Classification of Cells Based on Mobile Network Context Information for the Managment of SON Systems

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***Abstract*—Today's networks become increasingly complex due to the presence of multiple radio access technologies (RATs) and various network layers. The introduction of Self-Organising Network (SON) Functions that continuously modify the network's operating point support the operator on dedicated network management tasks, but need to be configured themselves in order to allow for achieving objectives for the mobile network. Another complexity that arises is that those operator objectives also change depending on the environment and the current conditions of the mobile network. It is therefore indispensable to introduce a SON management automation entity. A corresponding solution is introduced in this paper.**

Keywords—self-organising network; SON; cell classification; cell context; network management; son management; operational management; realistic scenario;

I. Introduction

In the heterogeneous topology of modern mobile networks, different cells play different roles in achieving the targeted network performance depending on various parameters such as the cell's type, employed technologies, type of the cell's environment, or density of the surrounding network topology to name a few. These different roles lead to individual targets per cell with respect to its Key Performance Indicators (KPIs) and furthermore individual parameterisations of the employed SON Functions. With thousands of cells being deployed in real networks, it becomes increasingly difficult to manually decide upon such individual settings. For this reason, the characterisation of cells is abstracted by introducing so-called context attributes describing the nature of the cell and the context it is working within. This enables the operator to express performance objectives in terms of these general attributes instead of considering each cell individually.

In this paper a mechanism to classify cells based on network context information will be introduced in order to tackle the complexity in the management of the network. Section I briefly introduces the concept of SON and SON Management and provides an example for operator objectives. After that, different applications and the methods to classify cells are explained in Section II. Finally, Section III provides a conclusion and an outlook.

A. Self-Organsing Networks

The field of SON has considerably evolved during recent years. While starting with single RAT and single layer SON Functions (with prominent examples such as Mobility Load Balancing (MLB) or Mobility Robustness Optimisation (MRO)), SON has moved towards multi RAT and multi-layer functions that change various (radio) parameters in the network [1].

But not only has the scope of the SON Functions changed, also the fundamental understanding in terms of adjusting the SON Functions themselves. Figure 1 shows the common control loop of a SON Function with a measurement phase, a calculation based on the measured values inside the SON Function, and the final (radio) parameter adjustment in the mobile network. In addition gear wheels symbolise SON Function Configuration Parameters (SCPs) whose values can be changed from outside (e.g. by the network operator). The assumption is that, by changing the SCP Values (SCVs), the behaviour of the SON Function changes.

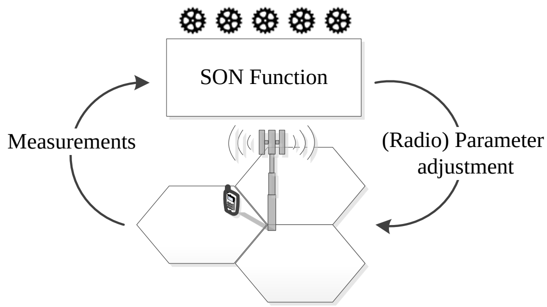

Figure 1: SON Function with control parameters

B. SON Management

The management of SONs aims at setting up SON Functions in a way that a SON-enabled network performs efficiently according to operator defined objectives. Hence, it is the main task of the SON Management to bridge the manual gap between operator objectives on the one side and SON Function configurations on the other side. In this paper, an approach based on a so-called SON Objective Manager (SOM) introduced in [2] and [3] is followed. The information that serves as input to the SOM is thereby split into two parts: The *operator* has to provide an *objective model* defining specific desires and a *context model* describing all the properties of cells in the network, e.g. technology, size or type. *Manufacturers* have to provide a description of their SON Functions in a *SON Function Model* (SFM) since SON Functions are usually delivered

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as black boxes. With those models, the SOM is able to determine SON Function configurations that lead to a network performance that best fulfils the operator objectives. An overview of SON Management components is given in Figure 2.

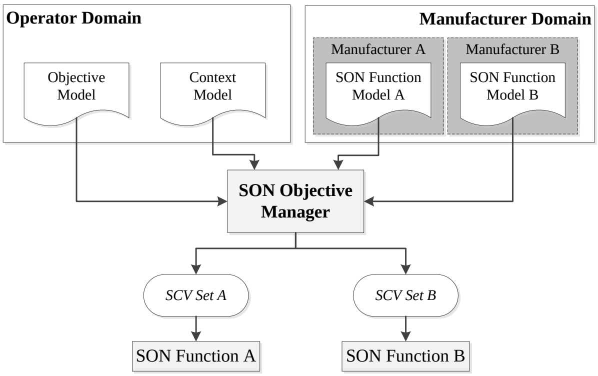

Figure 2: SON Management

C. *KPI Target Definition in the Mobile Network*

The KPI targets corresponding to the network operator's intentions need not be uniform or global for the whole network. In certain areas of the network the targets may vary in time and space. An example for temporally changing KPI targets is the following: Cells that cover a highway should show a low *Call Drop Rate* during commuting times, otherwise the target is a high *Handover Success Rate*.

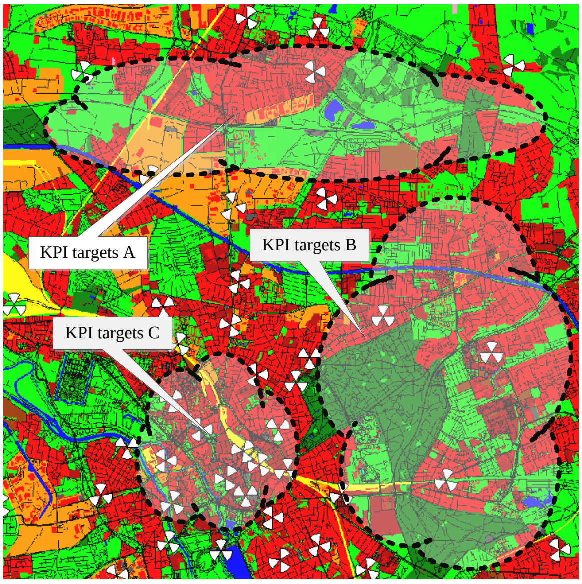

Figure 3: Example for different KPI targets in the network

Figure 3 is supposed to illustrate examples for spatially changing KPI targets. Certain areas in the mobile network are defined where different targets shall be achieved.

II. Context and Class Definition

An efficient management of individual KPI target values requires tools to automate their determination in order to reduce the amount of manual work to be done by the network operator. For this purpose, the concept of cell classification based on network context parameters will be introduced. In the context of the SOM, such classification can be applied at different levels[1].

A. *Terminology*

The following terms are of importance to understand the idea behind the determination of cell classes.

Context: The context provides an abstract description of a cell's properties and capabilities as well as the environment and situation it operates in. This may contain information such as the available technologies, cell type, location, or whether a busy hour is considered or not. The list below shall serve as a specimen for potential context attributes the operator can define.

- *CELL LOCATION* ∈ *{rural, urban}*
- *CELL SIZE* ∈ *{pico, micro, macro}*
- *CELL TECHNOLOGY* ∈ *{LTE, UMTS, GSM}*
- *TRAFFIC SITUATION* ∈ *{normal, busy-hour}*
- *MOBILITY PROFILE* ∈ *{normal, high-speed}*
- ...

The given set of context attributes spans a context space consisting of all possible context combinations that may exist. Figure 4 shows a simple context space for two available context attributes, namely the cell type and the cell technology. Note that for each additional context attribute an additional dimension is required which significantly increases the number of potential context parameter combinations.

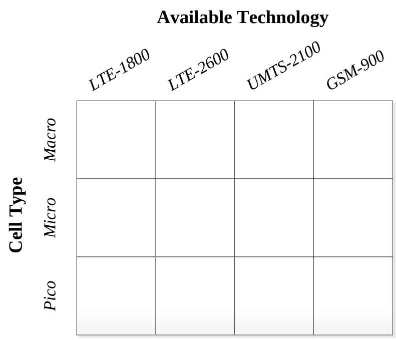

Figure 4: Example for a context space with two attributes

Class: In order to reduce the size of the context space, it may be partitioned into disjoint classes, where each class is a combination of context attributes that represents a certain cell type in the network. The specific classes are defined by the operator individually depending on which types of cells should be considered jointly, e.g. *CLASS 001* consists of the following context combinations:

- *CELL LOCATION = rural*
- *CELL SIZE = macro*
- *CELL TECHNOLOGY = {LTE, GSM}*
- *TRAFFIC SITUATION = normal*
- *MOBILITY PROFILE = high-speed*
- ...

[1] Please note: Those applications will be described in the following of this paper, but other application possibilities are thinkable as well.

Condition: The condition a cell is currently operating in can be expressed by various attributes. The most obvious one would be the time. Other attributes may be the traffic situation or the number of connected users.

Objective: An objective is a set of KPIs together with a condition for it [2]. These objectives may be defined globally or for each class individually, e.g. objectives for *CLASS 001* are:

- *CELL LOAD < 80 %, priority 2*
- *HANDOVER SUCCESS RATE > 95 %, priority 1*
- *AVG. USER THROUGHPUT > 2.5 Mbps, priority 3*
- ...

SCV set: An SCV set is a representation for a dedicated SON Function setting [4] as explained in the introduction, e.g. the *SCV set* "MLB 1" features the following SCVs:

- *MLB MAX LOAD = 80 %*
- *MLB STEP SIZE CIO = 0.5 dB*
- *MLB MAX CIO = 6 dB*
- ...

Behaviour: The behaviour describes the predicted impact that a SON Function parameterised with a certain SCV set has on the network. This prediction is provided by the SON Function [5].

B. *Application for Context and Classes*

The SOM, as described in Section I, has the purpose to find suitable SCV sets for the SON Functions implemented at each cell for every condition the cell may be in. This basic mapping is depicted in Figure 5.

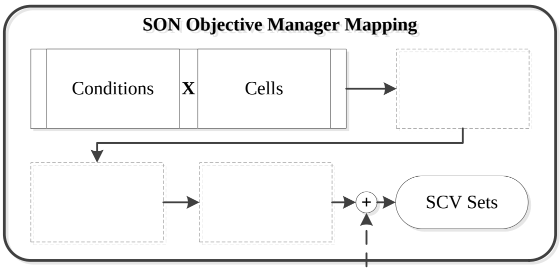

Figure 5: Goal for SON Objective Manager

In a network with tens of thousands of cells it is rather impossible to choose suitable SCV sets for each cell individually and manually.

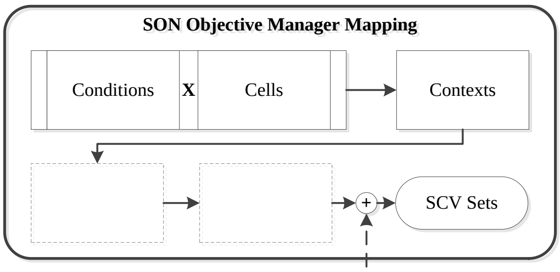

Figure 6: First reduction – Introduction of context attributes

In order to reduce the complexity of this task, the SCV set selection will be based on an abstract description of the cell's context instead of each cell individually. The assumption is that cells of the same type operating in the same situation and environment can be handled in a similar way. For this reason a characterisation of cells by means of context attributes for each condition is introduced that enables an aggregation of cells in that manner (Figure 6). An SCV set is suitable if it facilitates a SON Function in achieving an objective (Figure 7). Such objectives (cf. Section A) have to be available for the cells in question.

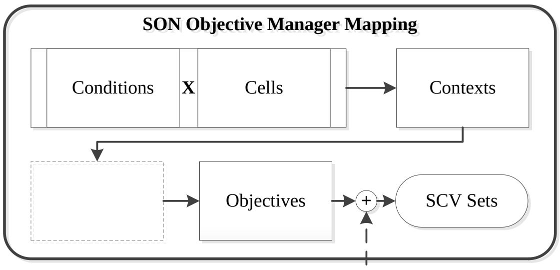

Figure 7: Introduction of objectives, formulated by the network operator

Since objectives depend on the cell's context, the role that the cell should play in the network is abstracted based on the context concept introduced above. Here the context space (as presented before) and a first application of classes come into play.

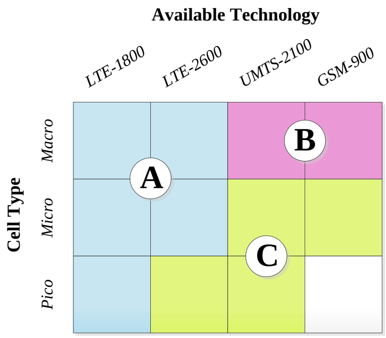

Figure 8: Example for a class definition done by the operator

Figure 8 shows an example where the context space presented in Figure 4 has been partitioned into three classes. With this the operator is able to a) reduce the amount of formulated objectives and b) ignore combinations that are not present in the network (e.g. pico GSM-900 cells). This classification can be achieved by defining context combinations that formulate a class. By checking the specific cell context attributes, such cells can be mapped to the appropriate class.

In other words, the provision of objectives for each of these context combinations would be too large to handle manually for complex context spaces. For this reason, the set of contexts may be partitioned into classes in which objectives are identical (Figure 9).

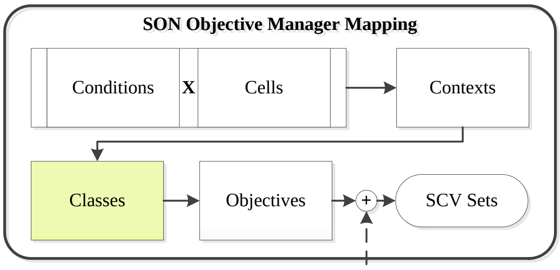

Figure 9: Second reduction – Introduction of classes that map context attribute combinations

A remaining major challenge is to find appropriate SCV sets that are in line with the defined network operator objectives. SFMs are supposed to predict, or at least give an indication about, the expected network behaviour in terms of KPIs if a certain SCV set is chosen. For example, a cell in an urban environment might experience different kinds of user mobility (and hence handover behaviour) or traffic requirements as a cell in a dense urban location. This difference should be reflected in a SFM, since the effect of SON Functions may differ depending on the cell characteristics, environment, or situation. In a specific context, different parameterisation of a SON Function yield different behaviour. It is assumed that the behaviour of a SON Function is similar for cells in the same context combination and hence the same class. These dependencies are depicted in Figure 10.

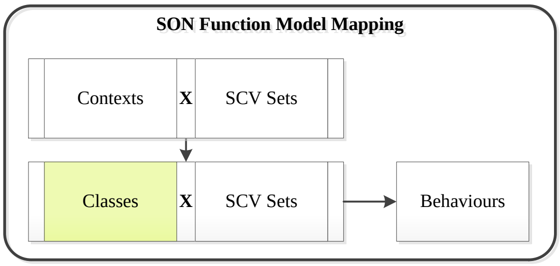

Figure 10: Contexts dependencies in SON Function Models

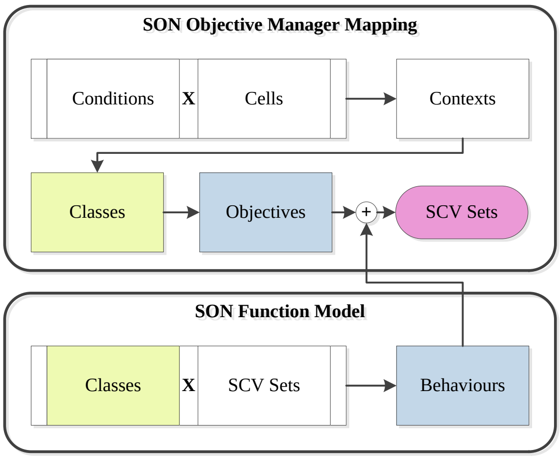

Figure 11: Combined transformation process

For a fixed context it remains for the SOM to find the SCV set which contributes the best towards the given objectives. This can be achieved by combining both mapping processes in order to reduce complexity. The SOM determines the appropriate objective for a given cell under a given condition. The SFM provides behaviour predictions for this cell with the described context attributes for each of the available SCV sets. This enables the SOM to select the SCV set that is in line with the given objective and the predicted SCV set behaviour for that context. Figure 11 illustrates the whole process.

C. *Context Class Assignment for Cells*

The methodology of determining suitable SCV sets for cells in the network described in Section I.B fundamentally relies on finding an abstract description of cells in their contexts in the form of context attributes. In this section, a mechanism to automatically determine a cell's basic context attributes is introduced and discussed.

1) *Context Attribute Identification Techniques*

The process of determining suitable SCV sets for cells based on their context described in the previous section relies on the availability of a significant description of the context of each class. This means that a sufficiently large set of context attributes has to be determined for each cell. A basic set of context attributes may be provided manually by the operator based on expert knowledge. However, with thousands of cells in modern mobile networks, manually determining even these basic attributes may be infeasible. Moreover, a cell's context may change with time, increasing the amount of context states significantly. The major part of the attribute identification and cell characterisation process has to be performed automatically, e.g. by considering the cells' surrounding environments, traffic situations, or other performance data. In the following, an algorithm will be introduced that automatically determines context attributes of a cell with regards to the type of land it covers, e.g. urban vs. rural, high-speed mobility vs. normal mobility.

The algorithm is based on analysing the footprint of a cell in terms of the character of the land. For this, a so-called land use map (or clutter map) is required. Clutter maps are usually provided in the form of pixel maps for which each pixel belongs to a distinct land use class, e.g. "low-density area" or "multi-storey building". Moreover, the algorithm makes use of pixel maps representing the received signal power for the cell in question and the powers of interfering signals. Such maps are usually available in network planning tools. The accuracy of the classification may be enhanced by using traffic intensity maps. In the first step of the algorithm, a histogram of the land use classes within the cell footprint is computed. The land use class of each pixel contributes to the histogram with a weight depending on the cell assignment probability. Such cell assignment probability is usually approximated using stochastic models based on the received signal strengths. If a traffic intensity map is available, the contribution of each pixel can additionally be weighted with its traffic intensity in order to focus on the areas that are relevant for the network. For each cell, the histogram of its covered land use classes gives an approximate description of the cell's environment. If, for example, a large part of the cell's footprint consists of the land use classes "low-density area" and "forest" and only a small area belongs to the classes "multi-storey buildings", the class may be classified as "rural". If the contribution of "road" and "highway" to the histogram is sufficiently high, one might consider classifying the cell as a "high-mobility" cell. For the second step of the process, such characterisation is performed by testing weighted sums of the histogram's bins against predefined thresholds. The concrete values of the weights and thresholds depend on the characteristics and level of detail of the land use map that is available and, e.g. have to be provided by the network operator. In the above example, one could think of characterising a cell as "high-mobility", if the sum of the value of the "road" bin with a strongly weighted value of the "highway" bin exceeds a certain percentage (it would receive a stronger weight since highways have a stronger impact towards a high mobility), e.g.:

$$hist(road) + 5 * hist(highway) > 10\%$$

The algorithm may be extended by adding additional characterising conditions such as the size of the cell footprint. In particular, if the considered cell is already established in the network, the use of historical performance measurement data may be used to enhance the attribute identification process.

2) Dynamic Context Changes

A cell's context may change over time. This may be obvious for context attributes such as "traffic situation", which changes dramatically from "low" during the nights to "busy hour" by day. For example, the traffic intensity maps can introduce strong dynamics, provided that they are used in the process. Cells that are identified to have a normal mobility type during most parts of the day may be characterised as "high-mobility" during rush hours, if the traffic intensity shifts from the building-related pixels to the street-related pixels. Also, in case individual cells are switched off, e.g. due to energy saving reasons, the footprints of the neighbouring cells expand, reaching into the area of the missing cell. This may lead to a change in their land use histograms and thus to a change in their classification. When designing automated management solutions using context classification such as the SOM described above, such dynamics have to be taken into account. This requires a continuous observation of the network performance and topology facilitating a timely reaction to changes in the cells' contexts.

3) Detection of Faults in the Assignment

Introducing automated mechanisms always raises questions about how results can be verified and how faults may be detected. Employing an automated context attribute identification algorithm, mechanisms are required to decide if a cell received inappropriate context attributes, e.g. a "rural" cell being characterised as "urban", or if context classes have been chosen poorly. It is the goal of the cell classification to group cells together that behave similarly in similar situations. With this in mind, it is possible to establish fault detection by analysing the similarity of the behaviour of cells belonging to the same context classes. Assuming that a statistically relevant set of performance measurements is available for cells belonging to a context class, the statistical variance of these measurements provide information about the quality of the classification of its containing cells. A small variance indicates that the cells belonging to the context class behave similarly, whereas a large variance indicates that the behaviour of the cells in this class is inconsistent and the class definition should be revised. A deeper analysis of the measurements could be performed using statistical outlier detection and classification methods. Cells generating measurements that have been identified as statistical outliers, behave differently than the remaining cells of the class statistically. This indicates that such cells have been characterised poorly or that they belong to a different class. With statistical analyses such as the ones described above, a fault detection mechanism may be implemented that observes the quality of the classification process.

III. Outlook and Conclusion

In this paper the need for cell classification on various levels in the mobile network has been motivated. In addition, different applications for classification have been described with examples. Self-learning techniques will be considered as a future work item. Especially when dealing with wrong cell class assignment an adjustment based on the historical network performance is necessary, since the means of detecting a wrong cell class are given but not the measures to overcome such errors. In addition it has to be mentioned that this work is meant to be one of the next steps towards allowing a unified management of a SON enabled mobile radio network. The ultimate goal is to facilitate the adjustment of cells and the SON Function running on that cell individually so that they contribute to the operator objectives in their best possible way.

Acknowledgment

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