

Mobility and QoS Prediction for Dynamic Coverage Optimization

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Abstract—This demonstrator shows, how Machine Learning (ML) based predictions can be used for closed-loop optimization in operational network management. It is based on data collected from an actual testbed deployed at the Hamburg Smart Seaport and uses a *digital twin* of the testbed to demonstrate how Coverage and Capacity Optimization (CCO) and Beam Adaptation (BA) functions can utilize mobility and Quality of Service (QoS) predictions to prevent service degradations. At the same time it studies the use of digital twins in operational network management automation and the robustness of ML models against changes in the environment.

Index Terms—Machine Learning, Cognitive Network Management, Closed-loop Automation, Digital Twin

I. MACHINE LEARNING IN THE TESTBED

A. The Testbed

The Hamburg Smart Seaport 5G testbed has been created as a part of the 5G Mobile Network Architecture (5G MoNArch) project [1] and demonstrates dynamic network slicing. A network slice is a virtual network instance, which can share the same physical infrastructure with other network slices. The testbed consists of one site with two cells that cover the entire harbor. In this work, we focus on the Internet of Things (IoT) slice, which is used for reporting emission sensor readings from barges moving in the harbor area.

We collected data from the testbed, both the (slice-specific) Base Station (BTS) Key Performance Indicators (KPIs) and the User Equipment (UE) measurements from up to three ships including position reported by the Global Positioning System (GPS), Reference Signal Received Power (RSRP), latency etc. The data collection took place over a time of 6 months in 5

second granularity, with all in all around 3 million records collected.

Certain parts of the testbed show low signal strengths, especially for the ships that are moving around the whole harbor area. This is caused partly by shadowing of the high river bank and tall buildings, partly simply by the long distances from the BTS. An example of such a shadowing effect from the collected UE measurements is shown in Figure 1; As the ship enters a shadowed area, the RSRP drops abruptly and latency increases. In this example, the shadowing even leads to a Radio Link Failure (RLF).

B. Mobility and QoS Prediction

Our initial research studied whether it is possible to use analytics and Machine Learning (ML) to predict these service degradations in the IoT slice. Two ML models were created based on the UE measurements: a radio propagation map and a deep Convolutional Neural Network (CNN) to predict the movement of the barges. With the CNN we wanted to see if additional context information (location, time of the day etc.) could be used to improve the accuracy of the mobility predictions. These models are depicted in Figure 2. The radio propagation map is shown on the left, indicating the areas with low RSRP values. The movement prediction is shown on the right. The blue line represents the input sequence of the reported ship locations, the purple line is the ground truth for the future trajectory and the red line is the prediction 8 steps ahead, which equals to 40 seconds.

We were able to predict 97.6% of 65206 sequences that ended in either an RLF or below $-120dB$ RSRP. We encountered altogether 96 false positives (0.14% of total observations, and 20% of true drops. There were 12 false negatives (0.02%

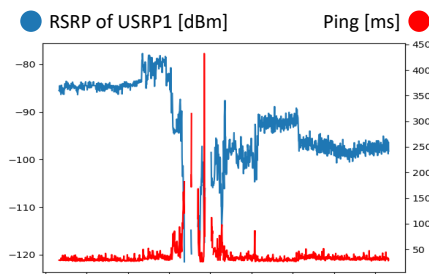


Fig. 1. Shadowing effects

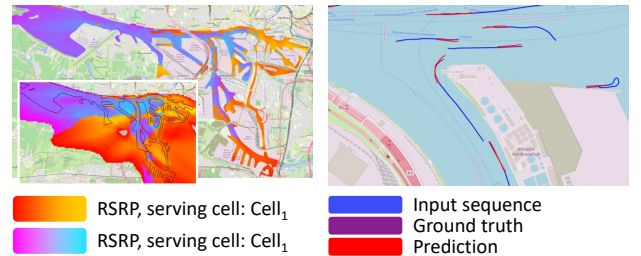


Fig. 2. RSRP and mobility prediction



Fig. 3. Digital twin of the Hamburg port testbed

of total observations, and 2.5% of true drops). In our case, false positives are not dangerous, since the corrective actions are not very intrusive. Also, many of the false positives were very close to our (arbitrary) threshold. The false negatives are potentially disruptive, but these were very few.

II. THE DEMONSTRATION

This demonstrator shows, how the mobility and Quality of Service (QoS) predictions can be utilized in closed-loop network automation to preemptively react to QoS degradations and to prevent them. The predictive capability allows configuring the optimization functions in a way, which saves resources and reduces conflicts between different optimization targets, while still ensuring an uninterrupted reliable service and dynamic reaction to different conditions.

For this purpose, a simulation environment was created, which includes a model of the city of Hamburg and especially of the harbor area, to create a *digital twin*, in which the testbed is replicated. Furthermore, recorded movement traces of the ships were imported into the simulation for realistic mobility. Figure 3 shows how the testbed is mirrored in the simulation and in its Graphical User Interface (GUI). With this setup, the detected coverage issues in the real testbed can be reproduced. Additionally, the digital twin is extended to simulate beam forming.

The architecture of the demo setup is shown in Figure 4. In addition to the simulated scenario and the mobility traces that are imported into the simulator, a Cognitive Network Management System (CNMS) integrates into its northbound interface. The CNMS implements a closed-loop automation cycle based on a ML pipeline [2]. The Data Collector collects UE measurements from the simulation. Based on the reported locations, Mobility Pattern Prediction (MPP) predicts

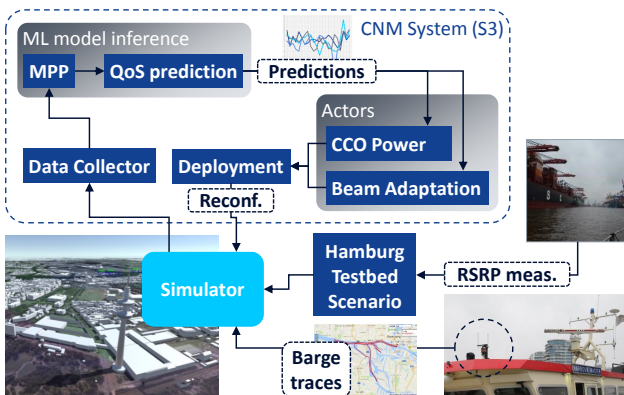


Fig. 4. The architecture of the simulation setup

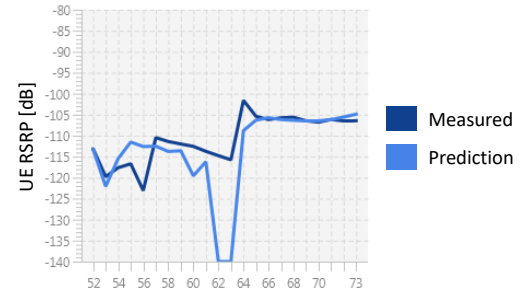


Fig. 5. Mobility and RSRP Prediction

the future location of the barge 40 simulated seconds ahead. The predicted location is again used by the QoS Prediction to determine the expected RSRP. The predictions are utilized by optimization functions (*actors*), which create recommendations for reconfiguration. In our demonstration, the selected actors are the Coverage and Capacity Optimization (CCO), adjusting cell transmission power and the Beam Adaptation (BA) function, optimizing beam configuration.

III. RESULTS AND CONCLUSION

The demonstrator shows how the CCO and the BA functions can prevent predicted degradations (Figure 5). The dark blue line is the RSRP measured by a ship and the light blue line is the predicted value. At point 62 a RLF is predicted. The CCO preemptively adjusts the cell transmission power and the BA function configures the beam forming so that when the ship is entering the shadowed area, a beam is already pointed there. If necessary, the BA function will also split a beam to be able to optimally serve the whole covered area. With these actions the ship experiences no degradation at all. Once the ships leave the shadowed area, the compensation is gradually configured back to the baseline to save resources and to reduce the compromises the compensating reconfigurations have on other UEs and slices.

A further demonstrated consideration is the robustness of the ML models against changes in the environment, including those based on the insights coming from the model itself. In this case, the reconfigurations change the observed signal strength and reduce the accuracy of the predictive models that were trained with a different network configuration. The advantage of separately predicting the future location and the expected QoS using two independent models, is that the reconfigurations only affect the radio propagation model, but not the MPP. We can then utilize the simulator as a digital twin of the network to model the RSRP. This demonstrates the advantages of a digital twin in operational network optimization, but of course depends on the availability of such a realistic twin. Other methods to mitigate the problem are further study items.

REFERENCES

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