. In order to account for different velocity classes, 3 different speeds are simulated as specified in Table 3. All users are dropped equally over the inner scenario area of 3x5 km².

Mobility	Random Walk Mobility
Simulated area	3x5 km²
Slowly moving users	1000 / 5 km/h
Medium moving users	1000 / 15 km/h
Fast moving users	1000 / 50 km/h

Table 3: Random Walk Mobility

2) *Realistic Mobility*

The realistic user mobility traces represent much more advanced mobility patterns for the simulation of SON aspects. A set of vehicular and pedestrian users is taken from the "Urban Hannover Scenario" as described in [10]. These users enter and leave the inner scenario area, and follow streets or paths. Moreover, semi-stationary indoor users are modelled according to [1]. They have been dropped almost equally over the inner scenario area (if there are no buildings, there are no indoor users). These users move inside their houses and apartments. The compilation is shown in Table 4.

Mobility	Realistic Mobility
Simulated area	3x5 km²
Indoor users	600 / semi-stationary
Pedestrian users	800 / approx 5 km/h
Vehicular users (SUMO)	1100 / up to 50 km/h

Table 4: Realistic Mobility

C. *Network Load / SINR Computation*

The LTE system level simulator gathers the current RSRP values for each user and performs standard handover decisions. The handover decisions, as well as the MLB handover decision depend on the load and the current SINR values. In literature, two different approaches to model these aspects are common and will be evaluated separately within this study.

1) *Full Load Interference*

All cells contribute with 100% interference in the SINR calculation, like it is mentioned in [12] and [13].

$$SINR = \frac{S}{N + \sum_k I_k}$$

2) *(Linear) Load Dependent SINR Computation*

In this case, the load situation of every cell is linearly reflected in the SINR calculation, like it is mentioned in [5], [6]. For cells with no or little load, a minimum load of 10% due to signalling and pilot traffic is assumed.

$$SINR = \frac{S}{N + \sum_k l_k \cdot I_k}$$

D. *Traffic Model*

For reasons of simplicity, a single service with a constant bit rate (CBR) is modelled. Since a varying number of users and different network topologies are given, the respective CBR is scaled to fit the scenario needs, so that approximately 5 to 10 cells in the scenario are in an overload situation in the beginning of each simulation.

E. *Scenarios*

As mentioned, the input data is predefined and thus simulations are deterministic. It allows for the separate evaluation of all 8 combinations of the aforementioned aspects.

IV. Simulation Results

The simulations have been realized for each scenario combination. Each simulated reality has a temporal duration of 10 minutes. The temporal resolution is 100 ms, which leads to 6000 consecutive simulation steps. Each scenario is simulated twice: Without MLB algorithm (baseline) and with MLB running on each cell. Additionally the results are presented for two methods SINR calculation: First, with full load interference assumptions, e.g. used in [12], [13]. And second with load dependent interference, e.g. used in [5], [6]. The MLB control parameters are set according to Table 5.

Name	Value
Max_Load	90%
Max_Load@SeNB	80%
Max_Load@TeNB	70%
CIO_Max	6 dB
CIO_Step	1 dB

Table 5: MLB Control Parameters

All simulation results for the different scenarios are evaluated in terms of network throughput. To be able to compare the different scenarios among each other a new performance indicator has been defined. The overall gain of MLB is derived by normalizing the aggregated amount of network throughput for each simulation step. This is done by dividing the results where MLB was active on each cell of the scenario with the results of the baseline scenario for the respective simulation steps. This leads to a coefficient that expresses the effect of MLB for the given setup. If the value is above 0, MLB has a positive effect in terms of network throughput performance. If the value is below 0, MLB led to throughput performance degradation.

A. Full Load Interference

If full load interference is considered in terms of SINR computation, the achieved gain by implementing MLB in the network is shown in Figure 4.

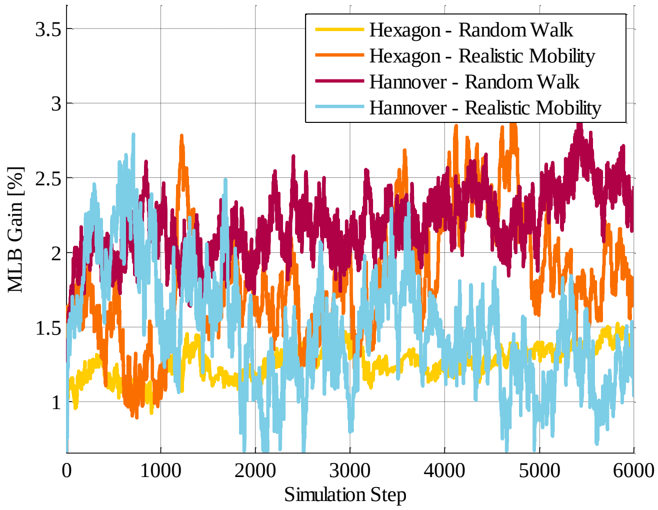

Figure 4: MLB gain for full load interference SINR computation

First of all, every scenario leads to a positive MLB gain around 0.5 and 3.0%. Still it can be seen that the gain is the lowest if the regular hexagon network layout is chosen in combination with a random walk mobility model. On the other hand the realistic Hannover network scenario with a random walk mobility model shows the highest gains out of all scenarios. This can also be seen in Figure 5, where the first and second order statistics are presented.

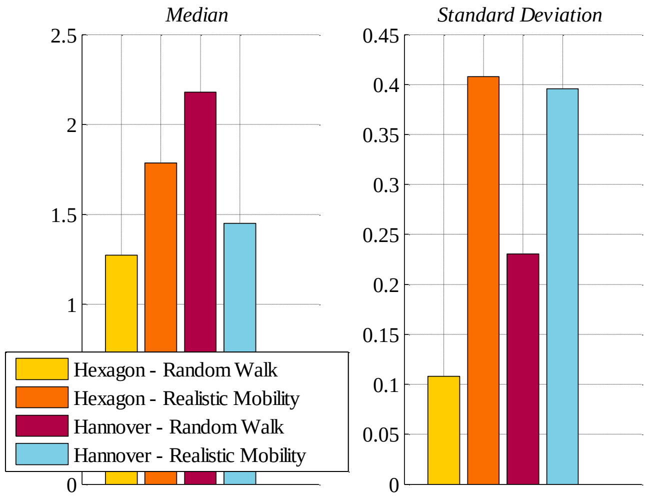

Figure 5: First and second order statistics of MLB gains (full load interference SINR computation)

Noteworthy is the fact that realistic user mobility leads to significant higher standard deviation for the MLB gain. This is due to the fact that parts of the available user trajectories are aim-oriented and move, given their boundaries, straight towards this aim. This means that load conditions in cells also might change quicker compared to a random walk model where users do not simply move straight through the cell area.

B. Load Dependent SINR Computation

Results obtained for the same scenarios but with a load dependent SINR computation are shown in Figure 6. Similar to the previous results (where full load SINR computation is used) the hexagon network layout combined with a random walk model features the lowest gains if MLB is active in the network, but the gain is always positive. In other scenarios it can be observed that MLB does not always lead to a positive gain. Especially in scenarios with realistic mobility models the MLB gain can drop below 0 at some time.

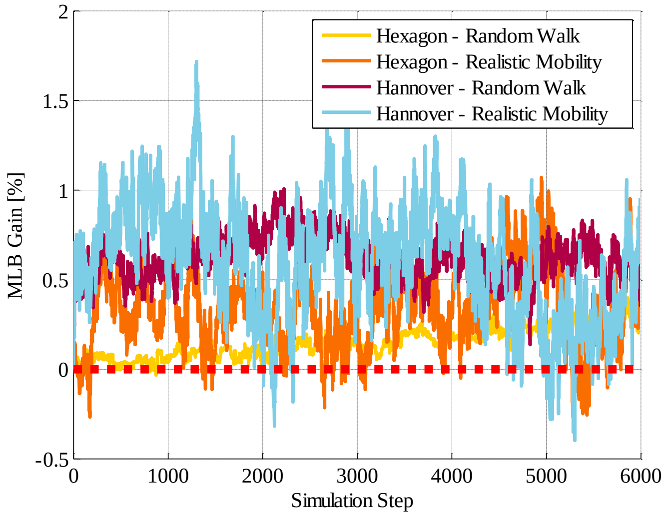

Figure 6: MLB gain for load dependent SINR computation

The first and second order statistics for this SINR computation are presented in Figure 7. It is again noticeable that realistic user mobility leads to a higher standard deviation. As the median values show, there is also a clear trend towards higher gains if the complexity of the scenario is increased, especially if realistic network scenarios are considered, even though the MLB gain drops below 0 at some time.

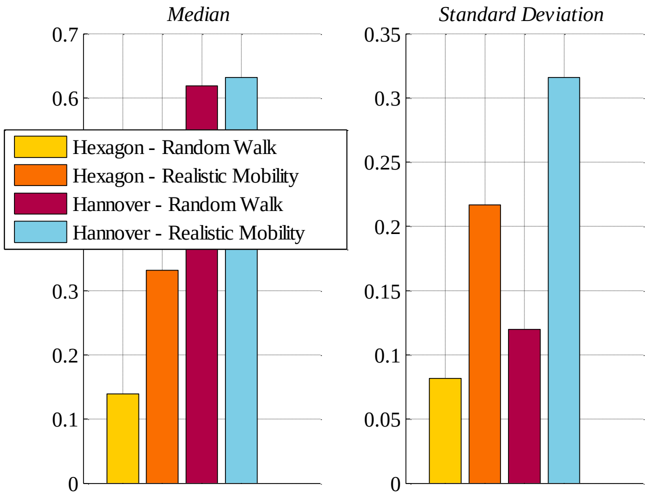

Figure 7: First and second order statistics of MLB gains (load dependent interference SINR computation)

V. Conclusion and Future Work

In this paper the effect of MLB in different scenarios is evaluated, starting with a regular hexagon network with random walk mobility up to a realistic network topology with realistic user mobility. Results are shown that the actual performance of MLB in the mobile network varies based on the underling simulation scenario. The following scenario characteristics are observed:

A. Positive gain and small variations for Random Walk Mobility

Given the first and second order statistics for both SINR computation methods, the standard deviation is always the smallest for the scenarios with random walk mobility. This is due to the characteristics of the resulting user trajectories. The direction of such trajectories changes a lot but the actual position in the scenario tends to change rather slowly. This is resulting in longer time periods where the user stays in a certain cell and with that load conditions are more stable.

B. Higher variations in MLB gain if realistic user mobility is considered

Referring to A there are higher variations if realistic user mobility is considered. With this mobility models user trajectories do not necessarily move all the time, but are aim orientated. By this users pass more cells so that the load situations also change quicker. Meaning that the MLB has to adapt the CIO values more often which result in varying MLB gains.

C. Lower overall gain if load dependent SINR computation is chosen

As one can compare the both SINR computation techniques it can be observed that the overall gain comes off lesser if a load dependent SINR computation is chosen. In this case the gain can be even below zero for a little while, but the overall gain is still positive. Since the user SINR calculation is not based on a worst case interference situation, but on the actual load values this is plausible. By offloading to other cells the overall network load naturally increases because users are most like not connected to best serving cell. This also implies that the user SINR will get worse which will lead to lower user throughput values and higher cell load values.

Future work in this area will consider the impact on simulation scenarios of other SON algorithms, e.g. mobility robustness optimization or coverage and capacity optimization.

Acknowledgment

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References

[1] D. M. Rose, T. Jansen, S. Hahn and T. Kürner, "Impact of Realistic Indoor Mobility Modelling in the Context of Propagation Modelling on the User and Network Experience," *7th European Conference on Antennas and Propagation (EuCAP 2013),* Gothenburg, Sweden, 2013.

[2] S. Hämäläinen, H. Sanneck and C. Sartori, LTE Self-Organising Networks (SON), Wiley, 2012.

[3] SOCRATES, "The SOCRATES Project," [Online]. Available: http://www.fp7-socrates.org/. [Accessed 13 March 2014].

[4] 3GPP, "Evolved Universal Terrestrial Radio Access Network (E-UTRAN); X2 Application Protocol (X2AP), Technical Specification TS 36.423," [Online]. Available: http://www.3gpp.org. [Accessed 14 March 2014].

[5] A. Lobinger, S. Stefanski, T. Jansen and I. Balan, "Load Balancing in Downlink LTE Self-Optimizing Networks," *2010 IEEE 71th Vehicular Technology Conference (VTC2010-Spring),* Taiwan, Taipei, May 16th-19th, 2010.

[6] Y. Yang, P. Li, X. Chen and W. Wang, "A High-efficient Algorithm Of Mobile Load Balancing in LTE System," *2012 IEEE 76th Vehicular Technology Conference (VTC2012-Fall),* Québec City, Canada, September 3rd-6th, 2012.

[7] N. Zia and A. Mitschele-Thiel, "Self-Organized Neighborhood Mobility Load Balancing for LTE Networks," *Wireless Days (WD),* Valencia, Spain, November 13th-15th, 2013.

[8] Y. Khan, B. Sayrac and E. Moulines, "Centralized Self-Optimization of Pilot Powers for Load Balancing in LTE," *Personal Indoor and Mobile Radio Communications (PIMRC),* London, UK, September 8th-11th, 2013.

[9] J. Turkka, T. Nihtliä and I. Viering, "Performance of LTE SON Uplink Load Balancing in Non-Regular Networks," *Personal Indoor and Mobile Radio Communications (PIMRC),* Toronto, Canada, September 11th-14th, 2011.

[10] D. M. Rose, T. Jansen, U. Türke, T. Werthmann and T. Kürner, "The IC 1004 Urban Hannover Scenario – 3D Pathloss Predictions and Realistic Traffic and Mobility Patterns," *European Cooperation in the Field of Scientific and Technical Research, COST IC1004 TD(13)08054,* Ghent, Belgium, 2013.

[11] 3rd Generation Partnership Project, "3GPP TR 36.814," 2010.

[12] F. Zhou, L. Feng, P. Yu and W. Li, "A Ripple Form RSRP Based Algorithm for Load Balancing in Downlink LTE Self-Optimizing Network," *Network Operations and Management Symposium (APNOMS),* Hiroshima, Japan, September 25th-27th, 2013.

[13] H. Wang, L. Ding, P. Wu, Z. Pan, N. Liu and X. You, "Dynamic Load Balancing in 3GPP LTE Multi-Cell Networks with Heterogenous Services," *Communications and Networking in China (CHINACOM),* Beijing, China, August 25th-27th, 2010.

[14] SEMAFOUR, "The SEMAFOUR Project," [Online]. Available: http://www.fp7-semafour.eu. [Accessed 13 March 2014].

[15] "SUMO - Simulation of Urban MObility," [Online]. Available: http://sumo-sim.org/. [Accessed 14 March 2014].