On The Advantages of Location Resolved Input Data for Throughput Optimization Algorithms in Self-Organizing Wireless Networks

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Abstract—Performing and evaluating Call Trace (CT) or also called Minimization of Drive Test (MDT) measurements entails additional expenses to the operator as well as to the users. However, by using location specific network data obtained from the measurements as additional information for self-organization procedures, we expect these procedures to perform essentially better since they can take their decisions upon an improved knowledge base. In this paper, we investigate the performance gain induced by the use of location specific input data for self-organization procedures. For this purpose we propose, evaluate, and compare two force field based algorithms, which are dedicated to optimizing the coverage as well as the user throughput in a macro cell deployment with heterogeneous traffic demand. The results of this work confirm the expectations: It is shown that using the additional location specific information the self-organization procedure investigated leads to higher average throughput gains and an improved robustness in the sense that the procedure was able to successfully handle all scenarios investigated.

Index Terms—Self-Organizing Networks, Call Traces, Minimization of Drive Test Measurements, Throughput Optimization, Force Field Approach

I. INTRODUCTION

Self-Organizing Networks (SONs) are dedicated to steadily adjusting the network’s control parameters in order to configure the network to the greatest benefit of operators and users. Apart from the possibilities of introducing new technologies to the network and to deploy more cells (e.g. small cells), the introduction of self-organizing procedures is considered as a major opportunity to improve the network’s performance in terms of quality of service and quality of experience. Therefore, current research in industry and academia is about the development of efficient SON concepts and algorithms (see, e.g. [1], [2]). At the same time, CT or also called MDT measurements have been standardized for LTE [3]. Using CTs, the network operator is able to obtain geographically resolved measurement data from its network, i.e. we can obtain advanced information like a map of traffic demand or a map of received signal strength. Researchers expect a performance gain for their SON algorithms if the location of certain events (e.g. traffic hot spots) is known, therefore, they propose to use location resolved measurement data as input for SON algorithms [4]. However, the usage of CTs also entails various disadvantages. One of them is the increase in power consumption at the User Equipments (UEs) not just for sending the call traces itself but also due to the measurements and the necessity of a central node which processes the CTs, called Trace Collection Entity (TCE).

This paper is a contribution towards answering the question about improvements which can be expected in the performance of SON algorithms, if CTs are accomplished, evaluated, and used as additional input data for the algorithms. We will show that algorithms which use location specific input data are easily able to outperform algorithms which refrain from using this data. Since this work is focused on highlighting the differences in performance we desist from creating highly complex optimization algorithms but rather use a low complexity (computation effort scales only linear with the number of cells) force field based approach for the algorithms. In this work we propose, evaluate, and compare two different algorithms, each trying to improve the 5th percentile of the user throughput while maintaining coverage. One algorithm uses location specific input data, which can be obtained by CT measurements, while the other algorithm does not. The algorithms, which are based on a force field approach, are explained in section III. In order to evaluate the performance of each algorithm, we carried out extensive simulations in a macro cell deployment with heterogeneous traffic demand. After having introduced the system model employed, the simulation assumptions, and evaluation metrics used in section II, we present the simulation results and compare the algorithms in section IV. Section V is dedicated to the conclusion and future work.

Please note, that this paper is a continuation of our work published in [5]. While we focused on introducing a force field approach for the creation of SON algorithms in [5], we concentrate in this work on applying the concept proposed.

II. ASSUMPTIONS AND METRICS

A. System Model

This work closely follows the system model introduced in [6]. Therefore, we present a shortened version of the system.
model employed. We model the downlink of a cellular OFDM network consisting of multiple three-fold sectorized macro Base Stations (BSs) serving an area \( L \in \mathbb{R}^2 \). Each sector serves one cell. The users are assumed to be distributed according to a well defined distribution \( \lambda(u) \) given in UEs per area. The cell load is modelled using a full buffer assumption, meaning that all Physical Resource Blocks (PRBs) are used as soon as there is a single user connected to the cell. The load of cell \( c \) can be written as

\[
\eta_c = \min(1, \int_{L_c} \lambda(u)du), \tag{1}
\]

where \( L_c \) is the area served by cell \( c \). Accordingly, we can write the signal-to-interference-and-noise-ratio \( \gamma \) (SINR) at location \( u \) as

\[
\gamma(u) = \frac{P_{rx,c}(u)}{\sum_{t \neq c} \eta_t P_{rx,t}(u) + \theta}. \tag{2}
\]

In the formula above, \( P_{rx,c}(u) \) denotes the signal power received at location \( u \) from cell \( c \), and \( \theta \) accounts the noise power. Following a resource fair scheduler approach, the achievable rate for a UE at location \( u \) connected to cell \( c \) is defined as

\[
r(u) = r_{\text{1PRB}}(u) \cdot \min(B_{\text{max}}, \frac{B_{\text{max}}}{N_c}), \tag{3}
\]

where \( r_{\text{1PRB}} \), \( B_{\text{max}} \), and \( N_c \) denote the rate achievable for a UE located at \( u \) with a bandwidth of one PRB, the maximum number of available PRBs, and the number of UEs connected to cell \( c \), respectively. The achievable rate for one PRB \( r_{\text{1PRB}}(u) \) is defined according to the Shannon capacity, considering an upper bound of \( 6 \text{ bps/Hz} \).

### B. Simulation Assumptions and Scenario

An overview of the simulation parameters considered is given in Table I. We calculate the signal strength received from BS \( c \) at location \( u \) by considering a distance dependent path loss according to [7] (choosing the urban macro scenario), a 3D antenna pattern [8], an antenna gain of 14 dBi, shadowing, and penetration loss. The overall shadowing map is modelled by an equally weighted superposition of location specific shadowing and BS specific shadowing. In order to evoke coverage holes with the initial tilt setting, we consider penetration loss for every location \( u \).

Nowadays, cellular networks are facing a considerably unequal distribution of traffic demand making an optimal utilization of the network’s resources very challenging. In order to examine relevant but still acceptably complex scenarios, we choose to create a heterogeneous traffic demand scenario by placing only a single circular Hot Spot (HS) in a certain cell in the middle of our scenario. The cell chosen is the dark blue cell in the centre of Fig.1, which we will call the computation cell in the remainder of this paper. Since a SON algorithm should be able to handle any HS location, we consider 5 different HS locations covering a broad range of possible locations (from close to the antenna to the very cell edge). Please note, that in every simulation we switch on just one HS. The HS’s locations are shown in Fig. 1. The UE density within the HS, called \( \lambda_{\text{HS}} \), as well as the UE density within the remaining area, called \( \lambda \), are constant. The relationship between the UE densities is assumed to be \( \lambda_{\text{HS}} = 60 \cdot \lambda \). In order to refrain from additional complexity, we arrange the 19 site macro cell deployment in a well-known hexagonal grid. All cells have the same initial tilt of 6°. Furthermore, we choose all traffic demand to be static and consider no mobility in our simulation.

### C. Metrics

We relate the metrics used in this work to three different areas: (i) the area covered by a certain cell \( c \), called \( L_c \); (ii) a certain computation area \( L_{\text{area}} \) defined as \( L_{\text{area}} = \{ u \in L | 154 \text{ m} \leq X/25 \leq 204 \text{ m}, 124 \text{ m} \leq Y/25 \leq 188 \text{ m} \} \) (compare Fig. 1). As metrics we shall use the mean UE throughput, the UE coverage, and the 5th percentile of the UE throughput. The 5th percentile is depicted as \( Q_5(L_c) \), \( Q_5(L_{\text{area}}) \), and \( Q_5(L_{\text{area}}) \) depending on the area to which we refer. Similarly, we depict the various throughput mean as

<table>
<thead>
<tr>
<th>Simulation Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier Frequency</td>
<td>2 GHz</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>10 MHz</td>
</tr>
<tr>
<td>BS Height</td>
<td>30 m</td>
</tr>
<tr>
<td>BS Transmit Power</td>
<td>20 dBm/PRB</td>
</tr>
<tr>
<td>BS Antenna Gain</td>
<td>14 dBi</td>
</tr>
<tr>
<td>UE Min. Receive Power</td>
<td>−120 dBm/PRB</td>
</tr>
<tr>
<td>UE Height</td>
<td>1.5 m</td>
</tr>
<tr>
<td>Thermal Noise</td>
<td>−121 dBm/PRB</td>
</tr>
<tr>
<td>Penetration Loss</td>
<td>20 dB</td>
</tr>
<tr>
<td>Spatial Resolution</td>
<td>25 \times 25 m</td>
</tr>
<tr>
<td>Inter Site Distance</td>
<td>1732 m</td>
</tr>
<tr>
<td>Initial Tilt</td>
<td>6 °</td>
</tr>
<tr>
<td>Shadowing STDV</td>
<td>8 dB</td>
</tr>
<tr>
<td>Shadowing Decorrel. Dist.</td>
<td>50 m</td>
</tr>
<tr>
<td>UE Density Low</td>
<td>8 UE/km²</td>
</tr>
<tr>
<td>UE Density High</td>
<td>480 UE/km²</td>
</tr>
<tr>
<td>Number of HSs</td>
<td>1</td>
</tr>
<tr>
<td>HS Diameter</td>
<td>250 m</td>
</tr>
</tbody>
</table>
\( \mathcal{L}_c, \mathcal{L}_{HS}, \) and \( \mathcal{L}_{area} \). In each case, we compute the throughput for a UE located at \( u \) using Eq. (3). Every uncovered UE contributes a zero throughput to the mean or the 5th percentile. The intention of referring the throughput and coverage to the computation area \( \mathcal{L}_{area} \) is to evaluate effects in the computation cell and its neighboring cells using only one metric.

We refer the UE coverage either to a certain cell area \( \mathcal{L}_c \) or to the computation area \( \mathcal{L}_{area} \). We define the generic UE coverage as

\[
C = \frac{\int_{\mathcal{L}_c} \lambda(u) du}{\int_{\mathcal{L}_2} \lambda(u) du}.
\]

Inserting \( L_2 = \hat{L}_c = \{ u \in L \mid P_{tx,c}(u) > P_{tx,l}(u) \forall t \neq c \} \)
and \( L_1 = L_c = \{ u \in L_c \mid P_{tx,c}(u) \geq -120 \text{ dBm} \} \) leads to the cell specific coverage, \( C(L_c) \). Choosing \( L_2 = \mathcal{L}_{area} \) and \( L_1 = \{ u \in \mathcal{L}_{area} \mid P_{tx,c}(u) \geq -120 \text{ dBm}, \text{for any } c \} \) leads to the coverage \( C(\mathcal{L}_{area}) \) that refers to the computation area.

III. THE ALGORITHMS

The algorithms developed in this work are based on a force field approach introduced in [5]. In the following, we will briefly outline this novel concept for joint optimization in wireless networks. For more details on the concept itself please see the reference mentioned above. In the force field approach, forces created by potentials act on the network parameters to modify them. Each force modifies the parameter in the direction required to minimize the potentials from which it originates. Each potential states the optimization goal for a certain Key Performance Indicator (KPI). Therefore, each potential is: (i) a convex function of a KPI considered in the optimization; (ii) minimized within the desired KPI value range; (iii) bears a higher cost for KPI values off the desired value range. From well-known laws in physics, the derivative of the potentials is proportional to the force. Similar to forces in physics, the forces created in this work are proportional to the first derivative of the potentials. Since all forces which act on a particular parameter interfere with each other, we concurrently consider all relevant KPIs when adjusting a particular parameter. An algorithm following this force field approach operates iteratively by taking the KPI values as an input, the algorithm generates forces using the potentials. In the next step, the forces act on the parameters and, therefore, modify the parameter’s value. New KPI values are obtained and the next iteration begins. Note that this approach requires no coordination entities even though it is a joint optimization approach. Furthermore, its complexity scales only linearly with the number of parameters and KPIs.

Goal of the SON simulated in this work is to shift or hold the \( Q_s(\mathcal{L}_c) \) of each cell above 400 kbps while maintaining \( C(\mathcal{L}_{area}) > 98 \% \). Both algorithms, presented in the following, are dedicated to run locally at every BS. We assume that each cell \( c \) can compute its \( Q_s(\mathcal{L}_{cell}) \) and its \( C(\mathcal{L}_c) \). While the former assumption can be read directly from throughput measurements of each UE connected to the cell, the latter assumption is not straightforward, but can at least be approximated, e.g. by call drop statistics.

The algorithms are dedicated to modifying the antenna tilt \( \varphi_c \), which can be the electrical tilt in practice. Furthermore, the algorithms grow or shrink cell areas by using a Cell Individual Offset (CIO) for each cell, depict by \( CIO_c \), for cell \( c \). In a real network, the CIO is involved in the handover process. Due to the lack of mobility in our simulations, we apply the CIO to the cell selection process of each UE. Hence, a UE connects to BS \( c \) if \( c = s(u) := \arg \max_c P_{tx,c}(u) + CIO_t \).

Accordingly, we modify the definition of \( L_c \) as follows: \( L_c = \{ u \in L \mid P_{tx,c}(u) + CIO_t > P_{tx,l}(u) \forall t \neq c \} \). We choose the continuous parameter range from –5 dB to 0 dB for the CIO, and the continuous range from 0° to 15° for the tilt. Please note, that in a practical application the CIO and tilt values may not be tunable in continuous values, however, we stick with the continuous range in order to obtain optimal solutions.

A. Algorithm 1

This algorithm is dedicated to reach the optimization goal mentioned above without needing location specific information, or the CIs which are collected and shared by a central unit. Hence, algorithm 1 has no information about the traffic demand distribution. The algorithm considers the KPIs \( Q_s(\mathcal{L}_c) \) and \( C(\mathcal{L}_c) \) \( \forall c \). Therefore, we define a potential for each KPI stating the optimization goals. The potentials employed are presented in Fig. 2 and 3. As can be seen clearly, no forces will be generated from the potentials if \( Q_s(\mathcal{L}_c) > 400 \text{ kbps} \) and \( C(\mathcal{L}_c) > 98 \% \). In the event of \( Q_s(\mathcal{L}_c) \leq 400 \text{ kbps} \), two forces will be created – one acting on the cell’s antenna tilt \( (\overline{F}_{Q_s(\mathcal{L}_c), CIO}) \), and the other on the cell’s CIO \( (\overline{F}_{Q_s(\mathcal{L}_c), CIO}) \).

By definition, these forces will increase the tilt and decrease...
In reality, we use the additional location information to steer the CIO. Hence, we use the UE distribution of the Global Navigation Satellite System (GNSS) and can demand which in practice has been processed and shared from increasing. The area, in which $f$ and $g$ are zero, is shifted towards negative $\Delta \varphi$ in order to reduce uptilting procedures.

the CIO. If $C(L_c) \leq 98\%$, the forces created ($F_{C(L_c), \varphi_c}$ and $F_{C(L_c), CIO}$) lead to a decrease in the antenna tilt and to an increase in the CIO, respectively. Note, that both potentials are not differentiable at their threshold making it impossible to derive the first derivative at this point. Therefore, we use the left-hand derivative at the thresholds. The effective direction of the forces is defined with the intention that increasing the tilt decreases the cell size, which leads to more available resources for the UEs remaining in the cell and, therefore, leads to higher rates. From a tilt decrease, we expect an increase in cell size leading to better coverage. In an equivalent manner, we decrease the CIO in order to decrease the cell size and vice versa. Note that in certain situations the algorithm can yield to, what we call, trade-off solutions, where both forces cancel each other out.

B. Algorithm 2

Algorithm 2 uses exactly the same potentials, parameters, and parameter ranges as defined for algorithm 1. However, in contrast to algorithm 1, algorithm 2 employs a map of traffic demand which in practice has been processed and shared from a TCE. The location information may be obtained by the usage of the Global Navigation Satellite System (GNSS) and can be reported by the UEs within the MDT measurements [3]. Hence, we use the UE distribution $\lambda(u)$ as an available input for this algorithm. For simplicity, we consider the location information to be absolutely correct, what may not be the case in reality. We use the additional location information to steer the forces originating from the KPI $Q_5(L_c)$ more cleverly than introduced in algorithm 1. The idea is to calculate the center of traffic demand of the area covered by a cell $c$, and use this outcome to calculate the tilt $\varphi_{\text{CoT},c}$ which would be required to focus the antennas directly at the center of traffic. In the case of $Q_5(L_c) \leq 400$ kbps, the same forces as in algorithm 1 are created. Since the current traffic distribution is known, we multiply these forces with the functions presented in Fig. 4. The deviation between the tilt $\varphi_{\text{CoT},c}$ and the current tilt $\varphi_c$ is defined as $\Delta \varphi_c = \varphi_{\text{CoT},c} - \varphi_c$. We multiply the force acting on the tilt with the function $f$, leading to the fact that we always tilt towards the centre of traffic. Similarly, we multiply the force acting on the CIO with function $g$ leading to the effect that we decrease the CIO in case of an uptilt and vice versa. In this way, we use the CIO to cleverly counteract a cell size increase in case of an uptilt and also counteract an increase of the cell area of neighbouring cells in case of a tilt increase. Basically, we use the additional information to decide whether we increase or decrease the tilt (and CIO) in case of a very low $Q_5(L_c)$. The coverage forces are identical to those in algorithm 1.

IV. Simulation Results

We focus our evaluation on the scenario, where HS 3 is switched on, and the scenario, where HS 4 is switched on, while we summarize the results in the other scenarios. For the detailed evaluation of the algorithm’s performance we consider the Cumulated Distribution Function (CDF) of the achievable rates $r$ with respect to the HS area as well as with respect to the computation area defined in section II-C. The figures 5 and 6 present the CDF of the achievable rate in the case where HS 3 is switched on, while the figures 7 and 8 refer to the case where HS 4 is switched on. For the former case, where the HS is almost directly in front of the antenna, it is visible that both algorithm 1 and 2 increase the achievable rates for the UEs. Algorithm 1 outperforms algorithm 2 for higher rates while it is the other way around for the cell edge users. The relative gain in the 5th quantile with respect to the initial situation (labelled as baseline in Fig. 5 to 8) referring to the HS area is 58% for algorithm 1 and 80% for algorithm 2. The reason for the better performance of algorithm 1 for higher rates is an improved distribution of the UEs among the various cells caused by increasing the tilt in the computation cell by more than what would be required to tilt directly at the traffic hot spot (final tilt and CIO at computation cell: 9.1° and $-0.8$ dB for algorithm 1, 8.6° and 0.65 dB for algorithm 2, respectively). For the same reason, the SINR in the HS is not as optimal as it is after running algorithm 2. Therefore, algorithm 1 performs worse than algorithm 2 for the cell edge UEs. However, both algorithms are able to improve the throughput in case where HS 3 is switched on. Looking at the case where HS 4 which is located at the cell edge and outside the main antenna lobe is switched on, we observe a different behaviour. On one hand, algorithm 1 degrades the achieved throughput values, and on the other hand, algorithm 2 can induce a gain. This difference is caused by the additional information used in the second algorithm. Considering the map of traffic demand, algorithm 2 decreases the tilt in the computation cell, while algorithm 1 increases the tilt. Since the HS is right at the cell edge, a tilt increase leads to less coverage and a worse SINR in the HS area, thereby, having a considerably worse impact on the performance in the larger computation area as well. Algorithm 2, however, improved the SINR at the HS and balanced the user distribution by diminishing the CIO in the computation cell. Also in the remaining cases where HS 1, HS 2, and HS 5, respectively are switched on algorithm 2 improves all metrics considered for evaluation: $Q_5(L_{\text{HS}})$, $Q_5(L_{\text{area}})$, $\bar{L}_{\text{HS}}$, and $\bar{L}_{\text{area}}$. Algorithm 1, however, worsens the metrics considered in the other cases, except for $Q_5(L_{\text{HS}})$ and $Q_5(L_{\text{area}})$ in the case where HS 1 is switched on. Owing to the coverage force, both algorithms are
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V. CONCLUSION AND FUTURE WORK

In this paper, we proposed, evaluated, and compared two throughput optimization algorithms. One of the algorithms considers location specific input data and the other does not. We have shown that, though the additional information required is rather low, the performance in terms of robustness and absolute gains of the throughput optimization can essentially be increased. Based on this insight, the results presented in this work indicate that the efforts to collect and evaluate location specific data are worth it, since they can generate essential performance gains in network optimization procedures, and therefore, help operators prepare their networks for challenges of the future.

Since the generation of the location information requires additional energy, e.g. for MDT measurements, we plan to also incorporate the metric energy consumption in future work. Furthermore, we plan to study the impact of faulty location maps on the performance of the algorithm using the location information as input data.

REFERENCES


