JYVÄSKYLÄ STUDIES IN COMPUTING
253

Muhammad Zeeshan Asghar

Design and Evaluation of Self-Healing Solutions for Future Wireless Networks

JYVÄSKYLÄN YLIOPISTO

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Esitetään Jyväskylän yliopiston informaatioteknologian tiedekunnan suostumuksella
julkisesti tarkastettavaksi yliopiston Agora-rakennuksen Auditoriossa 2
joulukuun 19. päivänä 2016 kello 12.

Academic dissertation to be publicly discussed, by permission of
the Faculty of Information Technology of the University of Jyväskylä,
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UNIVERSITY OF JYVÄSKYLÄ

JYVÄSKYLÄ 2016

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JYVÄSKYLÄ 2016

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Publishing Unit, University Library of Jyväskylä

URN:ISBN: 978-951-39-6885-4
ISBN 978-951-39-6885-4 (PDF)

ISBN 978-951-39-6884-7 (nid.)
ISSN 1456-5390

Jyväskylä University Printing House, Jyväskylä 2016

ABSTRACT

Asghar, Muhammad Zeeshan
Design and Evaluation of Self-Healing Solutions for Future Wireless Networks
Jyväskylä: University of Jyväskylä, 2016, 52 p.(+included articles)
(Jyväskylä Studies in Computing
ISSN 1456-5390; 253)
ISBN 978-951-39-6884-7 (nid.)
ISBN 978-951-39-6885-4 (PDF)
Finnish summary
Diss.

This doctoral dissertation is aimed at the creation of comprehensive and innovative Self-Organizing Networks (SON) solutions for the Network Management of future wireless networks. More specifically, the thesis focuses on the Self-Healing (SH) part of SON. Faults can appear at several functional areas of a complex cellular network. However, the most critical domain from a fault management viewpoint is the Radio Access Network (RAN). The fault management of network elements is not only difficult but also imposes high costs both in capital investment (CAPEX) and operational expenditures (OPEX). The SON concept has emerged with the goal to foster automation and to reduce human involvement in management tasks. SH is the part of SON that refers to autonomous fault management in wireless networks, including performance monitoring, detection of faults and their causes, triggering compensation and recovery actions, and evaluating the outcome. It improves business resiliency by eliminating disruptions that are discovered, analyzed and acted upon. With the advent of 5G technologies, the management of SON becomes more challenging. The traditional SH solutions are not sufficient for the future needs of the cellular network management because of their reactive nature, i.e., they start recovering from faults after detection instead of preparing for possible faults in a preemptive manner. The detection delays are especially problematic with regard to the zero latency requirements of 5G networks. In order to address this challenge, the existing SON enabled networks need to be upgraded with additional features. This situation pushes operators to upgrade their SONs from reactive to proactive response and opens doors for further reseach on SON and SH. This dissertation provides several contributions to this direction.

Keywords: Self-organizing Networks, Self-healing, Faults Management, Cell Degradation Detection, Cell Outage Management, Mobile Networks

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ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my PhD Supervisor Prof. Tapani Ristaniemi for his support and guidance throughout this research work. Also, my deepest appreciation goes to my co-supervisors Dr. Seppo Hämäläinen from Nokia Networks, Prof. Timo Hämäläinen from University of Jyväskylä.

I am grateful to the reviewers of my dissertation for their constructive comments and Dr. Tech. Jarno Niemelä for being my opponent. I wish to thank Department of Mathematical Information Technology at University of Jyväskylä and Magister Solutions Ltd. for supporting me financially and creating the conditions to make this research possible. I attended various conferences being supported by graduate school in computing and mathematical sciences of the University of Jyväskylä.

I thank all my colleagues from Magister Solution, Nokia Networks and Unviersity of Jyväskylä for their support. I thank Nikolas Meinke, Pauli Hieno, Jari, Dr. Richard Fehlmann and Dr. Henning Sanneck from Nokia Networks. I thank Dr. Henrik Martikainen and Dr. Janne Kurjenniemi from Magister Solutions, and Dr. Paavo Nieminen, Dr. Zheng Chang and Dr. Michael Cochez from University of Jyväskylä for useful discussions and support. I want to thank Prof. Muhammad Ali Imran for inviting me to 5G Innovation Center (5GIC), University of Surrey, UK for a three months research visit. This research visit proved to me very productive for my research. I thank Dr. Colin O'Reilly and Dr. Kayode Onireti from University of Surrey for their cooperation and meaningful discussions.

In my personal life I thank ALLAH Almighty may He be glorify and exalted, for great favors and blessings that He has bestowed upon me in both spiritual and worldly terms. I thank last Prophet Muhammad (Peace Be Upon Him) for conveying the message from ALLAH Almighty to mankind. I also like to thank Pakistan as a country who gave me an identity and all the education and life experience.

In my family, first I want to thank my grandparents Syed Abdul Waheed (late), Sarwari Begum (late), Muhammad Ashraf (late) and Maqbool Khatoon (late) for their prayers and priceless love. I like to thank my parents Dr. Muhammad Asghar(late) and Najma Asghar(late), for giving me understanding about different aspects of life and for giving me vision and motivation to do research, and for giving me strength to accomplish this great milestone in my life. I dedicate all achievements of my life to my parents. I like to thank my brothers Dr. Muhammad Nadeem Asghar, Muhammad Yasir Asghar and Dr. Muhammad Imran Asghar for their special kind treatment towards me. I thank my beloved wife Khaula and my lovely children Fajr, Abdullah and Yamha for their love, care, support and patience. I also thank my sister in law Sumreen Yasir and my cousins Ayesha, Sadia and Bushra for their care and affection. I am also grateful to my uncles and aunts Muhammad Zafar, Muhammad Akhtar and Alam Khatoon. I like to pay special thanks to my nieces and nephews Ali, Haris, Maryam, Uzma, Amina and Arfa for making my life joyful.

In the end, I would like to express my gratitude towards Finland as a country where I have been living for last 8 years. Finland is a great country and this is the reason I and my three brothers chose it for our PhD degrees. I am happy that we made a right choice.

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PII Muhammad Zeeshan Asghar, Seppo Hämäläinen, and Tapani Ristaniemi. Self-healing framework for LTE networks. *2012 IEEE 17th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)*, 2012.

PIII Muhammad Zeeshan Asghar, Richard Fehlmann, and Tapani Ristaniemi. Correlation-based cell degradation detection for operational fault detection in cellular wireless base-stations. *International Conference on Mobile Networks and Management*, 2013.

PIV Muhammad Zeeshan Asghar, Paavo Nieminen, Seppo Hämäläinen, Tapani Ristaniemi, Muhammad Ali Imran, and Timo Hämäläinen. Cell Degradation Detection based on an Inter-Cell Approach. *International Journal of Digital Content Technology and Its Applications (Accepted!)*, 2016.

PV Muhammad Zeeshan Asghar, Paavo Nieminen, Seppo Hämäläinen, Tapani Ristaniemi, Muhammad Ali Imran, and Timo Hämäläinen. Towards Proactive Context-Aware Self-healing for 5G Networks. *Computer Networks Special Issue "Survivability Strategies for Emerging Wireless Networks" (Accepted!)*, 2016.

1 INTRODUCTION

The network management of cellular networks is becoming challenging as the networks are highly dynamic and consist of a huge number of network elements. The number of network elements is continuously increasing with the advent of new radio technologies, making network management of such a huge system very difficult. The wireless links are dynamic as the radio signal strength are variable due to complexity introduced by the slow and fast fading effect of the propagation environment. The traffic patterns are constantly changing and the network settings need to be continuously adapted with the changing network resources needs. One example could be the network mobility procedures such as handovers between cells, and cell reselection etc. are required to update the settings to cope with the dynamic and constant changes in the mobility patterns of the users. Also, the traffic patterns are different for different times of the day, working day, weekend and special events such as sports event etc. There are different coverage environments such as urban, suburban and rural, that makes the network management tasks more complicated. Thus, the network settings and configuration parameters need to be updated in a continuous manner. In addition, the 5G networks would be a combination of all previous technologies such as 2G, 3G, High speed packet access (HSPA), Wideband code division multiple access (WCDMA), Long term evolution (LTE), LTE-Advanced, and Wireless local area networks (WLAN). The 5G networks consists of different type of cells, e.g., traditional macro cells, micro cells, pico, femto cells, and relays. This makes the network management of such a diverse and complex system more challenging. Faults can occur at any level of the network, the effect of fault may be different for different cell types. The faults can be broadly categorized into hardware, software and wrong configuration parameters settings. The hardware faults refer to the malfunctions in hardware components, e.g., in antenna amplifier or cabling. The software related errors, e.g., an outdated version of software, may cause problem in the network functioning. The faults manifest themselves in the alarm, there are different types of alarms based on the severity of the problem for example, at operation center there are three types of alarms, e.g., major, minor, and critical. Usually only critical alarms are handled by the operator and all other alarms are ignored. The alarms based performance monitoring is not suitable for the future wireless networks as the above mentioned challenges make it very difficult for an operator to manage them. Also, there may be many faults that do not manifest in alarm and cannot always be seen from KPIs such as sleeping cell failure is easily detectable using traditional alarm based monitoring system. Due to the above mentioned factors, the manual management of the wireless networks is very expensive, complex and error prone.

1.1 Research Objective

The objective of the research is to study the challenges of the network management of modern radio networks that arise due to the increased complexity, growing heterogeneity and highly dynamic nature of the wireless networks. From operator perspective, it is very important to find automated ways to reduce the number of outages and to reduce the duration of outages in the operational network in order to meet the operator's requirements on network availability, robustness, coverage, capacity and service quality.

Faults can appear at several functional areas of a complex cellular network however the most critical domain from a fault management viewpoint is the radio Access Network (RAN). The fault management of network elements is not only more difficult but also imposes high cost both in capital investment (CAPEX) and operational expenditures (OPEX). It is known that Self-organizing Network (SON) concept has emerged with the goal to foster automation and to reduce human involvement in management tasks. Self-healing (SH) functionality improves business resiliency by eliminating disruptions that are discovered, analyzed and acted upon. There are three major areas of SH enabled mobile system namely fault/degradation detection, root cause analysis, cell outage compensation, recovery actions. In current troubleshooting, most of these tasks are aided by a certain level of automation: collection of performance indicators, profile construction, evaluation of actual performance information against profiles are all done automatically. There is still need to improve the current situation as the output of these detection procedures is not suitable for the future needs of network management.

The goal of the study is to address these challenges and subsequently propose efficient SH solutions for the future wireless networks. To achieve this goal, the dissertation formulates the following tasks:

- Model and simulate faults and anomalies in the cellular networks
- Study the current tools used by operators for monitoring their networks
- Develop experimental systems using state-of-the-art tools to demonstrate the potential of SON
- Develop a SH framework for testing various SH functionalities
- Design proactive SH Solutions

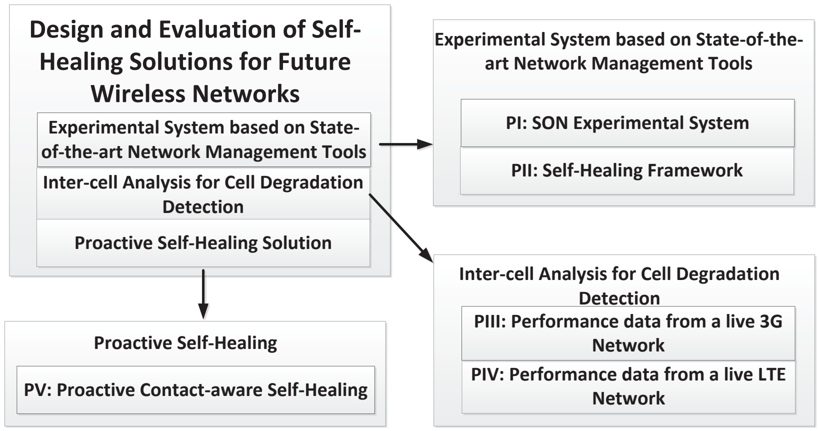

FIGURE 1 The structure of the PhD work

The scope of the thesis is limited to designing SH and self-optimization algorithms which reply on standardization measurements and interfaces introduced by 3GPP Release 10 and 11 specifications for LTE. The SON concept aims at automated solutions for the network optimization and fault management of cellular networks. The validation of the experimental system developed is done by conducting simulations with a state-of-the-art dynamic LTE system simulator. The SH and self-optimization algorithms are run on the top of the LTE simulator.

The main research questions of this thesis are as follows:

1. *RQ*1: How to automate the traditional network management for efficient and robust SON solutions by integrating standalone management products?
2. *RQ*2: How to enhance and automate the fault management with key performance indicators to provide efficient and robust SH solutions?
3. *RQ*3: How to integrate different SH functions such as cell degradation detection, cell outage compensation (COC) and recovering mechanisms, to provide a complete SH solution?
4. *RQ*4: Find practically feasible SH solutions that can be integrated to the operational networks without changes in the existing infrastructure and operator's current workflows?
5. *RQ*5: How to transform the reactive SH to proactive for the future needs of ultra dense heterogeneous networks?

1.2 Structure of the work

The format of this dissertation is a collection of articles. The earlier stages of the research are devoted to study the overall review of the research area and development of SON experimental system for testing various SON use cases in realistic scenarios. This experimental system is further extended to support SH use cases identified by 3GPP. Next, the performance data and alarm history collected from an operational 3G network is analyzed and cell degradation detection algorithms are proposed that do not need any change in the operator work flows. The results were promising. The last phases of the study consists of the requirements of the future wireless networks 5G. In 5G networks, different types of cells co-exist, which makes the cell degradation tasks more challenging. The existing SON solutions are not enough for the future needs of the wireless 5G networks. The main limitation in the existing SON solutions is that they are reactive in nature. We need a paradigm shift in the SON to shift the reactive response to proactive. A novel approach for shifting the SON focus from reactive response to a proactive response is proposed in this thesis. The structure of the work and related papers therein is presented in Figure 1.

The thesis is organized as follows. Chapter 2 introduces the background and the central concepts of this work, and cover some recent related works on the topics. Chapter 3 describes the main contributions of this thesis. Chapter 4, provides the summary of the included articles. Finally, Chapter 5 presents conclusion of the research.

1.3 Author Main Contributions

The author of this dissertation is the main contributor in all of the included articles. He has written the text of these publications. The author's contribution to the article **PI** is the development of the SON experimental system along with other team members, results analysis and writing the article. Nicolas Meinke contributed to the aspects of development of the SON experimental system. In article **PII** author was responsible for designing a SH framework by extending the SON experimental system. Author developed the SH framework, defined all the interfaces and KPIs required for SH use cases. In article **PIII** author developed a cell degradation detection method together with co-author Richard Fehlmann. The implementation of the proposed method and writing the paper was done by author. In article **PIV** the design and implementation of the cell degradation detection method was done by the author. The results analysis and paper writing were done with co-author Paavo Nieminen. In article **PV** the research problem was defined by the author. He implemented the method and analyzed results. Paavo Nieminen made minor contribution in writing this paper.

2 NETWORK MANAGEMENT IN CELLULAR NETWORKS

2.1 Network Management in Currently Deployed Networks

The cellular networks are very highly dynamic and consist of huge number of network elements. Besides the large variety of hardware like network elements, the backbone network, and routing components, there are also many different software stacks in these components. Hence, in practice, faults may happen on a regular basis. Typical examples of network faults are software faults, broken hardware components, and inappropriate network configuration settings. The fault troubleshooting, carrying out investigations and repair works are very expensive and therefore to save time and to reduce costs, operators look for a common corrective action such as restarting the cell for most of the network failures. This corrective action solves most of the software related problems however, hardware related problems can not be solved with restarting the cell. The fault management system uses the performance monitoring to evaluate whether the network is in a normal state. The key performance indicators (KPI) are computed using several network counters for example, a simple average of consecutive measurements during a time period or it can be more advanced statistical measure. The KPI measurements are usually collected for a fixed period of time and then recorded. The KPI can depend on user behavior, traffic patterns, the physical environment, and so on, for example, the downlink data rate in terms of downlink traffic is a KPI depending on user behavior, whereas the number of call attempts, percentage of dropped calls, and average channel quality indicator are less dependent on user behavior. The main characteristic of user-dependent KPI is that they are random or highly varying. Hence they are not very useful for defining the state of the network. These KPI that do not depend on user behavior are more obvious candidates for defining the network status and monitoring the performance of the network.

In the current process, Operations Support System (OSS) tools maintain the thresholds and profiles of the network. The KPI and also the low-level hardware and software related alarms) are directly presented to the operator who then filters out high quality alarms manually. The flow of uncorrelated alarms and big volume of alarms can be reduced by employing alarm correlation methods. However, these methods can only reduce the quantity of alarms but not help to increase their quality. In addition, the KPI measurements need to be processed along with available alarms, which is again done manually. Based on his or her observations, the operator may define the state of the network, i.e., faultless or degraded.

There are many challenges for the network management in cellular networks specially the fault management of the cellular network. The traditional approaches for fault management of cellular networks are not enough for future needs of cellular networks. As the network is going to be ultra dense and highly complex and heterogeneous with a flood of small cells in future wireless networks, SH solutions have become very crucial for the operators.

2.2 Self-Organizing Networks (SON)

In the perspective of wireless communication networks the term Self-organizing Networks refers to the automated network management where tasks of network configuration, network optimization and fault management are largely automated but the network operator will have final control over the decisions. The network management tasks are complicated and error prone. A high degree of manual interaction is required. Human interaction is required for tuning various radio parameters in order to achieve better network performance. The vision of SON is to shift human interactions to higher management level by introducing automation in operational procedures. This can be done by increasing automation in network elements, domain manager and the management system. By utilizing SON functionalities, the network management loop becomes closed and the human role becomes limited to only monitoring and designing policies and thus human intervention is no more required in basic management tasks. Therefore, SON can be used to reduce operational expenses by reducing manual workload and minimizing human errors (3GPP 2008; Amirijoo et al. 2008; NGMN 2008).

Self-organizing networks (SON), roughly following the definition of self-organization given in the survey (Aliu et al. 2013), are networks that are adaptive and autonomous and also scalable, stable and agile enough to maintain their services in the face of all potential environmental dynamics. The three categories of SON are self-configuration, self-optimization, and SH. There are many performance metrics/indications available for wireless networks that capture the network status at any given moment.

In general, a cellular network can be self-organized at different levels such as low level i.e. at base station level, operation and maintenance level i.e. at OSS level, and high level i.e. at network planning and policy making. The choice of

SON architecture relies on the specific needs, for example, if SON function needs fast reaction time then SON function should reside at network element and if SON function needs to take into account all cells in the network coverage area simultaneously to get meaningful results, then the SON function should reside at OSS level. There are different workflows in a self-organizing network such as Performance Management (PM) that collects performance measurements from the network elements, Fault Management (FM) which is responsible for alarms, and Configuration Management (CM) which ensures optimized setting of configuration parameters in the network elements.

The standardization of SON started in 3GPP Release 8(Hofmann et al. 2011). (3GPP 2010) and (3GPP 2011),(3GPP 2014a), (3GPP 2008) The SON engine will be the working on the policies provided by the operator and the self-learning algorithms. The 3GPP enhancement for SON are given below Release 12. These enhancement are focused on mainly interoperability aspects of existing features and some new features (3GPP 2013). The new feature consists of grouping of mobile users with similar capabilities and user specific handling. This will be very beneficial to enable mobility border negotiations per UE group and more robust traffic steering. Another feature is the Active Antenna System (AAS) that enables the automated optimization of the coverage and capacity by cell shaping, splitting and merging cells. However, AAS-based automated optimization impact MRO (Mobility Robustness Optimization). The impact may be mitigated if intereNB coordination is enabled, the standardization for such coordination mechanisms is foreseen in Release 13. Other enhancements include several aspects such as radio link failure and deployment of small cells to meet the growing capacity demands.

The scientific community has shown keen interest in the SON research since 3GPP Release 8. The SON related research projects includes Celtic GANDALF (2005-2006) (Altman et al. 2006), EU FP7 SOCRATES (SOCRATES 2008) and FP7 SEMAFOUR (Hahn et al. 2015). SEMAFOUR is a European project where different research institutes and companies contribute to the automation of the network planning and maintenance. A unified self-management system for multi-RAT and multi-layer networks, is developed (Hahn et al. 2015). The key features of a unified self-management system are conflict resolutions between SON fucntions, mapping of high-level objectives to particular SON functions, and interpretation of global network policies through high-level objectives, are identified (Litjens et al. 2013). Furthermore,leading companies and vendors such as (Nokia 2015) and (Ericsson 2015) have also developed efficient and cost-effective SON solutions for network management.

In future wireless networks, SON enabled operations are expected to be the default operational mode and SON functions will have to operate in an environment with multiple operators, vendors and radio access technologies (Aliu et al. 2013; Bhushan et al. 2014; Imran, Zoha, and Abu-Dayya 2014). Examples of SON for 5G and new requirements and system features call for new approaches and techniques for automation. Cognitive radio network is a concept of going one step further beyond current SON. The vision of cognitive network is to shift the human role to the define high level policies, and SON engine applies certain actions based on those high level policing and self-learning algorithms.

2.2.1 Self-Configuration

The self-configuration aims to automate the process of network element installation and autonomous integration to Operational, administration and maintenance (OAM), RAN and core network (CN) to allow for a faster deployment of a wireless cellular network. The self-configuration is based on the plug-and-play functionality of network elements where the initial configuration and the radio configuration are fetched from the network after network element is powered up and has established connectivity to the core network. The main use cases for the self-configuration are plug & play, Automatic neighbor relation (ANR) and Auto configuration of Physical Cell Identifier (PCI) (Hu et al. 2010; Peng et al. 2013). Plug & play aims at automated software download, transport and logical interfaces setup. ANR aims at neighbouring cells addition with the support of UE measurements. PCI aims at automated configuration of the physical cell IDs for the cells to avoid collisions and confusions among cells.

2.2.2 Self-Optimization

The network optimization begins after network elements are in an operational state. The self-optimization aims at monitoring the network performance continuously, detecting the sub-optimal performance and autonomously adjusting the network configuration parameters to achieve better performance. The main use cases for self-optimization are Coverage and Capacity Optimization (CCO), Mobility Load Balancing (MLB),Mobility Robustness Optimization(MRO), Intercell Interference Coordination(ICIC), Energy Saving Management (ESM), Random Access Channel (RACH) Optimization and Adaptive Antenna System (AAS)(America 2011; Peng et al. 2013). CCO aims at adaptation of the transmission parameters (e.g., TxPower and antenna tilt) to overcome coverage holes and improve the overall network performance. MLB aims at adjustment of handover and cell reselection parameters to balance the traffic load among the cells MRO aims at adjustment of handover and cell reselection parameters for the purpose of handover failure rate and ping-pong rate minimization. ICIC aims at coordination for interference minimization in time and frequency dimensions including macro and HetNet scenarios. ESM includes mechanisms for switching off cells during low traffic periods and adjusting neighboring cells transmission parameters for coverage assurance in the areas where the cells were switched off. RACH Optimization aims at adjustments of the RACH parameters to improve the access probability and decrease access delays in different cells. AAS aims at capacity improvements while keeping the interference at minimum.

2.2.3 Self-Healing (SH)

The fault management includes detecting faults in the network, diagnosis and fixing the problem. The manual troubleshooting of a cellular network is a complex task as it is time consuming and laborious. The self-healing aims at automating the overall fault management process by automating the detection, root cause analysis, and compensation and recovery mechanisms (Hämäläinen, Sanneck, and Sartori 2012; Ramiro and Hamied 2011). The self-healing mechanism can not only increase the efficiency of fault management process but also provides cost saving in terms of capital expenses (CAEX) and operational expenditures (OPEX). The main use cases are Cell Outage Detection (COD), Root cause analysis, Cell Outage Compensation (COC) and Recovery mechanisms. Cell Outage Detection aims at identification of cells outages. Root Cause Analysis aims at finding the cause of the outage. An outage can be caused by poor planning, broken hardware or software failures. COC aims at adaptation of the transmission parameters to provide coverage in the adjacent cells that experience outages. Recovery of the outage cell involves the rolling back to the network's original settings.

2.2.4 Supporting Functions

2.2.4.1 SON Coordination

Each SON function works towards a common goal of network performance improvement and user satisfaction. The decisions of different SON functions could lead to the conflicts and the performance gains can not be achieved. There is a need for coordination mechanism that can resolve such conflicts based on policy settings provided by operator (Bandh et al. 2011; Hämäläinen, Sanneck, and Sartori 2012). For example, the mobility robustness optimization (MRO) decisions could be contradictory to the mobility load balancing (MLB). The SH functions are of higher priority to the self-optimization functions.

2.2.4.2 Minimization of drive tests (MDT)

The drive tests are employed by the operators to carry out various field measurements to make sure sufficient coverage is achieved at different locations. The MDT aims at collecting field measurements from UEs in idle and connected mode to decrease the need for drive tests (3GPP 2014c). The main use cases of MDT are Coverage optimization that includes detection of coverage holes, weak coverage areas, overshoot coverage areas and low quality of service.

2.3 Self-Healing Network

A fault in cellular network can be defined as a defect at the hardware component or software which significantly degrade network performance and eventually leads to dissatisfaction of the users. There are almost all the time some errors and problems present in network due to complex and uncertain nature of the radio communication links. However, all errors do not necessarily term as faults and it is important to further investigate the detected error or anomalies in the network. The term cell degradation refers to the case where the actual performance of the cell in handling traffic is significantly lower as it is supposed to be. Degradations may not be measured directly as they do not necessarily trigger alarms for example, a special type of cell degradation is called sleeping cell where the degradation is not detected while cell is under-performing. Degradations can be classified in terms of their severity i.e. from worse performance to complete outage.

Furthermore, there could be two kind of degradations: temporary and permanent. The temporary degradation refers to the situation when a cell performance is degraded for a short period of time and recovers back after a while, without any external support. These degradations are very common in operational networks and almost always exit in the cellular network. However, these degradations contribute to the false positive rate and sometimes, they mislead the troubleshooting process. The permanent degradation refers to the situation when cell is degraded for a longer period of time and it causes negative impact on the cell performance. These are caused by faults in the cell. The situations where malfunctioning in the network is not visible to the network operator until negative feedback from the customers in terms of complaints and loss of revenue at the coverage area, is known as sleeping cell problem. These degradations should be detected as soon as possible and counter measure should be taken to resolve the problem or immediate compensation to the lost coverage should be triggered.

The effect of these degradations can be visible in one or several KPIs and alarms are raised in case of severe degradations. In traditional cell degradation detection in cellular networks, it is a common practice to trigger a cell reset as it solves most of the simple software related problems. If this reset solves the problem then usually no further action has to be taken and no effort is invested to find the root cause of the problem. Another reset must not be triggered if number of resets had already been exceeded the predefined limit within a given time period and the fault still has not been rectified. Under such circumstances engineers will be sent to the site to investigate the problem. Such cases often require the replacement of several hardware units until the faulty component has been identified. It is not often possible to respond to the faults on time when troubleshooting is carried out manually. However automated analysis of alarms may reduce the number of alarms as well as it lead directly to the root cause of a problem. In this way automation reduces the effort needed to manually evaluate alarms. Once the root cause of a problem is determined corrective measures can be taken in time. This leads to the concept of self-healing. SONs SH functionality can contribute to optimize the handling and resolving of faults in different situations.

Self-healing (SH) refers to autonomous fault management in wireless networks, including advanced performance monitoring, detection of faults and their causes, triggering compensation and recovery actions. SH improves business resiliency by eliminating disruptions and ensuring network availability, reliability and retainability. In the SH enables networks, the tasks of troubleshooting including detection, diagnosis, corrective actions are largely automated but the operator will have final control over the decisions. Earlier research on SH focused on sole automation, but in more recent efforts more focus has been given to the intelligent characterization of the network state.

There is a lot of research conducted on the detection and diagnosis of faults in cellular networks where Bayesian networks are utilized mainly for fault diagnosis. (Barco, Díez, et al. 2009; Barco, Lázaro, Díez, et al. 2008; Barco, Lázaro, Wille, et al. 2009; Barco, Nielsen, et al. 2002; Barco, Wille, Diez, et al. 2006; Barco, Wille, and Díez 2005; Barco, Wille, Díez, and Toril 2010; Coluccia, Ricciato, and Romirer-Maierhofer 2011; Khanafer et al. 2008; You 2009). The diagnosis of the faults is performed using cell level statistics and network failures are considered as conditions which trigger the diagnosis process. The main advantage of Bayesian networks is useful for probabilistic representation of different states and their relations to the symptoms. However, construction of Bayesian network model, model parameters selection, discretization of symptoms are slow and time consuming tasks. An automatic root-cause analysis using traces are presented in (Gomez-Andrades et al. 2016). There is other studies on SH using neural networks (Barreto, J. C. M. Mota, et al. 2004; Barreto, J. C. Mota, et al. 2004; Kumpulainen and Hätönen 2008; Laiho et al. 2005).

Good examples of recent practical approaches to SH in real operational networks are found in (G. F. Ciocarlie, Cheng, Connolly, Lindqvist, Nitz, et al. 2014; G. F. Ciocarlie, Cheng, Connolly, Lindqvist, Nováczki, et al. 2014; G. F. Ciocarlie, Connolly, et al. 2014; G. F. Ciocarlie, Lindqvist, et al. 2013; G. Ciocarlie et al. 2014). For example, (G. Ciocarlie et al. 2014) addressed the problem of verifying the effect of network configuration changes by monitoring the state of the network. The main focus of the work is to determine which configuration changes resulted in network performance degradations. The proposed framework consists of an anomaly detector and a diagnosis component. The anomaly detector monitors a group of cells using topic modeling. The diagnosis component, in turn, uses Markov Logic Networks (MLNs) to generate probabilistic rules that distinguish between different causes. An initial study of incremental topic modeling approach was proposed in (G. F. Ciocarlie, Cheng, Connolly, Lindqvist, Nováczki, et al. 2014). In that approach the authors followed a modified version of Hierarchical Dirichlet Processes (HDP) which utilizes a stochastic gradient optimization to allow the training process to evolve incrementally over time. The authors adapted that method to input all KPIs as multivariate. For the evaluation of the incremental topic modeling method real-world data was used. The incremental algorithm is run for HDP by randomly choosing timestamps from the 3G dataset and updating the model parameters accordingly. The adaptability to different cell scopes is achieved by first applying clustering to the largest scope. The state of the network can be determined for subsets of the largest number of cells. One drawback of this approach is that it requires a very large dataset to achieve the reliable detection and diagnosis. The work investigated initial feasibility of the incremental topic modeling approach in the context of cellular network data however, the results are not mature yet.

(G. F. Ciocarlie, Connolly, et al. 2014) proposes an ensemble method for change detection in the cellular networks. Several univariate and multivariate methods were employed to build the ensemble classifier. The poorly performing methods are removed from ensemble with the passage of time. Also, the proposed method takes configuration change as input and trigger new model. The main drawback of this method is that it requires manually prepared labeled data and data should be collected over a significant amount of time for a reliable detection.

In (Nováczki 2013) more detailed use of KPIs is presented. The presented detection and diagnosis framework uses more refined KPIs for detection and diagnosis of faults. The study presented in (Novaczki and Szilagyi 2011; Szilágyi and Nováczki 2012) exploited the idea of KPI profiling. The KPI profiles are built using averaged values of KPIs over a small number of samples. The detection is carried out using a sliding window of last n samples. The abnormality level is used to calculates the likelihood of a failure case. The target with largest likelihood value is considered to be the diagnosed failure. The drawbacks of this method is that although the KPI profiles are built automatically however a calibration constant is used which significantly impacting the abnormality level of the KPI. Secondly, the training requires substantial time of several days or week, which is not suitable for operational networks scenarios where the normal behavior of network changes over time.

The study (Szilágyi and Nováczki 2012) is further improved in (Nováczki 2013) where the problem of manual selection of normal network behavior is addressed. The proposed system is able to learn all normal modes of operations and built profiles for each normal mode. A Kolmogorov-Smirnov two-sample test is used to measure the distance between statistical distribution of cell KPI profiles and to derive a minimal set of such profiles. The proposed system is able to distinguish between different patternsof normal behavior and carry out diagnosis through classification of faulty cases.However, the drawback is that a significant amount of time is required for training and then detection and diagnosis part will take at least 100 hours to identify faults.

Another anomaly detection is proposed by (Liao and Stanczak 2015). In the paper, a framework for network monitoring and anomaly detection presented using dimension reduction and fuzzy classification techniques. The state of the network is characterized using a set of metrics (i.e., KPIs and other network measurements). The proactive anomaly detection is achieved by using kernel-based semi-supervised fuzzy clustering with an adaptive kernel parameter. These algorithms are evaluated using simulated data collected from a LTE system level simulator. The principle component analysis (PCA) was applied on 16 dimensional network metrics. The network states were visualized with 3 principle components. The quality of clustering was defined in terms of accuracy and entropy of the clusters. The entropy measure was defined, which measures the distribution of fault classes in the cluster. The authors claim that this framework proactively detects network anomalies associated with various fault classes. However, they did not describe the drift that can be introduced in the network.

Recent research on 5G heterogeneous networks (Damnjanovic et al. 2011) has proposed with a split control and data plane architecture of the 5G heterogeneous networks for meeting future capacity, quality-of-service, and energy efficiency demands (Mohamed et al. 2015). A SH solution for 5G heterogeneous network (HetNet) architectures has been presented in (Onireti et al. 2016) with separate detetion methods for control and data plane respectively. The cell outage detection is achieved using Minimization of Drive Tests (MDT) with user position information.In this approach the idea of incorporating users direct reports including localization information, in the cell outage detection was presented. However, the outage detection using MDT approaches is mainly done offline. Also, except user position information and received signal strength, no other information was included. The analysis was done on an elementary reference scenario using very limited network failures. Therefore, the usage of user context in the analysis has been limited so far and also a comprehensive application of such information is not addressed.

2.4 Context-aware Self-healing (CASH)

The context-awareness is getting popularity in SH research as the recent advances in indoor localization techniques where user equipments data are being employed for cell degradation detection and diagnosis solutions. The NGMN and 3GPP have identified other inputs for failure management, such as direct KPI reporting in real time, subscriber and equipment traces, minimization of drive tests to get UE reports, and location information (Hämäläinen, Sanneck, and Sartori 2012). The other information outside the network or even much information available inside network is not being utilized effectively (Imran, Zoha, and Abu-Dayya 2014). Recently, there has been work towards context aware SH (CASH), which takes into account more of the context information, for example, location information is utilized in the cell degradation detection and diagnosis (Fortes, Barco, and Aguilar-Garcia 2016). In (Fortes, Barco, Aguilar-García, et al. 2015) user context information was used to support root cause analysis that provided better diagnosis results than traditional approaches. The user context was defined by location, user category and service condition. For the indoor scenario, positioning information is very useful as the small cells are overlapping and without positioning information it is not possible to detect faults. Recently, location-aware self-organizing methods are presented in (Aguilar-Garcia et al. 2015). Major challenges of small cell deployments are identified in (Fortes, Garcia, et al. 2016).

– Reduced monitoring (limited information)
– Irregular and overlapped cell areas
– Performance variations

– Low deviation from the normal behavior

The reduced monitoring refers to the limited availability of troubleshooting information. Irregular and overlapped cell areas makes the fault detection difficult because a fault would not create coverage holes or complete outage. There are variations in performance due to a low number of users connected to the cells. It generates situations where there may not be enough information about a failure for a long time. It is not always possible to have a long period of measurements to generate a reliable profile for the small cells. Another problem is that the fault cases usually do not deviate from the normal behavior enough to provide a significant statistical difference. Addition of context information will help in distinguishing a fault scenario from the normal ones. For example, if the user is at a cell border, the received power will be low and this case could be similar to a fault case. However, with context information, the cell border measurements could be separated from fault cases.

As the small cell has limited computational capacity, the available information for troubleshooting is limited too. Due to the variations and overlap of small cells, meaningful indicators cannot be calculated. For example, Fortes, Garcia, et al. (2016) addressed the above challenges by incorporating user context in degradation detection process thus avoiding false conclusions that would have resulted due to scarce and variable UE distributions. Incorporating user context in the detection and diagnosis involves some challenges such as context data storing, processing and overhead caused by transmitting extra context information over the air interface. However, the feasibility of context inclusion has been already demonstrated Baladron et al. 2012.

2.5 Proactive Self-healing

It is wise to predict the near-term future rather than attempting long-term prediction forecasts. In the indoor and small-cell scenarios, the near-term future is more relevant than things far ahead. The small cells are so dynamic that it does not make sense to make long-term predictions based on radio measurements and KPI collected for small-cells. However, in these dynamic and complex indoor environments, the short-term predictions of near future are very relevant and important. In this situation, the prediction of near-future context will provide a base for forecasting the near-future network performance and the failure probabilities of the network elements. It is known that before a cell goes to a complete outage, its performance first starts to degrade and then only after a while the cell becomes under-performing or totally dead. Finding the early signs of cell outage is very challenging because the signs may not be strong enough to be detected. In addition, it is not at all possible to detect faults that present no signs of degradation in the observed performance indicators. This is where context information comes to help by providing extra background information. In practice, the prediction of failures is not much different than early detection of the very first signs of performance degradations. By having the predicted future context, it is possible to detect those early signs of performance degradations which would lead to failures in near future.

3 CONTRIBUTIONS

The research work was conducted in two phases: 1) between 2010 and 2013. 2) between 2015 and 2016. Prof. Tapani Ristaniemi at the Department of Matehmatical Information technology, University of Jyväskylä, supervised the research for whole period of the study. During the first phase author was working with Nokia Networks (former: Nokia Siemens Networks) as an external employee through Magister Solutions Oy. The research work was supervised by Seppo Hämäläinen at Nokia Networks. The informal discussions between the author and co-authors from Nokia Networks contributed to the dissertation, for example, Nicolas Meinke contributed to the aspects of development of the SON experimental system and Richard Fehlmann contributed for the aspects of SH concepts. During the second phase of research Timo Hämäläinen at department of Mathematical Information technology, University of Jyväskylä supervised the thesis. A research visit to 5G Innovation Center (5GIC) at University of Surrey, UK played an important role in pushing the research into the next level. Prof. Muhammad Ali Imran at University of Glasgow, UK contributed to two journal publications during the second phase of my PhD research.

The main contribution of this thesis can be categorized into three parts

- Integration of the standalone network management modules to achieve automation that yields significant improvement and high reliability
- Evaluation of Real-world data and proposing feasible solutions for detecting cell degradations in 3G and LTE networks
- Design of proactive SH solutions to meet the requirements of 5G networks

3.1 Developing an Experimental System for SON

This section describes the tools used for the SON research. The SON aims at cost efficient radio network architecture which poses a great challenge for the operation and management of cellular networks. There is much work done based on LTE system level simulations however, the work for a comprehensive testing of the SON functionalities has been limited. Testing in an operational live network is not feasible and operators do not want to compromise their network performance because of testing theoretical and/or simulation based solutions. The SON functions need to be verified before actually being deployed on the real operational networks. There is a clear need for an alternate platform where SON functions can be verified and their performance evaluated in realistic scenarios. This experimental system for SON can be viewed as a bridge between LTE system level simulations and the actual implementation of SON functions on the operational network. The experimental system as shown in Figure 2, is built on top of the commercial network management tools. The main research question was "how to integrate standalone network management modules in order to achieve automation that yields significant performance improvement with high reliability in realistic scenarios?" To address this question we chose a modular approach to achieve required integration of different standalone network management tools. First the functionality of each network management tool was observed in isolation. Then interfaces between those tools were implemented so that they may communicate with each other in an effective and reliable manner. The SON experimental system consists of Radio Network Simulator, OSS and Radio Network Optimizer, the SON algorithms are implemented on top of the optimizer. The SON use cases evaluated were Antenna Tilt Optimization, Transmission power optimization and Mobility Load Balancing. Several simulation runs show that centralized self-optimization of antenna parameters and transmission powers can improve system performance significantly. The simulated network before Self-optimization is shown in Figure 3, the black color shows the coverage holes between the cell id 2,6 and 18. The effect of Self-optimization is shown in 4 where the coverage holes disappear as the neighboring cells extended their coverage towards the coverage holes. The detailed results can be found in **PI**

3.2 Developing an Experimental System for SH

The experimental system discussed in section 3.1 was further developed to provide SH functionalities. The experimental system for SH networks shown in Figure 5 consists of Radio Network Simulator and Self-Healing functionalities. An artificial 3G network plan of Helsinki is used to emulate the real environment. In order to create the real environment two graphical user interfaces (GUIs) were developed to visualize the alarms monitoring and to control the SH functionalities. The main functionalities tested on this experimental system were advance monitoring of network performance, KPIs profile building, inducing artificial cell outage in the network, detection of cell outage, triggering cell outage compensation (COC) to compensate the lost coverage, and recovering mechanisms when the broken cell is recovered. The LTE radio network simulator performs contin-

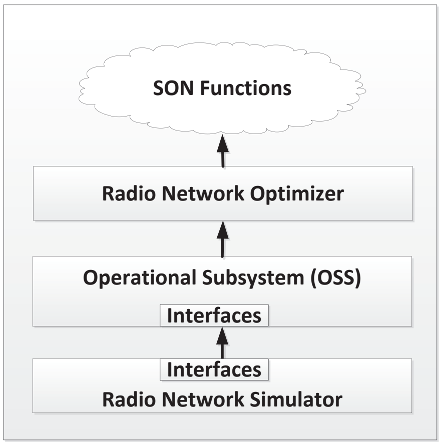

FIGURE 2   Experimental System for SON

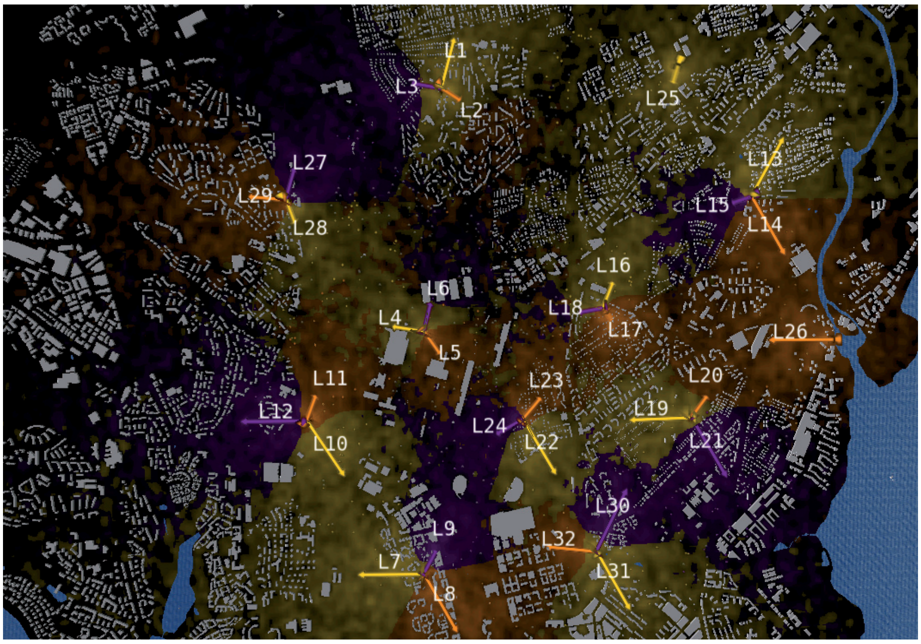

FIGURE 3   Before Optimization

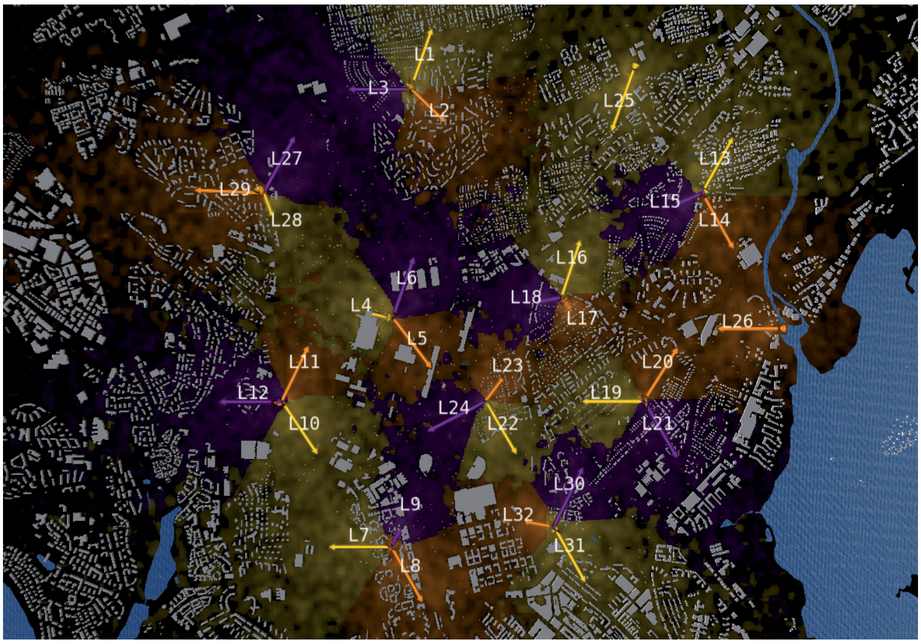

FIGURE 4 After Optimization

uous calculation of radio network performance. It generates KPIs for the network healing use cases. The SH module fetches those KPIs from the simulator after a regular time interval and builds KPI profiles for each cell during the normal/faultless network conditions. The malfunctions can be induced in the selected cells by using fault generator. SH module continuously monitors the KPIs and the detection is done through assessment of KPIs from their predefined profiles. The output of the detection is the problematic cells ids that can be fetch by the COC module to perform immediate compensation of outage area and it provides new network configuration parameters to compensate the area affected by a cell in outage. Results are shown in terms of number of connected users and number of radio link failures (RLF). The snapshot of the demo screen is shown in Figure 6. The three cells (i.e. cell id 16,17 and 18) are in outage state as shown in the Figure 7. The cell outage is compensated by cell id 15 and cell 23 as shown in Figure 8. The detailed results can be found in **PII**

3.3 Evaluation of Real-world Data Collected from an Operational 3G Network

The main objective was to work with the operator and observe the network monitoring tools closely and propose Self-healing solutions for the operational 3G and

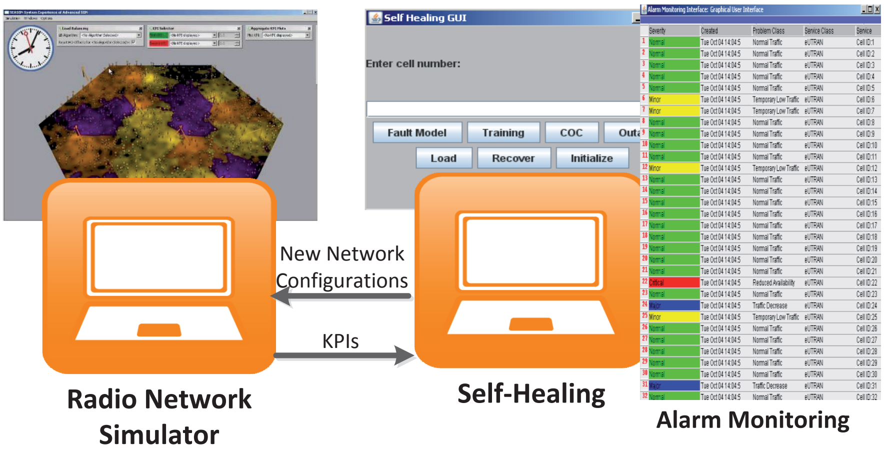

FIGURE 5 Self-healing framework

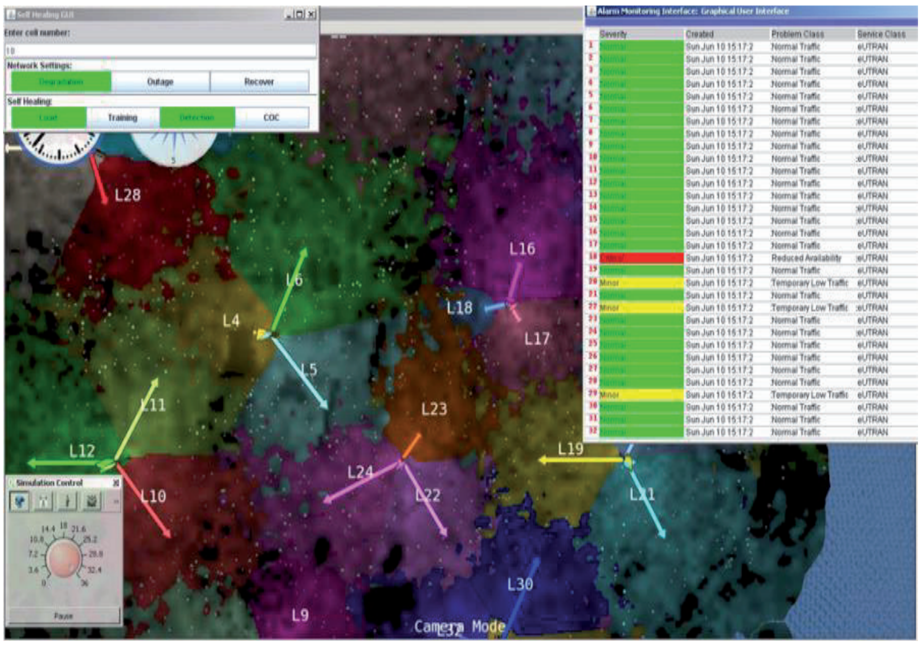

FIGURE 6 Self-healing demo

FIGURE 7 Three Cells Outage

FIGURE 8 Cell Outage Compensation

LTE networks. As testing on the operational network is not desirable, this research was focused on employed the existing infrastructure and tools to develop an automated cell degradation detection method. A cell degradation detection method was developed to detect anomalies and faults in the network. The developed method detects the abnormal and special events using the available performance data. The alarm history and the expert knowledge was used to validate the effective of the developed method. The detailed description of the work can be found in **PIII** and **PIV**

3.4 Context-aware and Proactive Self-Healing

This research work is devoted to the use of context-awareness in the SH research. The use of context information is very important in future network management as the traditional SH solutions are not adequate for the dynamic and complex nature of the future ultra dense small cells networks. For example, the small cells scenario is the main use case scenario for the research of the context-aware SH networks. However, the main drawback or limitation in the current approaches is that they are reactive in nature. This reactive approach is not suitable for the future wireless networks where the requirements for the network availability and the reliability are very tight.

To best of my knowledge, the proposed proactive SH idea in this thesis is the first step towards proactive SH solutions. The objective of this work was to address the challenges posed by the advent of the 5G technologies where the traditional SON solutions are not sufficient for the future needs of the cellular networks, for example, zero latency requirements. The use of context-awareness in SH and fault management has not yet been exploited to its full potential. If the context of the near-future can be predicted based current context, then it is possible to correctly predict and diagnose the upcoming failures and preventive measures can be triggered.

Therefore, in this research the need for the near-term future prediction is identified. As the 5G networks are so dynamic, the long-term forecasts do not stay relevant, for example, in the indoor scenarios where small cells are deployed for the capacity enhancement purposes in ultra-dense environments. The prediction of near-future context using current context will provide a base for accurate and successful predictions of future values of radio measurements. Once the future context for the next few hours is correctly predicted, the forecast of the near-future performance of the network can be successfully calculated. This would lead to the assessment of the failure probabilities of any network element in near future. Eventually this would lead to reduce the number of outages and the duration of outages to meet the operator's requirements for the network availability, reliability and coverage, capacity and service quality.

The Proactive CASH framework is an extension to the CASH framework presented in Fortes, Garcia, et al. 2016. The CASH consists of following ma-

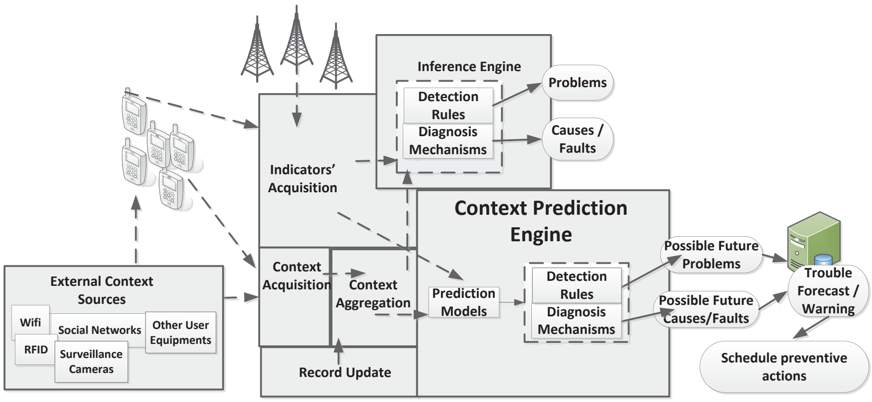

FIGURE 9 The proactive Self-healing solution

jor blocks, i.e, indicators' acquisition, context acquisition, context aggregation, inference engine, record update blocks and predictive context engine as shown in Figure 9. The indicators' acquisition block collects network and user measurements and accumulates them in independent buffers. A profiling window is used to select a group of samples for statistical profiling of UE. This block considers current measurements for generating profiles, and old samples are discarded. The context acquisition block builds the current context by combining the data obtained from different sources. The context aggregation block associates the current context with the previously recorded situations and retrieves the contextualized profile of the KPI with the same context. The inference engine block performs the detection and diagnosis of problems by comparing current KPI distributions with the contextualized profiles obtained from the context aggregation block. The record update block stores historical KPI measurements.

It has been traditional to use current measurements to diagnose the root cause of a current problem. We propose that the same analysis methods could be used also to predict future failures and their causes. This scheme is illustrated in our figure that contains the same blocks as in Fortes, Garcia, et al. 2016 but adds the CPE component that includes a prediction model that feeds a duplicate of the inference engine with predicted future values. Also the outputs of the CPE are of the same form as in the original inference engine, but they relate to the near-future predicted situation, thus giving a forecast of possible problems and their possible causes. These outputs could be used to schedule preventive actions before the problems ever occur.

3.5 Invention

It is worth highlighting that during the research work, the author of this thesis came up with novel ideas that are published in the form of research articles and some are filed as patent. For example, author of this thesis is an inventor of a cell degradation detection method, US Patent No: 9326169, that shows the unique value of this research work for the telecommunication industry.

4 SUMMARY OF INCLUDED ARTICLES

4.1 Experimental System

This sections described the tools used for the research.

4.1.1 PI Experimental system for self-optimization of LTE networks

Muhammad Zeeshan Asghar, Seppo Hämäläinen, and Meinke, Nikolas. Proceedings of the 7th ACM workshop on Performance monitoring and measurement of heterogeneous wireless and wired networks, Paphos, Cyprus, 2012, ACM, pages. 91-98.

4.1.1.1 Research Objective

The objective of this paper was to develop environment for testing different 3GPP use cases for LTE Self-organizing Networks. The SON functions need to be tested and verified before being deployed on the operational networks. There is a clear need for an alternate platform which can act as a bridge between LTE system level simulations and the actual implementation of SON functions on the operational networks. In this platform, the effectiveness of self-optimization algorithms can be evaluated in realistic environments.

4.1.1.2 Findings and Contribution

The SON experimental system is built on top of radio network simulators and commercial network management products. In this work, different commercial network management products such as Radio Network Optimizer, Radio Network Simulator and Operational Subsystem (OSS) Middleware are integrated to provide automatic and efficient SON solutions, thus reducing human effort on the one hand and improving network performance in terms of coverage, capacity and service quality on the other. The network performance impacts of remote electrical antenna tilt (RET) optimization and transmission power optimization could be shown with the tool. Average cell throughput and per physical resource block (PRB) throughput are shown for constant bit rate (CBR) service before and after optimization. Coverage improvements are seen in improvements in handover (HO) failure statistics. Robustness and convergence time of optimization algorithms are studied.

4.1.2 PII Self-healing framework for LTE networks

Muhammad Zeeshan Asghar, Seppo Hämäläinen, and Tapani Ristaniemi. IEEE 17th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD), Barcelona, Spain, 2012, IEEE, pages. 159-161.

4.1.2.1 Research Objective

The objective of this research was to develop a SH framework for 3GPP Long Term Evolution (LTE) networks and to provide a platform where SH functions can be evaluated. Fault management is an important part of the operations and maintenance subsystem (OSS) of cellular mobile networks. Perhaps the most important reason is to reduce the number of outages and duration of outages in the network in order to meet the operator's requirements such as network availability, robustness, coverage and capacity etc. Increasing complexity of the cellular networks has significant impact on the operations and maintenance of the network. Automation is necessary to protect the operational as well as capital expenses of the cellular network.

4.1.2.2 Findings and Contribution

In this paper, we extended the experimental system presented in **PI** and explored how to incorporate automated detection and compensation tasks in realistic environment. In order to incorporate support for SH functionalities to the experimental tool developed in **PI** two graphical user interfaces (GUI) were developed for better visualization of the fault detection and controlling SH functionalities.

Although 3GPP use cases are focused on 'cell outage', we adopt a more general concept of 'cell degradation' which refers to the case where a significant difference exists between expected and actual performance of the cell. Degradations may not be measured directly as they do not necessarily trigger alarms. Degradations can be classified in terms of their severity, i.e., from worse performance to complete outage. Usually a faulty cell starts degradation prior to going in an outage state. We evaluated the following use cases in SH framework:

1. Cell-degradation detection: caused by any hardware failure or wrong parameter settings.
2. Cell-outage Detection: The cell outage is defined as the cell carries no traffic or cell is switched off/dead.

3. Site-outage Detection: The site outage is the case when all sectors, i.e., cells of the same site, go down.
4. Cell/Site-outage Compensation: The corrective actions include changing configuration parameters of neighboring operational cells so that they may compensate the network performance as much as possible.
5. Cell/Site-outage Recovery (includes roll back to original configuration settings): It is possible that the environmental conditions might have changed when an cell outage recovers. Therefore, turning back to the initial parameter settings would not help much. However, for the sake of simplicity, we assumed that the network conditions are not changed at the time an outage cell recovery. Hence, the turning back to the initial settings is a solution.

The impact of early fault detection and timely execution of compensation tasks are shown in terms of radio link failures and number of connected users.It is clear from the results that Self-healing significantly compensates the coverage loss created by cell outage, by changing parameters of neighboring cells. The overall performance of the system is improved because of the SH process, it is indicated by increased number of connected UEs and deceased number of RLF.

4.2 Analysis of Perfomance data and Alarm history collected from operational 3G network

4.2.1 PIII Correlation based Cell Degradation Detection for Operational Wireless Networks

Muhammad Zeeshan Asghar, Richard Fehlmann, and Tapani Ristaniemi. International Conference on Mobile Networks and Management, Cork, Ireland, 2015, Springer.

4.2.1.1 Research Objective

The objective of this research work was to propose a practically feasible SH solution that can easily be integrated into the operator's network seamlessly, without being obtrusive or interfering with the operator's existing deployed workflows. For the SH solutions that require the operator to perform major modifications of the existing infrastructure and established processes, would result in the rejection of the SH solution.

In addition to being practically feasible, a SH solution has to be flexible enough so that it is able to adapt to these different environments, for example, urban and rural areas, network element vendors, and software versions.

4.2.1.2 Findings and Contribution

In this work, we proposed a new method for cell degradation detection using a set of available performance data and alarm history collected from operational network in a European city for evaluation of the method. In this paper we exploited the idea that there are many cells in the network coverage area having similar behavior irrespective of their geographical locations. We had the opportunity to get access to a real 3G network and observe its performance data over a period of time. The observed network consists of thousands of cells and is located in a European city. The granularity of the performance data is one hour, thus each sample corresponds to one hour of measurements. Our analysis suggests that the correlation coefficient between cell pairs can be utilized as a means for the detection of degradations in cells. Also, this method can be integrated to the operational network without any changes in the operator's network infrastructure and work flows.

4.2.2 PIV InterCell Analysis of Performance data collected from live Networks

Muhammad Zeeshan Asghar, Paavo Nieminen, Seppo Hämäläinen, Tapani Ristaniemi, Muhammad Ali Imran, and Timo Hämäläinen. International Conference on Mobile Networks and Management, 2016.

4.2.2.1 Research Objective

The status of the base stations is usually monitored by well-defined key performance indicators (KPIs). The approaches for cell degradation detection are based on either intra-cell or inter-cell analysis of the KPIs. In intra-cell analysis, KPI profiles are built based on their local history data whereas in inter-cell analysis, KPIs of one cell are compared with the corresponding KPIs of the other cells. The objective of this research was to explore the use of is inter-cell approach for difficult cases of cell degradation detection. As the traditional intra-cell approaches are not always be effective in difficult cases such as sleeping cell detection.

4.2.2.2 Findings and Contribution

In this work, we argue in favor of the inter-cell approach and apply a degradation detection method that is able to detect a sleeping cell that could be difficult to observe using traditional intra-cell methods. We demonstrate its use for detecting emulated degradations among performance data recorded from a live LTE network. The method can be integrated in current systems because it can operate using existing KPIs without any major modification to the network infrastructure. We find the results supportive of the argument that the inter-cell analysis approach is well-suited to cases difficult for traditional methods, such as sleeping cell detection.

4.3 Proactive Self-healing solutions

4.3.1 PV Towards Proactive Context-Aware Self-healing for 5G Networks

Muhammad Zeeshan Asghar, Paavo Nieminen, Seppo Hämäläinen, Tapani Ristaniemi, Muhammad Ali Imran, and Timo Hämäläinen. Computer Networks Special Issue "Survivability Strategies for Emerging Wireless Networks", 2017, Elsevier.

4.3.1.1 Research Objective

The objective of this research was to suggest new research direction and a future vision for Self-healing. The problem to be solved is that the traditional Self-healing solutions may not be sufficient for the future needs of cellular network management because of their reactive nature, i.e., they start recovering after detecting already occurred faults instead of preparing for possible future faults in a preemptive manner. The detection delays are especially problematic with regard to the zero latency requirements of 5G networks. To address this problem, existing SONs need to be upgraded from reactive to proactive response. One of the dimensions in SH research to employ more holistic context information that includes, e.g., user location and mobility information, in addition to traditional context information mostly gathered from sources inside the network. Such extra information has already been found useful in SH.

4.3.1.2 Findings and Contribution

We suggested a new research direction and a future vision for Self-Healing (SH) in Self-Organizing Networks (SONs). We suggested how user context information can not only be incorporated in SH but also how future context could be predicted based on currently available information.

We overviewed recent developments towards the inclusion of context information in Self-Healing solutions for Self-Organizing Networks. We suggested a way to make Self-Healing proactive via the prediction of near-future context, which should be especially useful in the small-cell scenarios in future 5G networks. As a technical example of plausibility, an earlier case study for predicting a user's mobility pattern is presented. Training accurate prediction models requires more data than was available in the small case study presented here. We presented a user mobility case study as an example to illustrate our idea.

4.4 Summary of the results

The results of the papers have contributed to three main aspects of SH solutions i.e, developing an experimental system, designing and evaluating cell degrada-

TABLE 1 Summary of the results of included articles

Obtained Results	Description	Article no:
a) SON System	Development of SON experimental System	[P1]
b) Self-healing System	Development of Self-healing Framework	[P2]
c) Correlation based Cell Degradation Detection	Method development	[P3]
d) Inter-cell Analysis approach	Method Application	[P4]
e) Context-aware Self-healing	Overviewed recent developments towards the inclusion of context information in Self-healing	[P5]
f) Proactive Self-healing	Design of Proactive Self-healing Solution	[P5]

TABLE 2 Positioning of obtained results to each research question

Research Questions	Obtained Results
RQ1	OR(a,b)
RQ2	OR(b,c,d)
RQ3	OR(b)
RQ4	OR(c,d)
RQ5	OR(e,f)

tion detection method, and designing a proactive SH solution. The main results are summarized in Table 1. The obtained results are compared to the original research questions in Table 2. First an experimental system is developed using standalone commercial network management tools. Then the performance indicators from operational 3G network were analyzed and the feasibility of the SH solutions were studied. The SH for the future ultra dense and heterogeneous networks is researched and a proactive solution is proposed.

The most essential findings related to the research are:

- The automation in the network management is needed to provide cost effective and efficient SH solutions.
- The extra knowledge of the user behavior is very beneficial for an efficient Self-healing solution.
- Current SH solutions are reactive in nature which are not sufficient for future needs of a self-organizing network.
- A paradigm shift is needed for robust, efficient and proactive SH solutions for future wireless networks.

Altogether, the results presented above were proven useful for both the operators and academic research perspective. Even if there was no completely new detection method presented, the applications of the existing methods provided novel approaches. Probably the most beneficial results was the proposed paradigm shift in SH solutions from the state-of-the-art reactive to proposed proactive SH solutions. Its diverse application make it possible for the operators to meet the requirements of the 5G networks.

5 CONCLUSION AND FUTURE RESEARCH

Fault management is a crucial for cellular network operations. The network operators are facing great challenge nowadays because of the exponential growth of the mobile users has been seen in recent years. The main challenge of operating a radio network comes from the huge and ever increasing capacity demands. The other challenge is the strict requirements of the network availability, reliability and robustness. The ever increasing capacity demands push the operators introduce massive amount of small cells that contributes to the network densification. The network architecture is becoming heterogeneous and difficult to manage manually. The automation of network operations is the need of the hour as managing such a heterogeneous network of such a size is very difficult. The SON solutions are standardized by the 3GPP provide cost efficient automation for configuration, optimization and fault management of the radio networks. The supporting functions such as SON coordination and MDT measurements are essential for a complete SON solution. The coordination between SON functions is necessary to avoid any conflicts between different SON functions decisions. The MDT provides an automated way of user measurements collection from user mobiles that makes it possible to acquire useful knowledge of users' perspective of the network coverage and service quality. Currently the network management is mainly based on the networks counters and KPIs, thus providing only network perspective. With the network densification, massive deployment of small cells have made the network management more difficult and challenging. Most of the time the small cells are not well planned. In this situation, the user's perspective of the network coverage and service quality plays a crucial role in better management of this type of heterogeneous network. Therefore, it would be very beneficial to incorporate the user context in the SH process. Another great challenge is that current SH functions are reactive in nature, they only trigger when a problem has occurred. This reactive fault management is not sufficient for the future needs of the 5G networks. For 5G networks, a faster response time is needed to meet the zero latency perception requirements. This leads to the concept of failure prediction that means instead of waiting for the fault to occur, failure should be predicted beforehand and preventive actions should be triggered. This proactive approach will substantially reduce the system response time and achieve better performance.

The research is an ongoing process. During the last few years the concept of SON has been accepted as a way forward for the future network management needs of a cellular network. Recently a paradigm shift in SON research took place where the need of proactive SON solutions has been identified. The future work is devoted to further development of SH solutions for the more challenging and realistic scenarios such as heterogeneous small cell networks. The ultimate goal would be to integrate the developed SH solutions to the real-world networks. For this purpose collaboration with network operators and vendors is anticipated.

YHTEENVETO (FINNISH SUMMARY)

Itsekorjautuvien menetelmien kehitys ja arviointi tulevaisuuden langattomissa verkoissa

Tämän väitöskirjan tarkoituksena on kehittää kokonaisvaltaisia ja innovatiivisia itseorganisoituvia verkonhallintaratkaisuja tulevaisuuden langattomin verkkoihin. Erityiskohteena työssä on itsekorjautuvien (*engl.* Self-Healing, SH) menetelmien kehitys itseorganisoituvissa verkoissa (*engl.* Self-Organizing Networks, SON). Vikatilanteiden hallinta on kriittinen osa-alue mobiiliverkkojen kokonaishallinnassa. Monimutkaisissa mobiiliverkoissa on useita toiminnallisia osa-alueita, joissa esiintyy monenlaisia vikoja. Vianhallinnan kannalta kaikkein tärkein osa-alue on radioverkko (*engl.* Radio Access Network, RAN). Verkon elementtien vianhallinta ei ole vain vaikeaa, vaan se myös aiheuttaa suuria investointi- ja toimintakustannuksia. Henkilöresurssitarpeen pienentämiseksi automaation kautta on syntynyt itseorganisoituvien verkkojen SON-konsepti. Itsekorjautuvat menetelmät ovat osa SON-konseptia. Ne viittaavat juuri automaattiseen vikatilanteiden korjaamiseen langattomissa verkoissa. Ne pitävät sisällään suorituskyvyn monitoroinnin, virheiden havainnoinnin ja niiden aiheuttajat, laukaisevat korjaavat toimepiteet ja suoritettujen korjaustoimenpiteiden arvioinnin. Itsekorjautuvuus parantaa verkkoliiketoimintaa vähentämällä häiriötilanteita ja varmistamalla verkkojen saatavuuden, luotettavuuden ja kannattavuuden. 5G-verkkoteknologioiden yleistyessä itseorganisoituvien verkkojen hallinta tulee yhä haastavammaksi. Perinteiset itsekorjaavat verkonhallintaratkaisut eivät riitä tulevaisuuden mobiiliverkkojen hallinnassa, johtuen niiden reaktiivisista piirteistä eli siitä, että ne aloittavat korjaavat toimenpiteet virhetilanteen jo tapahduttua, kun korjaavat toimenpiteet pitäisi tehdä jo enakkoon ennustavalla tavalla. Virhetilanteiden havainnointiviivet ovat erityisen ongelmallisia 5G-verkoissa niiden viiveeseen liittyvän nollatoleranssivaatimuksen vuoksi. Jotta päästään tähän viiveen nollatoleranssivaatimukseen, olemassa olevien itseorganisoituvien verkkojen hallintaan tulee lisätä uusia ominaisuuksia. Mobiilioperaattoreiden tulee päivittää verkkojaan reaktiivisista ennakoivaan suuntaan. Samalla avautuu uusia mahdollisuuksia itseorganisoituvien verkkojen ja itsekorjautuvien menetelmien kehitykselle. Tässä väitöskirjassa esitellään useita askelia kohti 5G-verkkojen tavoitteita.

Avainsanat: itseorganisoituva, itsekorjautuva, vikojen hallinta, solun tilan heikkeneminen, solun katkosten hallinta, mobiiliverkot

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International Journal of Digital Content Technology and Its Applications (Accepted!)

Cell Degradation Detection based on an Inter-Cell Approach

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Abstract

Fault management is a crucial part of cellular network management systems. The status of the base stations is usually monitored by well-defined key performance indicators (KPIs). The approaches for cell degradation detection are based on either intra-cell or inter-cell analysis of the KPIs. In intra-cell analysis, KPI profiles are built based on their local history data whereas in inter-cell analysis, KPIs of one cell are compared with the corresponding KPIs of the other cells. In this work, we argue in favor of the inter-cell approach and apply a degradation detection method that is able to detect a sleeping cell that could be difficult to observe using traditional intra-cell methods. We demonstrate its use for detecting emulated degradations among performance data recorded from a live LTE network. The method can be integrated in current systems because it can operate using existing KPIs without any major modification to the network infrastructure.

Keywords*: Fault Management, Network Management Automation, Self-Organizing Networks (SON), Self-Healing, Long Term Evolution (LTE), Inter-cell analysis, Correlation based Cell Degradation Detection, Real LTE Network*

1. Introduction

The massive increase in the number of mobile subscribers and consequently a dramatic increase of mobile phone services have put operators under pressure for better quality of service and network reliability. The exponential growth of mobile broadband traffic is certainly caused by both the increasing demand for known and new data services, such as mobile internet access, online social networking and location-based services [1]. The usage of tablets, smart phones, application stores, social media and the data exchanges between end-users and clouds are all growing at a rapid pace. The use of these devices has also increased the demand for wireless video applications to a large extent and has put tremendous pressure on the wireless network infrastructure. In parallel to the exponential growth of mobile broadband traffic and high data rates, the small cells, e.g. pico and femto cells, on top of macro cells, have made network management more challenging. Furthermore, the competition between mobile operators is increasing and pushing them to provide better network performance in terms of network availability, robustness, coverage, capacity, and service quality. In order to tackle these challenges and eventually be able to attract and retain subscribers, the network operations need to be optimal all the time. Through a good performance of the network elements and low failure probability, the network can operate more efficiently reducing the necessity for equipment investments. It is not enough for operators to employ economic incentives to modify user behavior by adjusting tariff structures, but operators must also improve network capacity and network availability.

In addition to the coverage and capacity needs, the tasks of operation and maintenance of mobile cellular networks are vulnerable to errors as a huge amount of manual effort is needed to monitor and execute these tasks. In order to improve the fault management of cellular networks and to improve the efficiency and reliability of the networks, automation has to be introduced. These developments have triggered the concept of Self-Organizing Networks (SON) which is a built-in feature in Long-Term Evolution (LTE) and LTE-Advanced networks [2]. SON has been seen as an efficient solution for network management by the 3rd Generation Partnership Project (3GPP) [2], Next Generation Mobile Networks (NGMN) [3] and FP7 SOCRATE projects [4]. A detailed overview of the SON technology and the network management automation is given in [5] and [6]. The major domains of SON enabled networks are self-configuration, self-optimization and self-healing. Of these domains, the work presented in this paper focuses on self-healing which aims at automatic troubleshooting where detection and diagnosis of anomalies, temporary compensation of the effect of faults, and corrective actions are largely automated.

A fault in a cellular network refers to a defect at the hardware or/and the software level, which significantly degrades network performance and eventually leads to dissatisfaction of the users. Errors and problems almost always exist in networks due to the complexity and uncertainty of radio links. However, some errors may also be temporary and thus never develop into faults.

Although 3GPP use cases are focused on "cell outage", we adopt a more general concept of "cell degradation" which refers to the case where the performance of a cell in handling traffic is significantly lower than it is supposed to be. There are two types of cell degradations based on time duration: temporary and permanent. Temporary degradation refers to the situation when a cell performance is degraded for a short period of time and then recovers without external support. These degradations almost always exist in a cellular network. Permanent degradation refers to the situation when a cell remains degraded for a longer period of time. During the resulting period of degraded performance, users will not experience services with acceptable availability, reliability and quality of service (QoS) which may cause serious revenue loss for the operator. From the network management point of view, these fault situations should be handled quickly. SON's self-healing functionality can contribute to optimize the handling and resolving of faults in different situations. In principle, the degradations caused by faults should be detected, countermeasures should be taken to resolve the problem, and immediate compensation to the lost coverage should be triggered.

The fault management is performed at the operations support system (OSS) in which measurements are collected from network elements. The OSS usually stores all information of the network, e.g., network counters, configuration measurements, fault measurements etc. Several key performance indicators (KPIs) are computed from the network counters. Consecutive measurements of a KPI constitutes a time series that can be used for fault detection and triggering alarms. The performance of each cell can be characterized using KPIs and fault measurements, e.g., alarms.

Degradations might not be easy to detect, though, because they might not necessarily trigger alarms even when users are affected. Such a cell is called a "sleeping cell" in cellular network fault management research. It means the malfunctioning in the network is not visible to the operator until negative feedback from the customers is received in terms of complaints and loss of revenue at the coverage area. It is difficult to detect such a problem with traditional monitoring tools as in many cases the threshold is not violated and no alarms are generated.

This paper focuses on improving the detection part of self-healing, especially with respect to detecting sleeping cells. The rest of the paper is organized as follows. In Section 2, earlier work on the field is explored. In Section 3, the real-world LTE data used in our method evaluation is described. In Section 4, the method itself is outlined. In Section 5, computational experiments on the dataset are documented. Section 6 concludes the paper with some outlines for further research.

2. Related work

A method to detect coverage and dominance problems and to identify interferers in WCDMA networks was introduced in [7]. Signaling messages exchanged through the radio interface were used to calculate certain metrics for every cell during normal network operations reflecting real traffic distributions and geographical user locations. Competitive neural algorithms were used for fault detection and diagnosis in 3G cellular networks in [8]. Another cell outage detection algorithm based on the neighbor cell list reporting of mobile terminals was introduced by Mueller in [9]. An experimental system was developed for self-healing of 3GPP LTE networks in [10] where detection and compensation of cell outages were evaluated in a realistic environment. The impact of self-healing on KPIs such as the number of connected users and radio link failures was explored.

In [11][12][13] a series of cell degradation detection research was conducted. An ensemble method approach was proposed for modelling cell behavior and cell anomaly detection that computes a numerical measure, referred to as the KPI degradation level, to indicate the severity of degradation. The authors also claimed that their method was able to cope with concept drift as well. The papers dealt with the network's ability to automatically detect problems such as performance degradation or network instability stemming from configuration management changes.

In [14] a data mining approach for fuzzy diagnosis systems was proposed. In this paper a knowledge acquisition learning algorithm based on fuzzy logic was proposed for fault troubleshooting in LTE. Recently, in [15] indoor localization and user equipment data was employed for better sleeping cell detection and diagnosis for 5G ultra dense networks. In [17] a cell degradation detection method was proposed that uses correlation-based comparisons of observed KPI time evolution patterns against fictitiously degraded ones. The authors observed that comparison using longer trends is better than the traditional way of looking at single averages. A novel approach for cell degradation detection where the information of failed attempts in establishing a connection to a cell is communicated to the next connected cell is presented in [18]

The above approaches for cell degradation detection are based on intra-cell analysis of the operational base stations. In intra-cell analysis, profiles of different KPIs are built based on their history data. The current KPI levels are compared with their respective profiles and degradation is detected if the KPI exceeds a certain predefined threshold level. However, this threshold and profile approach has certain drawbacks. One of the disadvantages of the intra-cell approach is that large variations in KPIs lead to wide profiles, and, while complete outages are detected, degradations or sleeping cells are more difficult.

Initial work on inter-cell analysis can be found in [18][19][20]. The proposed methods characterize the normal behavior of the cell and build profiles for the faultless network behavior by either looking at its earlier behavior or comparing it to similar systems. Significant deviations from the profile are identified as abnormal behavior and an alarm is triggered if the deviant behavior persist for certain period of time. The correlation-based algorithm uses the correlations of cells within a geographical neighborhood. It is assumed that there exists an appreciable level of correlation between neighboring cells. The same operational fault detection (OFD) approach is followed by a statistical hypothesis test framework for determining faults.

In our proposed approach, the degradation detection is based on inter-cell analysis. It refers to the situation when KPIs from several cells are compared to corresponding KPIs of other cells instead of their own history based profiles. The main advantage of the inter-cell approach over the intra-cell approach is that it is less sensitive to the individual KPI variations. We exploit the idea that there are many cells in the network coverage area having similar behavior irrespective of their geographical locations. The idea was used in [21] in which it was suggested that the correlation coefficient between cell pairs can be used as a means for degradation detection in cells. In addition to the inter-cell analysis point of view, a main contribution of this work is the use of real-world KPI data collected from a live LTE network. Fictitious patterns resembling realistic sleeping cell scenarios are created to evaluate the method.

3. Sleeping cell detection using real-world data

In our computational experiments, we use one month (700 hours) of real-world data recorded from a live LTE network. The examined KPI time series consist of the downlink physical resource usage percentage (DL PRB) averaged over each of the 1 hour intervals in each of the cells in the network. In order to simplify the analysis somewhat, we selected only those 89 cells that had no missing values and no obvious periods of downtime. The cells are identified by their indices in the selected subset. We also applied two rounds of filtering consisting of a median filter (window size 3 hours) followed by convolution with a three-hour kernel of coefficients (0.25 0.5 0.25). Edge effects of the filtering were simply cut away as the original data set was slightly longer than the 700 hours selected for this study. Each of the time series was then scaled to the range of [0,1]. These simplifying preprocessing operations could easily be used also in a real usage scenario. Figure 1 shows the complete preprocessed time series of three arbitrarily selected cells. The problems involved in real-world data can be seen in this kind of figures: even though a natural 24-hour pattern emerges when averaging over all the cells, the peaks of any single cell are sporadic and long periods of inactivity occur amidst the peaks.

As the data is real, we cannot be sure whether actual degradations or faults exist in the recorded data. For the purposes here, we assume that the network was at least mostly healthy during the observation time. For method evaluation, we create artificial degradation patterns by gradually attenuating the time series with a linearly decreasing window function. A tiny amount of Gaussian noise is also added in order to maintain realism. Figure 2 illustrates the concept. The figure shows the original DL PRB of a cell (included also in Figure 1) and a simulated degradation that starts at time step 600 and reaches full depth (with no recovery) in 20 steps. We feel that the result is a valid approximation of a cell that quietly dies for some unknown, slowly accumulating, and possibly undetectable, causes lurking in the complexities real network hardware and software. For example, in Figure 2 we can see how a peak in the "dying-out" period is still present but with a lower magnitude than in the original, healthy, data.

For method evaluation, we compare the detection algorithm outcome of the original time series against the artificially degraded one for each of the cells. The number of detections for the degraded patterns yields the number of true positive identifications whereas the number of false positive ones is given by detections for the original patterns. Naturally, we would like the number of true detections to greatly overwhelm the number of false ones. An individual detector is trained for each cell using the part of the data that is not degraded for the testing phase.

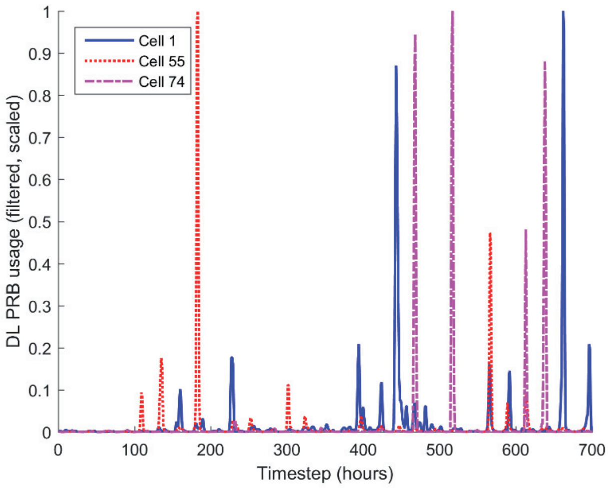

Figure 1. Examples of the KPI time series.

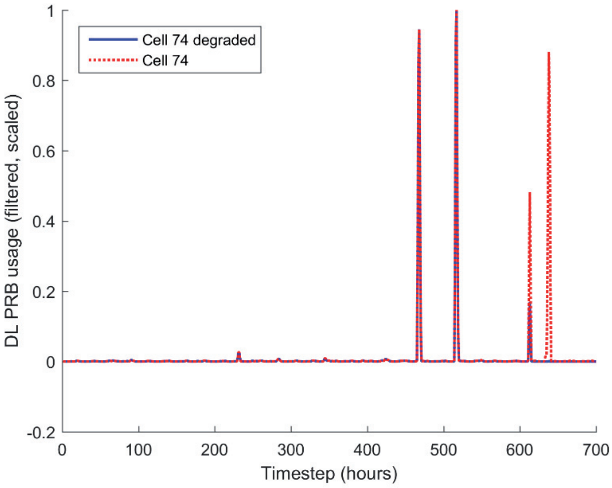

Figure 2. Example of the simulated degradation resembling the sleeping cell scenario.

4. Proposed Approach

This section presents our inter-cell analysis approach for cell degradation detection in cellular networks, consisting of the training phase of selecting comparing cells and the detection phase based on values derived from correlation values. We note that while we experiment now with the DL PRB, any other KPI, such as the number of active users, could be used.

4.1. Training phase and selection of comparing cells

In real networks, user behavior varies strongly depending on the time of day, the geographic location, and other factors. Although it might be that cells located near to each other would experience similar environmental conditions, this is not always true. It is possible that some cells exhibit behavior to each other independent of their geographic location. This might be caused due to a similar kind of user behavior depending mainly on the time of the day. It is vital to choose the right cells as comparing cells. This is done in an initial cell pair selection process.

The examined KPI of cell j is a time series $x_1^{(j)}, x_2^{(j)}, \dots, x_n^{(j)}$. In both training and detection phases, we shall be looking at windows of L consecutive values leading up to time step t, i.e., $x_{t-(L-1)}^{(j)}, \dots, x_{t-1}^{(j)}, \dots, x_t^{(j)}$. Our method is based on the usual correlation coefficients $r_t^{(j,k)}$ between the time windows of two cells:

$$r_t^{(j,k)} = \frac{\sum_{i=0}^{L-1}\left(x_{t-i}^{(j)} - \bar{x}^{(j)}\right)\left(x_{t-i}^{(k)} - \bar{x}^{(k)}\right)}{\sqrt{\sum_{i=0}^{L-1}\left(x_{t-i}^{(j)} - \bar{x}^{(j)}\right)^2}\sqrt{\sum_{i=0}^{L-1}\left(x_{t-i}^{(k)} - \bar{x}^{(k)}\right)^2}},$$

where the mean values $\bar{x}^{(j)}$and $\bar{x}^{(k)}$are computed over the window. We aim to train a detector for each target cell under examination. The training phase encompasses the selection of a number of "comparing cells" that are highly correlated with the target cell. The number of comparing cells K is a parameter of the method, as is the window length L. No other parameters need to be selected by the user.

The coefficients are first computed for all the time stamps in a selected training set of windows and for all cells. Then the cells are scored by how many times they have appeared in the set of K most correlating ones within any of the time windows used for training. The K overall highest-scoring cells are selected as the set $C^{(j)}$ of comparing cells for the target cell. The minimum correlation coefficient values observed during training is selected as the correlation threshold $\tilde{r}^{(j)}$.

4.2. Detection value and time-since-detection

After the selection of the parameters, two further measures can be computed for any time window ending at step t: The "detection value" $d_t^{(j)}$ that we define as the number of comparing cells falling below the threshold, $d_t^{(j)} = \#\{k \in C^{(j)}: r_t^{(j,k)} < \tilde{r}^{(j)}\}$ and "time-since-detection" $s_t^{(j)}$ which is the number of time steps that $d_t^{(j)}$ has remained at its maximum possible value K. These measures are computed for the training time windows and the actual detection threshold $\tilde{s}^{(j)}$ is selected as $\tilde{s}^{(j)} = \max\{ s_t^{(j)}: t \in \text{training}\}$.

Once trained, the detector will continue working on unforeseen time windows, evaluating the two measures for each. An alarm is triggered at $x_t^{(j)}$ whenever $s_t^{(j)} > \tilde{s}^{(j)}$.

5. Experiments

For the experiments, we selected 24 as the time window size and 3 as the number of comparing cells. For training, we used the first 576 time windows, and the rest were used as the testing set for each cell. A degradation was always emulated starting from hour 600 in the way that was depicted in Figure 2 of Section 3. The detection value and time-since-detection were evaluated for both the healthy and the degraded time series versions. Figures 3 and 4 show the values for some selected cells. In Figure 3, the target cell was Cell 77 and the comparing cells automatically selected by our algorithm were Cells 78, 73, and 80, in the ranking order of the algorithm. From the indices we can tell that not all cells were located in the same site geographically (while Cells 77 and 78 may very well be, in fact). The figure shows the values of the detection measures both for the clean data used in training and the testing series with the emulated degradation in the end. The values are the same up to time step 576 which was the end of the training phase in our experiment. In the latter part, we can see that the detector has picked up the degradation and made a correct detection. A temporary rise in the time-since-detect value can also be seen, but the value never exceeds the threshold selected as the alarm trigger. Figure 4 shows the same values for a different case where an actual false alarm took place. Yet, the time-since-detect value never gets as high as it does for the degraded test pattern.

In total, the number of correctly detected degradations was 64 which amounts to 72 % of the cases available for testing. The number of false detections for the healthy time series was 12 which amounts to only 13 % of the cases. We conclude that, overall, the method is able to detect degradations while the level of false detections is considered acceptable.

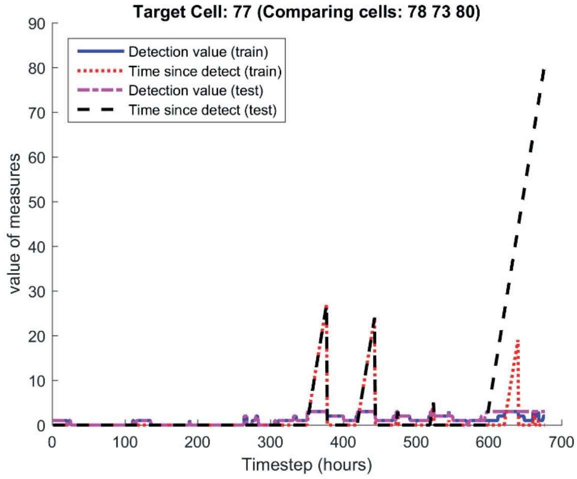

Figure 3. Detection values and time-since-detection indicators for selected cells.

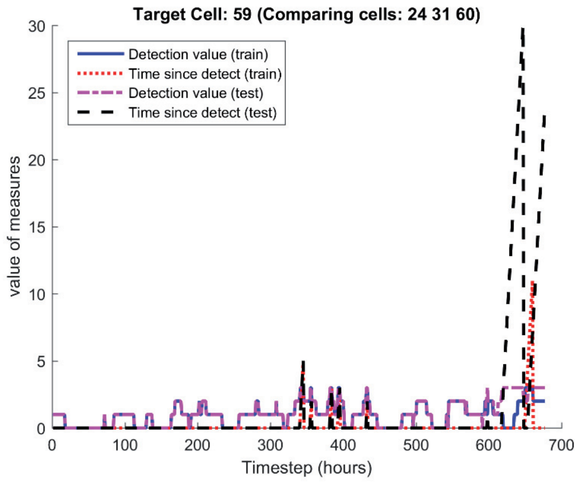

Figure 4. Detection values and time-since-detection indicators for selected cells.

6. Conclusion

In this paper we modified a correlation-based cell degradation detection method [21] and demonstrated its use on real-world KPI data recorded from a live LTE network. We find the results supportive of the argument that the inter-cell analysis approach is well-suited to cases difficult for traditional methods, such as sleeping cell detection.

This method can be easily integrated with traditional troubleshooting tools because all the measures are computed based on KPIs available in current infrastructures with no need for additional modifications. Indeed, future work is devoted to extending this method for more complex scenarios involving more KPIs. Future work also includes observing more data in a real network together with the operators' knowledge about a "ground truth" of any problems and faults that might have existed during the observation periods so that degradations would not have to be artificially emulated in order to perform method validation.

In theory, the training phase could be running all the time, thus allowing the comparing cell selection to adapt to changes in the operating environment. The identified cell pairs would then be better correlated all the time. If some, but not all, of the comparing cell correlations fall below the detection threshold, some additional cell performance monitoring would be needed in order to determine if it is in fact one of the comparing cells that is degrading instead of the target cell. Additional performance monitoring could include tracking other KPIs of the cells and checking if they pass certain thresholds that operators have set in the traditional way. Incorporating context to the self-healing research will help increase the detection accuracy. Some good examples of recent context-aware self-healing solutions can be found in [22][23][24].

7. Acknowledgement

The authors acknowledge the great support, both in terms of technical advice and provision of anonymized data of a real network, from Dr. Adnan Ahmed Khan, NUST, Pakistan and Prof. Ismail Shah, PTA, Pakistan.

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TOWARDS PROACTIVE CONTEXT-AWARE SELF-HEALING FOR 5G NETWORKS

by

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Computer Networks Special Issue "Survivability Strategies for Emerging Wireless Networks" (Accepted!)

Towards Proactive Context-Aware Self-Healing for 5G Networks

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Abstract

In this invited paper, we suggest a new research direction and a future vision for Self-Healing (SH) in Self-Organizing Networks (SONs). The problem we wish to solve is that traditional SH solutions may not be sufficient for the future needs of cellular network management because of their reactive nature, i.e., they start recovering after detecting already occurred faults instead of preparing for possible future faults in a pre-emptive manner. The detection delays are especially problematic with regard to the zero latency requirements of 5G networks. To address this problem, existing SONs need to be upgraded from reactive to proactive response. One of the dimensions in SH research is to employ more holistic context information that includes, e.g., user location and mobility information, in addition to traditional context information mostly gathered from sources inside the network. Such extra information has already been found useful in SH. In this paper, we suggest how user context information can not only be incorporated in SH but also how future context could be predicted based on currently available information. We present a user mobility case study as an example to illustrate our idea.

Keywords: Self-Organizing Network, Self-Healing, User Context, Context Aware System, 5G Networks

1. Introduction

At the time of 1G and 2G networks deployment, mobile terminals were dumb devices and processing was done on the network side. At the advent of 2.5G, 3G, and 4G technologies, the terminals started to become more intelligent, and nowadays mobile phones are called smart phones because they have much of the processing power and intelligence that was previously believed to be done only by the network. Now mobile terminals can contribute to the network management by providing more data about the service quality, channel quality index (CQI), reference signal received power (RSRP), device location, and many other attributes. This opens new opportunities to gather data from User Equipment (UE) and to make the network better aware of the user perspective of the network coverage and services. Currently, all the data available from millions of mobile devices is not yet being fully used for network operation purposes, though. Instead, network operation and management is mostly based on only a few Key Performance Indicators (KPIs) measured from inside the network, thus using only a network perspective. Much of data available outside the network is being wasted. The requirements set by 5G technologies and the massive deployments of small cells such as micro and pico cells along with macro cells,

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have made network management more challenging [1, 2]. The traditional network management tools are not enough to capture the complete behavior of the system and to propose optimal configurations.

Roughly following the definition of self-organization given in the survey [3], Self-Organizing Networks (SONs) are networks that are adaptive and autonomous and also scalable, stable, and agile enough to maintain their services in the face of all potential environmental dynamics. In future wireless networks, SON enabled operations are expected to be the default operational mode, and SON functions will have to operate in an environment with multiple operators, vendors, and radio access technologies [2, 3, 4]. The three categories of SON are Self-Configuration, Self-Optimisation, and Self-Healing (SH).

SH refers to autonomous fault management in wireless networks, including performance monitoring, detection of faults and their causes, triggering compensation and recovery actions, and evaluating the outcome. SH improves business resiliency by eliminating disruptions and ensuring network availability, reliability and retainability.

Traditional fault management based on KPI thresholds neglects user behavior and mobile phone usage patterns. Consider the situation, where many mobile users send text messages frequently and the text activity is high. Then, because of some problem in the network, the messages fail to go through. When users will experience delays or no service at all, they may silently stop using the service and may eventually shift to another operator. The operator would assume that the network is functioning well all the time. On the other hand, if user behavior was being monitored and used for anomaly detection, the problem could have been noticed and diagnosed.

The SH functions of 3G/4G are designed in such a way that they would trigger only when a problem has occurred, which makes the fault management reactive in nature. A certain time is required to observe the situation, diagnose the problem, and then trigger the compensating action. For example, a cell outage compensation function is triggered when the cell outage has been detected and user calls started to drop already. The network operator would already start losing revenue. This reactive fault management of current SONs will not be able to meet the performance requirements or the targeted quality of experience (QoE) levels of 5G network, especially the zero latency perception requirements.

Instead of detecting problems that have already occurred, an optimal SH system could also predict problems beforehand, and prevent them, thus transforming network management from reactive to proactive. Even if all problems cannot be predicted beforehand, the proactive approach could substantially reduce the intrinsic delay between the observation and compensation phases compared to current state-of-the-art SH.

Proactive fault management has been explored in the broader computer systems area, e.g., in [5]. Inspired by [5], we differentiate between root cause analysis (diagnosis) and failure prediction in communication networks as illustrated in Figure 1. The fault diagnosis mechanisms refer to the process of identifying the causes ("faults") of an already degraded network performance. On the other hand, failure prediction tries to assess the risk of a future degradation leading to a possible loss of service ("failure"). For example, in case of cell outage detection, the diagnosis mechanisms try to identify what the reason for the cell outage is, e.g., broken network element or software errors. The failure prediction refers to the assessment of whether an outage is likely to occur in the future. A possible way to achieve this goal could be the strengthened use of context built from the available user perspective and other relevant data.

In this paper, we briefly overview some very recent proposals towards SH in 5G networks. We then build upon the recent concepts by suggesting the addition of a context prediction component. For example, user behavior, such as mobility from place to place, can be modeled and used to predict future resource needs of the network to enable proactive and pre-emptive, rather than reactive, network management. Our main contributions are the following:

- A proposal of using user context and predictor models to transform SH from reactive to proactive response.
- A case study demonstrating future context prediction.

The remainder of this paper is organized as follows. In Section 2, we explain the background and the central concepts of this work, and cover some recent related works on the topics. In Section 3, we propose an approach to incorporate further context

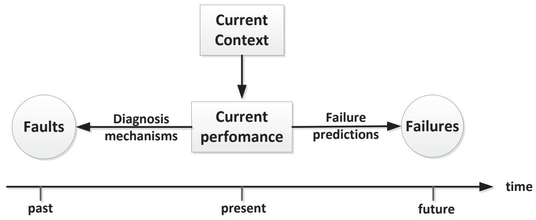

Figure 1: Difference between fault diagnosis mechanisms and failure prediction (cf. [5]).

information and especially future context prediction in SH. In Section 4, we present a practical example of context prediction. Finally, Section 5 concludes this paper.

2. Background and Related Work

2.1. Classical Approaches

Modern networks are very complex pieces of equipment [6, 7]. Besides the large variety of hardware like antennas, the backbone network, and routing components, there is also a myriad of different software stacks in these components. Furthermore, these devices are deployed in harsh environments. Hence, in practice, faults happen on a regular basis. Typical examples of network faults are software faults, broken hardware components, and inappropriate network configuration settings.

There are many performance metrics/indicators available for wireless networks that capture the network status at any given moment. These measurements are the low-level network counters and KPIs derived from them. Each KPI describes a specific aspect of the network. A KPI can be a simple average of consecutive measurements during a time period, or it can be a more advanced statistic. Typically, KPIs describe the success or non-success rates of the most important events such as handovers or dropped calls. The operator usually sets the time window for collecting network counter values before recording them as KPIs. The length of this window is a balancing act between how fast the operator can act upon a problem in the network, window size required to detect the problems, and how much data can be transferred from the base stations to the place where the SH functions are running.

When the network does not contain any (known) faults, it is possible to collect one or more KPIs and create what is called a profile of the network. This profile contains the typical values of the different indicators. The profile can be built on a per-cell basis, for each base station, or even on a wider aggregation layer (e.g., considering traffic in a cluster of base stations). Once the profile is built, continuous monitoring of the KPIs is conducted and statistically significant deviations from the profile will trigger an alarm. Often a deviation is determined by using a fixed threshold and the alarm will be triggered if the value goes beyond this bound. For example, an alarm could be raised when the call drop rate exceeds 0.1%.

Typically, the thresholds and profiles of the network are maintained in centralized Operations and Maintenance Centers (OAMs) where the KPIs and alarms are directly presented to the operator who then filters out high quality alarms manually. There can be multiple alarms generated by one fault and the same single alarm may be generated by multiple faults. It is also possible that alarms are generated without the presence of a fault. For example, any external factors, e.g., bad weather, could cause some alarms when there is no real malfunction. Sometimes it is also possible that alarm messages are not conveyed to the OAM. So alarms are not a complete/reliable source of information for fault diagnosis.

The flow of uncorrelated alarms and the big volume of alarms can be reduced by employing alarm correlation methods [8]. The alarm correlation consists of interpretation of multiple alarms, combining low level alarms to form high level alarms. The alarm correlation is an important part of SH, but alarms alone do not provide enough information to determine the root cause of the observed problems [9]. Furthermore, these methods can only reduce the quantity of alarms but not help to increase their quality. One drawback of the threshold based approaches is that they essentially quantify the KPIs into a binary space, i.e., normal and abnormal, which makes it difficult to detect performance degradations which have not yet developed into complete outages or total losses of performance.

2.2. Developments in SH Research

Earlier research on SH focused on sole automation, but in more recent efforts more focus has been given to the intelligent characterization of the network state.

Good examples of recent practical approaches to SH in real operational networks are found in [10, 11, 12, 13, 14, 15]. For example, [10] addressed the problem of verifying the effect of network configuration changes by monitoring the state of the network and determining if the changes resulted in degradations. The proposed framework consists of an anomaly detector and a diagnosis component. The anomaly detector monitors a group of cells using topic modeling. The diagnosis component, in turn, uses Markov Logic Networks (MLNs) to generate probabilistic rules that distinguish between different causes. Another anomaly detection approach using refined KPIs is presented in [12].

An incremental topic modeling approach was proposed in [15]. In that approach, the authors followed a modified version of Hierarchical Dirichlet Processes (HDP) which utilizes stochastic gradient optimization to allow the training process to evolve incrementally over time. The authors adapted that method to input all KPIs as multivariate. For the evaluation of the incremental topic modeling method, the authors used real data collected from a 3G cellular network. The incremental algorithm is run for HDP by randomly choosing timestamps from the 3G dataset and updating the model parameters accordingly. The adaptability to different cell scopes is achieved by first applying clustering to the largest scope. Then, the state of the network can be determined for subsets of the largest number of cells. The incremental approach for topic modeling will gradually update the clusters with information from the larger scope. The paper presented the initial feasibility of the incremental topic modeling approach in the context of cellular network data but the results are not mature yet.

In [16], an experimental system for comprehensive testing of different 3rd Generation Partnership Project (3GPP) Self-Optimization use cases is developed. In [17], the system is further extended to a SH framework for 3GPP Long Term Evolution (LTE) networks where detection and compensation of cell outages are evaluated in a realistic environment. The impact of SH on the KPIs such as the number of connected users and radio link failures is also shown in the paper. In [18], the authors suggested that the correlation coefficient between cell pairs can be used as a means of degradation detection in cells. In these works, the KPIs are used for detection and diagnosis of faults.

A framework for network monitoring and proactive anomaly detection is proposed in [19], using principle component analysis (PCA) for dimension reduction and kernel-based semi-supervised fuzzy clustering with an adaptive kernel parameter. The algorithms are evaluated using simulated data collected from a LTE system level simulator. The authors claim that this framework proactively detects network anomalies associated with various fault classes.

2.3. User Measurements in Traditional SH

So far, the SH research has been focused mainly on data collected from KPIs, network counters, alarms, and drive tests. In addition to these, Next Generation Mobile Networks (NGMN) and 3GPP have identified other inputs for fault management, such as direct KPI reporting in real time, UE traces, Minimization of Drive Tests (MDT) via UE reports, and location information [6].

A SH solution for 5G heterogeneous network (HetNet) architectures has been presented in [20] with separate detection methods for the control and the data plane in the split architecture of 5G (see [21, 22]) respectively. The cell outage detection is achieved using MDT with user position information. In this approach, the idea of incorporating direct reports from UEs including localization information was presented for detecting cell outages. However, the outage detection using MDT approaches is mainly done offline. Also, except user position information and received signal strength, no other information was included. The analysis was done on an elementary reference scenario using very limited examples of network failures.

The recent advances in indoor localization and UE data are utilized to provide sleeping cell detection and diagnosis solutions for 5G ultra-dense networks in [23]. An automatic root-cause analysis method using UE traces is presented in [24].

Although user measurements have been used in network management systems, the use has been limited so far, and comprehensive applications of such information have not been fully addressed.

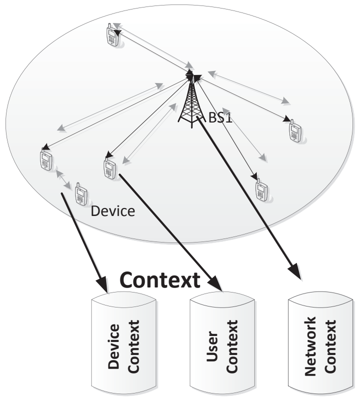

Figure 2: Three types of context: device, user, and network.

2.4. Context-Awareness

The term Context-Awareness (CA) was first introduced in the research area of pervasive computing [25]. According to the authors, CA is the ability of computing systems to acquire and reason about the context information and adapt the corresponding applications accordingly. During the last years, there has been an increasing interest in ways to share and exchange context information among remote and heterogeneous CA systems. Developments in the definition of "context" is surveyed in [26]. The early definitions, roughly to the effect of numerical state information resulting from interactions, were more primitive and limiting than the current ones, which deal more with the dynamical flow of information and knowledge within a system. One example of the use of CA in heterogeneous wireless connectivity management is [27].

There could be several types of context depending on the perspective we consider. In Figure 2, three types of context are illustrated: *Network context* consists of input from the network side, such as radio measurements, performance indicators, network configuration settings, history of configuration changes, network commissioning and planning information, etc. *User context* consists of all information about users, such as their mobility patterns, behavior, preferences, etc. *Device context* consists of the information and the influence of nearby devices which can be used in device-to-device communication (see [28]).

Traditionally, all the data for fault management was collected within the network. More recently, e.g., in [23], further kinds of data, including user context, are proposed to be considered. Context information can be broadly collected from the following three major sources:

1. UEs: location, call logs, GSM and WLAN connections, etc.

2. Cellular Network: network down for maintenance purposes, configuration changes, switching on new base stations, etc.

3. Environment: weather reports, new constructions, new buildings, railway station, events in the city or the indoor facility, etc.

A general framework for empowering SONs with big data is provided in [4]. In that paper, the authors list and categorize many possible data sources for context information applicable in SH. Here we give a few examples:

- Configuration Parameters: information on the actual configuration of network elements.

- Alarms History: messages generated by network elements when faults are detected.

- Network Counters: measurements from the network elements periodically transferred to the OAM.

- KPIs: combinations of other measurements.

- Drive Tests: field measurements related to, e.g., coverage and interference, performed in a certain area by specialized equipment such as measurement terminals and GPS.

- Mobile Traces: information from UEs.

- Call Logs: calls history information.

- Traditional context information: time, estimated UE location.

2.5. Context-Aware Self-Healing (CASH)

Recently, there has been work towards Context-Aware Self-Healing (CASH), which takes into account more of the context information. In [29], contextualized indicators for failure diagnosis are presented. The authors claim that context information can be used to support root cause analysis that provides better diagnosis results than traditional approaches. In their work, the user context was defined by location, user category and service. Recently, location-aware self-organizing methods are presented in [30].

Major challenges of small cell deployments are identified in [31]. One is "Reduced monitoring" which refers to the limited availability of troubleshooting information. Another one is "Irregular and overlapped cell areas" which makes the fault detection difficult because a fault would not create coverage holes or complete outage. Yet another one is "Performance variations" which refers to the problems occurring due to a low number of users connected to the cells. These variations generate situations where there may not be enough information about a failure for a long time. Another problem is that the fault cases usually do not deviate from the normal behavior enough to provide a significant statistical difference.

According to [31], addition of context information will help in distinguishing a fault scenario from a normal one. For example, if the user moves to a cell border, the received power will be low just as in the case of a fault. However, with context information, the cell border measurements could be separated from fault cases. For the indoor scenario, positioning information is very useful as the small cells are overlapping.

The CASH framework presented in [31] consists of 5 major blocks, i.e, *indicators' acquisition*, *context acquisition*, *context aggregation*, *inference engine* and *record update* blocks, as shown in Figure 3. For the purposes of this paper, the illustration is simplified from the original in [31]. The indicators' acquisition block collects network and user measurements and accumulates them in independent buffers. A profiling window is used to select a group of samples for statistical profiling of UEs. This block considers current measurements for generating profiles, and old samples are discarded. The context acquisition block builds the current context by combining the data obtained from different sources. The context aggregation block associates the current context with the previously recorded situations and retrieves the contextualized profile of the KPI with the same context. The inference engine block performs the detection and diagnosis of problems by comparing current KPI distributions with the contextualized profiles obtained from the context aggregation block. The record update block stores historical KPI measurements.

Incorporating user context in SH involves some challenges such as context data storing, processing, and overhead caused by transmitting extra information over the air interface. However, the feasibility of context inclusion has been already demonstrated [32].

3. Towards Proactive CASH

As observed in [5] with online failure prediction, our vision on proactive CASH can be well expressed in the words of the Greek poet C. P. Cavafy [33, p. 53]: "Ordinary people know what's happening now, the gods know future things because they alone are totally enlightened. Of what's to come the wise perceive things about to happen".

3.1. Vision of Context Prediction Applications

It is wise to predict the near-term future rather than attempting long-term prediction forecasts. In the indoor and small-cell scenarios, the near-term future is more relevant than things far ahead. The small cells are so dynamic that it does not make sense to make long-term predictions based on radio measurements and KPIs collected for small-cells. However, in these dynamic and complex indoor environments, the short-term predictions of near future are very relevant and important. In this situation, the prediction of near-future context will provide a base for forecasting the near-future network performance and the failure probabilities of the network elements.

It is known that before a cell goes to a complete outage, its performance first starts to degrade and then only after a while the cell becomes underperforming or totally dead. Finding the early signs of cell outage is very challenging because the signs may not be strong enough to be detected. In addition, it is not at all possible to detect faults that present no signs of degradation in the observed performance indicators. This is where context information comes to help by providing extra background information. In practice, the prediction of failures is not much different than early detection of the very first signs of performance degradations. By having the predicted future context, it is possible to detect those early signs of performance degradations which would lead to failures in near future.

The current CASH proposals deal with current measurements, and they are thus still reactive in nature. In what follows, we augment the SH system shown in Figure 3 to make it more proactive and pre-emptive, in order to better meet the network availability requirements of 5G.

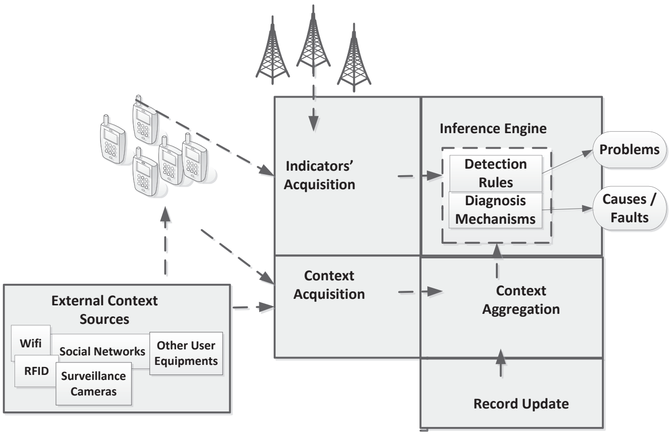

Figure 3: A simplified illustration of the CASH system presented in [31].

3.2. Proposed Augmentation: Context Prediction Engine

Our proposed extension to the system described in [31] is shown in Figure 4. What is added, is a Context Prediction Engine (CPE). It has been traditional to use current measurements to diagnose the root cause of a current problem. We propose that the same analysis methods could be used also to predict future failures and their causes. This scheme is illustrated in our figure that contains the same blocks as in [31] but adds the CPE component that includes a prediction model that feeds a duplicate of the inference engine with predicted future values. Also the outputs of the CPE are of the same form as in the original inference engine, but they relate to the near-future predicted situation, thus giving a *forecast of possible problems and their possible causes*. These outputs could be used to schedule preventive actions before the problems ever occur.

3.3. Data Processing and Analysis

Basically, any of the usual predictive methods from the machine learning vocabulary, e.g., [34] could be used. Not one method fits all purposes, so the methods should be customized and selected for each of the key attributes that are deemed worthy of inclusion in the engine. Common to these methods is that they require a comprehensive training dataset of numerical data.

The major steps required in training a predictor for one output variable usually include roughly the following:

1. Selection of the base model(s), learning algorithm(s) and the features, i.e., input measurements, to use.

2. Pre-processing and transformation of the data into a representation that is useful for the selected base algorithm(s).

3. Tuning and validating model parameters, and selecting the best-performing model for actual use.

4. Possibly combining a selected subset of the models into an ensemble that works better than any of the individual models.

4. A Case Study for Prediction of Future Context

The seeds for the idea presented in this paper were sown already some years ago when the first author of this paper participated in the Nokia Mobile Data Challenge organized by Nokia [35]. The task in the challenge was to create a user-specific predictor that learns from the user's mobility history, and predicts, based on the current user context, the next location he will visit. The next location would be considered future context, which is exactly what our proposed CPE should provide. In this paper, we use the method created for the challenge as a case study that illustrates the plausibility of the CPE.

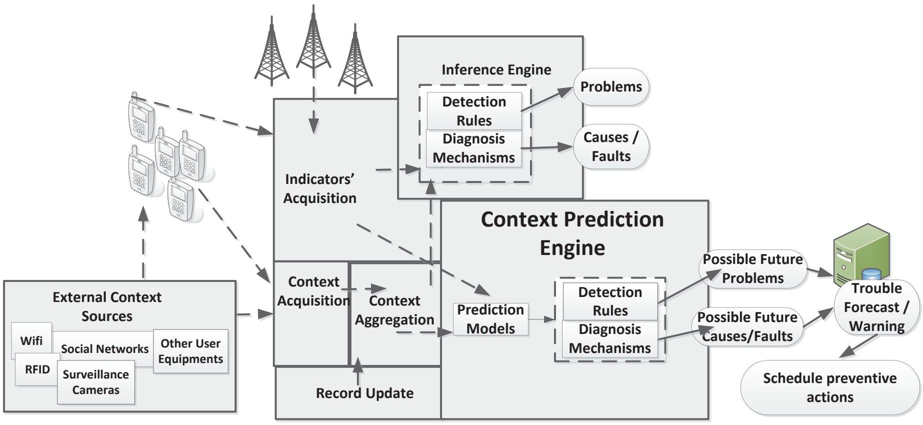

Figure 4: The CASH system of [31] augmented by a Context Prediction Engine (CPE).

The prediction of future location of a mobile user is beneficial to a network management system because of its potential application in traffic planning, radio network optimization, location-based services and also fault detection and cell outage compensation.

While, in this case study, we present the prediction of the future state of one context attribute (future user location) from the already known current context, similar methods could be used for the prediction of other attributes just as well, which could be useful in CASH.

The challenge dataset consisted of data collected from the mobile phones of 80 users, over periods of time varying from a few weeks to two years. As this was a competition, only a training dataset was given, and the final scoring was based on a testing dataset for which the true outputs were not disclosed. The sets contained smartphone data logs from disjoint time periods.

4.1. Selection of Base Models and Algorithms

The first step is to select a suitable model and useful features to use. In our scenario, the problem statement can be expressed clearly: "Given the finite set of possible locations where a mobile user can reside at a time, where will the user be next, given the current context information". This is clearly a case of classification, i.e., the prediction of the next "place ID" based on some appropriate features that can be extracted from the wealth of data obtainable from a smartphone. As usual in supervised learning tasks, the dataset was given with labels that indicate the true classes, in this case, the true destination place IDs.

From among the methods available for classification, the easiest choice during the time of the challenge was to use a specific implementation of a Multi-Layer Perceptron (MLP) that was being developed by a contemporary research group close to the competition participant. The implementation had been used earlier for continuous variable prediction in [36] and it had been found to work well also for classification tasks in other industrial projects. For further comparison and verification of the functionality of the MLP, we used also the standard, widely used, Classification and Regression Tree (CART) method available in Matlab [37].

MLPs belong to the class of feed-forward artificial neural networks [38]. They are models that comprise a number of layers of computational units, each of which performs a weighted summation and a possibly nonlinear transformation. Each unit feeds its output forward to each of the units on the next level. The structure of an MLP is illustrated in Figure 5. In this case study, only two layers were used. The knowledge acquired by an MLP is stored in the numerical values of the connection weights.

A simple MLP can be written out and computed using a compact matrix notation addressed, e.g., in [39]:

$$\mathbf{o}^0 = \mathbf{x}_i, \quad \mathbf{o}^l = \mathcal{F}^l(\mathbf{W}^l \hat{\mathbf{o}}^{(l-1)}) \quad \text{for} \quad l = 1, \ldots, L. \tag{1}$$

Here the "zero-th" output vector $\mathbf{o}^0$ is the input vector $\mathbf{x} \in \mathbb{R}^n$, i.e., the n selected numerical

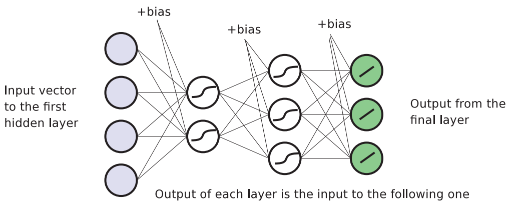

Figure 5: Schematic of a MLP neural network.

features of the current user context. For the remaining L layers, the output vector of the previous layer is always prepended with an initial element of value 1, which is denoted in the equation by a circumflex (a "hat"). The prepended vector is then multiplied by a layer-wise weight matrix, and operated element-wise by an activation function $\mathcal{F}^l$. This way the bias terms of layer l can be written as the first column of the matrix $\mathbf{W}^l$. The activation function used was the hyperbolic tangent on the inner layer and identity function on the output layer.

For compatibility with the MLP, the classes (place IDs) were encoded as binary vectors where the element with the index corresponding to the place ID is given the value 1, and the others are given the value -1. Each label c_i in a training set $\{(\mathbf{x}_i, c_i)\}_{i=1}^N$ was also thus encoded, yielding the set $\{(\mathbf{x}_i, \mathbf{t}_i)\}_{i=1}^N$ with target vectors $\mathbf{t}_i$. With an encoding like this, the MLP output will be decoded back to a class index by taking the index of the largest component. Numerical input features were scaled to the range $[-1, 1]$. For training the network, the conjugate gradient method was used. For further details on the formulation, we refer to [39]. The CART [37] of Matlab was used with the default parameters.

What matters in the end is that the predictions are made as accurately as possible for all the users recorded for the dataset, in average. Before comparisons of methods by their measured validation accuracies were deemed meaningful, some idea needed to be found about what is possible to achieve, e.g., by random guessing or similar crude, "baseline" methodology.

The frequencies of visits in different places differed greatly. The target class frequencies were determined by finding the total number of visits to each place during the available data collection period, which also varied between tracked individuals. Based on the class frequencies, we determined the most common place IDs, i.e., the places where the user is most likely to reside at any given time. For the baseline guess of the destination place IDs, we used the most common place always. This provided a baseline for the prediction of the next destination. By always predicting the most common place, the validation result would equal the class frequency, which turned out to be 32.5% on the average over all the different persons. *Anything above this accuracy would be an improvement* to the most naïve guess. Conversely, any method with a result worse than 32.5% would be practically useless. In this case, *even the naïve guess is better than uniform random guessing* due to the prior knowledge employed.

4.2. Selection and Generation of Features

From among the various features available, we first tried only the number of available WLAN connections and GSM cells present during particular time intervals. This was not enough information to create a classifier better than the naïve baseline guess. After experimentation, we ended up with the following features:

- Time of a visit: day of week (1-7), hour of day (0-23), and the length of the visit. It was assumed that much of human behavior can be explained by the rhythm of the society, where different things tend to happen on office days than during weekends, for example.

- The place of current visit. A person's mobility patterns could repeat themselves, as in possibly going to the supermarket directly from work every day.

- GSM and WLAN information: number of available WLAN connections and GSM cells present during the current visit. Perhaps such "connectiveness information" could give clues about the kind of location, even if it was not exactly the same as some other similar location.

- Call log information: we computed the number of calls made during a visit, number of text messages sent or received, and total duration of the calls. A person might relocate as a response to communication such as an invitation, or a certain level of communication could be indicative of some activity (e.g., work/hobbies) regardless of the current location.

- Other integrative measures of phone system information: whether the phone was charged during a visit, whether new media was noted, and whether media player had been active. These details would give further clues of what kind of activity was taking place, which might bear information about the situation preceding the next relocation.

Details including characteristics of the dataset, its partition, and the availability of different portions for the various challenge tasks are described in [35]. After the framework was built, it would have been very easy to append new, more elaborate features based on some kind of modeling of the rich smartphone data available, including, e.g., detailed data from the acceleration sensors and the actual identities of GSM cells, WLAN devices and phone numbers. Alas, there was a limited time for the competition, so a lot had to be left as future work for novel studies.

We focused on a sequence of place visits longer than 20 minutes. Besides the user identity, each entry consisted of current place ID, start and end times (normalized to hour-of-day, taking different time zones into account), and whether the visit's start, end, and transition to the next location were to be trusted (i.e., tracking data had been available between the locations). We considered only the trusted transitions in this study. Also, many place IDs occurred only once or twice in the training dataset. No classifier could have enough samples to do classification with regard to such rare occurrencies. Thus the training based on those place IDs would not be reliable for the test data, and we decided to disregard those.

4.3. Pre-processing and Transformation

We opted for a modular approach to address the problem: All users had to be modeled separately because the data was anonymous and user-specific. Also, the mobility of each user was independent of other users. A future research challenge would be to average activity patterns between models of different users of a network or a part of a larger network. After loading all available data, we pre-processed it: Anonymized user-specific strings were converted to integral numbers to make it easier to read in Matlab which was our chosen tool. Then we built a fully numeric input matrix. Each row of the input matrix represented one time period and the columns represented the features available that constituted our context during the current place being visited by the user.

4.4. Measuring of the Accuracy for Validation

We developed a prediction and validation framework to check the performance of the classifiers. The true labels can be used for evaluating validation accuracy on data rows that have not been used in training the model. A common way is to use some 70% of a given dataset for training and the remaining 30% for validation. However, in this case, for some users the data was very limited, and to make better use of all the available data, we chose to use cross-validation using 5 folds: Out of 5 randomly chosen subsets of the data, 4 subsets were used for training the model, and the remaining 1 (unseen during training) for measuring prediction accuracy. The overall accuracy, i.e., the percentage of correct predictions, was taken as the average over the 5 different divisions of the folds. Both the MLP and CART classifiers were employed in such a way. More folds were initially used, but after experimentation we found that the results were not greatly different when using only 5, which was suitable from the point-of-view of computational time.

During the training phase, a classifier looks for patterns in the training data. Here it tries to find out the patterns that connect the the mobile user's current context to the next place the user will visit. The patterns discovered may be spurious and noisy, i.e., they may be valid in training data but not valid or not strong in the test data. Validation attempts to alleviate this phenomenon.

4.5. Final Selection of the Classifier and Feature Set

Table 1 lists the cross-validation accuracies obtained with different classifiers and feature subsets. Observe that the models were generated independently for each user in the dataset, and what is shown is the average performance over all the 80 different users in the dataset. From top to bottom, the table shows the accuracies for CART, MLP and the naïve baseline guess for various selections of feature combinations:

- "all" means that all the features listed in Section 4.2 were used.

- "t&p" means that only the time and place features were selected.

Table 1: Cross-validation accuracies for method and feature selections (% correct: mean, worst, and best over all users, and average weighted by the users' occurrence in the data).

method	feat.	mean	min	max	wtd
CART	all	41.9	0	64.7	45.4
	t&p	43.1	0	62.6	46.4
MLP	all	42.1	10.0	63.1	45.9
	t&p	**45.5**	10.0	**69.4**	**49.1**
	t	43.4	10.0	65.3	46.6
	g&w	36.7	9.5	69.4	39.7
	calls	29.6	0	52.6	30.7
	other	33.4	10.0	62.6	35.8
	ens1	**46.4**	10.0	**71.2**	**49.9**
baseline		32.5	6.2	53.8	32.7

- "g&w" means that only the GSM and WLAN features were selected.
- "calls" means that only the call log feature was used.
- "other" means that the last feature set of Section 4.2 was used.

The first numerical column of the table contains the average (mean) accuracy of each method over all the users. The second column (min) gives the worst result obtained among the users. There were some very difficult cases with very few example measurements available. The third column (max) gives the best result obtained on a single user. The last column (wtd) gives an estimate that is weighted using the number of data points available for each user. For the competition, and possibly also for a real use scenario, such a measure, even if optimistic, could be more realistic, because it compensates for the difficulties posed by rare and possibly irrelevant users.

The accuracy percentages seem low at first (less than 50% when weighted with user data abundancy), but one has to understand that the data was extremely sparse and originated from a noisy real-world collection endeavour. Further feature modeling would certainly have helped. For the competition, and thus these results, there was barely enough time to create an MLP ensemble classifier that uses a weighed vote of the classifiers trained with other features. The weights were determined by trial and error.

All of the prediction results show a *clear improvement over naïve guessing*, and they could certainly have been made better with more elaborate feature extraction. From the results, we can conclude that the feature based on the number of calls and messages was bad, giving results worse than guessing. All other features, on the other hand, showed consistently better accuracy than guessing. The MLP performed better than the standard CART, and the very best results were obtained by an ensemble that combined the information from other classifiers. This, in part, supports the hypothesis that different features obtainable from the context contain different aspects of the user activity. Prediction of future situations based on the current and obtainable information is possible using machine learning methods.

5. Conclusion

In this paper we overviewed recent developments towards the inclusion of context information in Self-Healing solutions for Self-Organizing Networks. We suggested a way to make Self-Healing proactive via the prediction of near-future context, which should be especially useful in the small-cell scenarios in future 5G networks. As a technical example of plausibility, an earlier case study for predicting a user's mobility pattern was published here for the first time.

Training accurate prediction models requires more data than was available in the small case study presented here. Should obvious ethical and legal issues be resolved, long-term tracking and storage of user data would enable such models to become increasingly accurate within areas where the same users appear often.

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