Learning Based Proactive Handovers in Heterogeneous Networks

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Abstract. Today, the number of versatile real-time mobile applications is vast, each requiring different data rate, Quality of Service (QoS) and connection availability requirements. There have been strong demands for pervasive communication with advances in wireless technologies. Real-time applications experience significant performance bottlenecks in heterogeneous networks. A critical time for a real-time application is when a vertical handover is done between different radio access technologies. It requires a lot of signalling causing unwanted interruptions to real-time applications. This work presents a utilization of learning algorithms to give time for applications to prepare itself for vertical handovers in the heterogeneous network environment. A testbed has been implemented, which collects PHY (Physical layer), application level QoS and users context information from a terminal and combines these Key Performance Indicators (KPI) with network planning information in order to anticipate vertical handovers by taking into account the preparation time required by a specific real-time application.

Keywords: Vertical Handover, Heterogeneous Network, Key Performance Indicator, Machine Learning, Quality of Experience.

1 Introduction

Next generation communication systems provide a wide range of services and aim to provide sufficient QoE (Quality of Experience) to users anywhere and anytime. This involves using heterogeneous networks to provide services effectively and efficiently. It is very challenging for mobile operators to balance the load in networks of multiple radio access technologies, for example LTE, UMTS and GSM. On the other hand, with the advent of smart mobile terminals supporting multiple network technologies, mobile applications also have options to select the most appropriate network to support their own requirements. This leads to the requirement of transition from one access network to another seamlessly providing better quality options for users. These challenges are dealt with emerging IEEE 802.21 specification, which supports handovers between IEEE 802 and non-IEEE 802 (3GPP) access technologies to enable seamless mobility in next

D. Pesch et al. (Eds.): MONAMI 2013, LNICST 125, pp. 57–68, 2013.

generation heterogeneous wireless network [1]. To facilitate better management of multi-access networks for operators and to assist users in making suitable network selection, automation through cognitive management mechanisms is seen as a potential solution for optimal utilization of multiple access networks. Our motivation was to implement a platform to evaluate different learning based algorithms to be utilized in the vertical handover decision-making. The objective was to fuse real-time monitored KPIs and predicted location and speed dependent KPIs in order to enable foresight decision-making, and thus give mobile applications enough time to prepare themselves for vertical handovers.

Network performance can be estimated based on three orthogonal dimensions: coverage, capacity and QoS [2]. Better user experience requires better QoS and large capacity while network operators are more focused on coverage and capacity. The current trend seems to be moving towards a QoE centric approach, as device intelligence is increasing. However, the operators viewpoint cannot be overlooked as they are providing the network services. Our motivation is to find configurations that satisfy both viewpoints and hence maximize mutual benefits. However, it requires real-time information from both terminal and network sides to find correct configurations. Cross-layer communications and network monitoring play a key role in providing real-time context information.

To investigate the topic, we used the testbed called HET-Q. HET-Q is designed to collect location, real-time PHY/MAC (Medium Access Control) and application level QoS information from a user in all available networks. Intelligent elements observe current network conditions, learn from their earlier decisions, and adapt their operations accordingly. For implementing an intelligent handover mechanism, different machine learning algorithms can be applied, such as Self-Organized Map or a Normal Bayesian Classifier [3] [4]. Both terminal and network sides are designed to have cognitive functionalities. Foresighted selection of the best network requires utilization of the users location and network planning information. Furthermore, along with multi-radio access network aspects, multi-operator aspects with different service classes need to be considered.

In this paper, we will present the architecture of our testbed that supports cognitive handovers. We also present cognitive concepts to assist in making proactive handovers among available networks. The test cases illustrate the ability of the testbed to make use of machine learning algorithms for selecting an appropriate network and to allow time for a mobile application to prepare for a vertical handover.

2 HET-Q Architecture

The architecture of the HET-Q testbed is depicted in Fig. 1. The testbed includes a server side application, HET-Q server and a client side application called HET-Q client. Communication between the applications is done over UDP or TCP/IP connections. The mobile HET-Q client collects MAC/PHY level KPIs, application level QoS KPIs, and location information. Location information is retrieved from a GPS device while outdoors. While indoors, location information is retrieved from an indoor positioning system. The QoS parameters are collected with the measurement tool QoSMeT [5] [6] which is installed on the HET-Q client and server. The QoSMeT server is monitoring a large set of application level QoS KPIs over a point-to-point connection. The PHY/MAC layer information is obtained from wireless modules locked on specific radio access technologies. The PHY/MAC data is retrieved using low level interface queries, such as Hayes command set, also called AT commands. The testbed enables both real-time as well as offline measurements. A commercially available network monitoring tool (Nemo Outdoor) was used to provide offline measurements for validation purposes. The server combines the incoming information with network planning information, and gives the aggregated data to a decision-making algorithm. The algorithm makes a proactive decision beforehand whether the terminal using specific service class (web browsing, video streaming or FTP downloading) should make a vertical handover to another available network or not. The decision is sent as a forced-HO or proposed-HO command to the terminal. In the latter case, the terminal decides whether it obeys the proposal or not. The handovers are executed either using an Intelligent Vertical Handover (IVHO) controller [7] or by directly commanding wireless modules through internal interfaces.

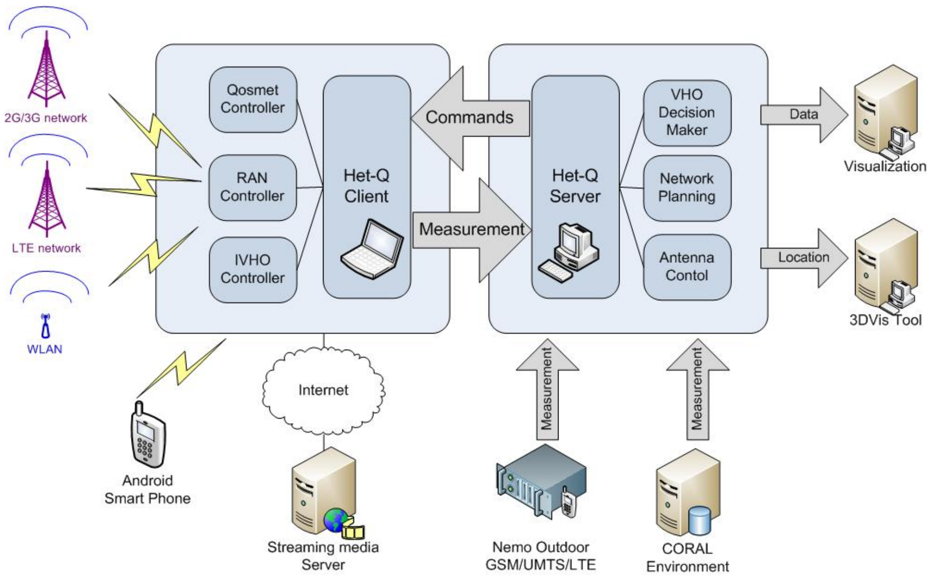

Fig. 1. HET-Q testbed with main components and interfaces

The HET-Q server is run on a server computer. Its GUI is shown in Fig. 2. It shows detailed information about the defined network layouts and a view of a 3D propagation environment including terrain height, clutter and building information. The real time measurement can be controlled by the HET-Q server.

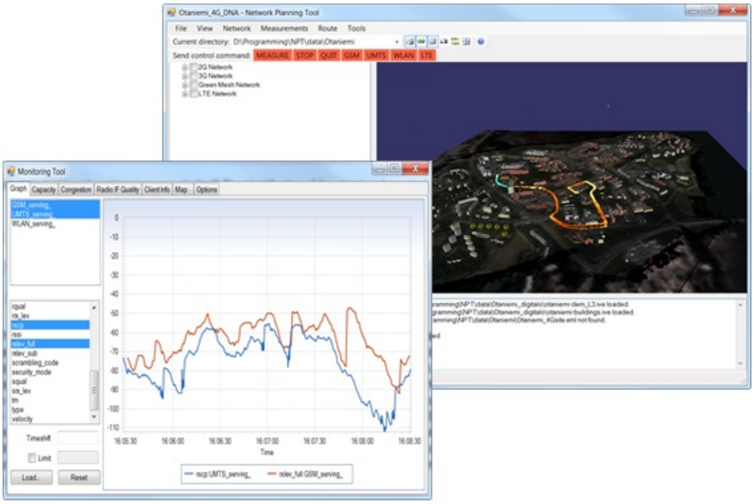

Fig. 2. HET-Q User Interface with main components and interfaces

An auxiliary Monitoring Tool is typically used for visualizing measured and computed MAC/PHY and application level QoS KPIs. Furthermore, QoSMeTs GUI is also used for visualizing application level QoS KPIs. The QoSMeTs real-time point-to-point monitoring views are presented in Fig. 3.

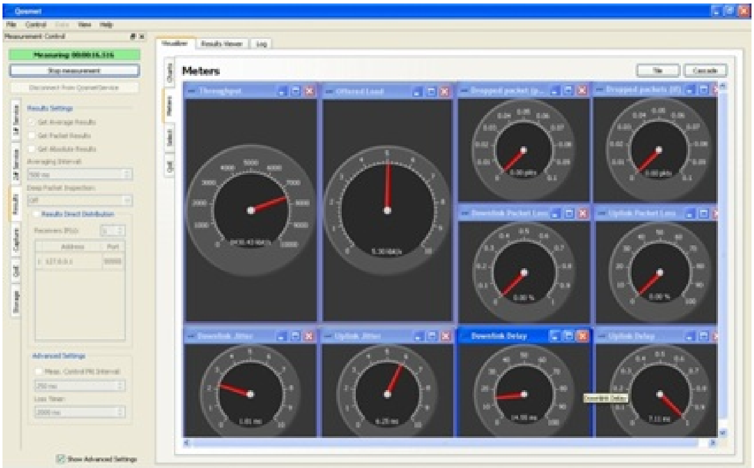

Fig. 3. QoSMeT GUI for monitoring QoS KPIs

3 Utilization of Cognitive Concepts

Cognitive functionality is utilized in the HET-Q testbed in three ways:

– Machine learning algorithms
– Network planning information
– Cognitive radio parameters

3.1 Utilization of Machine Learning Algorithms

Machine learning algorithms were experimented to assist vertical handovers in heterogeneous networks. Experimented algorithms were K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Normal Bayesian Classifier (BAYES), Expectation-Maximization (EM), Multi-Layer Perceptron (MLP), Boosting algorithm (BOOST), Decision Tree (DTREE) and Random Tree (RTREE). We used the OpenCV library implementations of these algorithms [8]. The algorithms were implemented in the HET-Q servers decision-making module. The data flow of the decision-making process is shown in Fig. 4.

Learning algorithms are taught to select the most appropriate radio access technology for a user based on the used service type, measured and predicted KPIs, and location. Training data consists of aggregated information from real-time measurements, network planning data, and users location. Classifying the training samples is done by using prior knowledge of human experts by continuous scrutiny of PHY and MAC parameters. Classifying means that we select the most suitable radio access technology for the application being used. The classified data provides the most suitable network for each measurement sample. Learning algorithms construct their knowledge according to training data. The

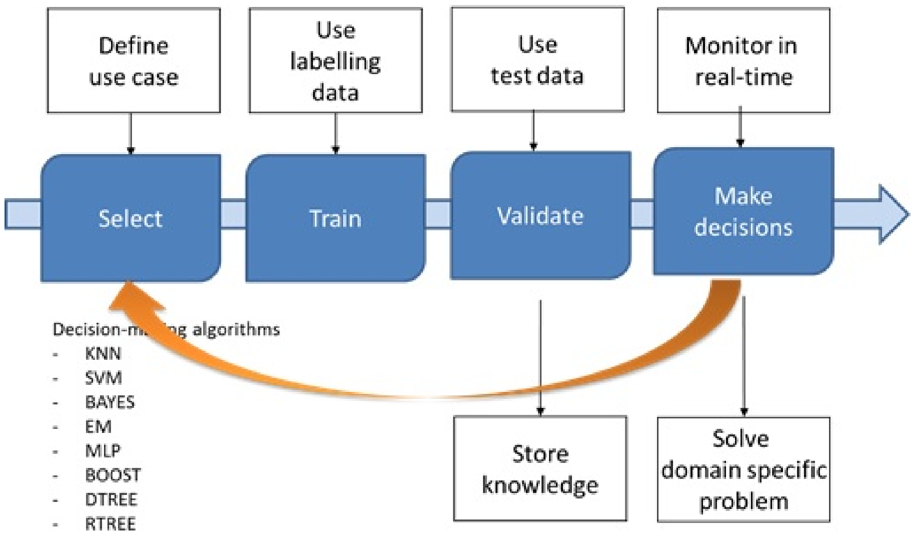

Fig. 4. Data flow of the decision-making process

reliability of the trained algorithm is validated with test data. An algorithm having the highest percentage of correctly classified samples (reliability) is selected for operational use.

3.2 Utilization of Network Planning Information

The HET-Q server uses network planning information in order to give a terminal enough time to prepare for a vertical handover which is critical for real-time streaming applications. Coverage, interference, and data rate prediction results are computed beforehand for the test scenario area using a network scenario and appropriate propagation model. These predictions are fine-tuned and validated with field measurements. Predicted KPIs are calculated at a presumed location of a user using the users current location, heading, and speed. The foresighted decision whether to make a handover relies on the accuracy of network planning information, e.g. coverage, and a users predicted location.

Coverage, interference, and data rate predictions depend on a base stations radio parameters and the modelling precision of the propagation environment. Measurements from dedicated measurement tools e.g. HET-Q client, Nemo Outdoor can be used for fine-tuning prediction models in order to get better equivalence between measured and predicted values.

The availability of digital map information has significantly increased in recent years. Moreover, the 3D virtual modelling and similar tools have matured enough to enable the creation of realistic 3D propagation environments, which include terrain, vegetation, and building information. The used 3D propagation environment models were obtained from National Land Survey of Finland. Unfortunately, most propagation models (called 2.5D models) take neither vegetation nor building shapes into account. Therefore, additional clutter parameters were added to those propagation models to improve prediction accuracy. The clutter parameters

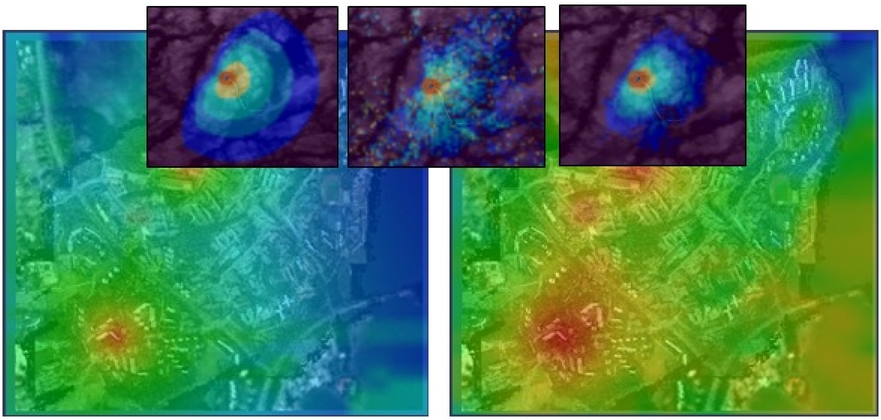

Fig. 5. Predicted coverage of a base station (background) calculated with a propagation model and then optimized (top) with the help of field measurements and location information

are optimized using field measurements. The tuning of a propagation model is illustrated in Fig. 5. The first picture shows a base stations coverage computed with a coverage prediction model, the second one after the clutter parameter tuning, and the last one after a so-called sanity-check. The last step ensures that clutter types attenuation factors are obeying laws of physics e.g. a forest type cannot amplify the signal. During the sanity-check, coverage areas are typically optimized to be a bit pessimistic in order to provide sufficient margins e.g. for fast fading.

3.3 Utilization of Cognitive Radio Parameters

Channel utilization level of WLAN APs is obtained from a CORAL platform which is designed for research purposes to experiment with Cognitive Radio Networking features [9]. The platform reports, which reports the occupancy level of each WLAN channel. The information is used to avoid unnecessary handovers to WLAN if WLAN channels are highly congested. Performance indicators given by CORAL can be considered as cognitive radio parameters. The CORAL platform plays an important role in the HET-Q testbed when a WLAN network is included in the scenario. The monitored PHY/MAC and QoS parameters cannot give adequate indication of what is the load level in the target access point (AP) when a vertical handover is about to occur. Moreover, the end to end QoS measurement tool QoSMeT is limited to measure QoS KPIs only in the active network (network the terminal is currently connected to). If the target AP has a high load, then the terminal is likely to be forced to return to the original network or to re-select another AP. The drawback is that much control signalling is required in the case of a vertical handover, and re-selection will degrade the users experienced QoS. The CORAL framework is used to tackle this problem. The AP is storing information about the channels utilization levels, which can be translated into load percentage. This information can be queried from a CORAL database before making a vertical handover, and thus unnecessary handovers can be prevented. HET-Q server queries data from the CORAL database and uses channel utilization information in decision-making.

4 Experimental Results

An experimental drive test was performed in Otaniemi, Espoo, Finland. The trial included experimentation with real-time vertical handover decision-making. The platform is designed to be real-time so that changes in network performance after a VHO decision can be assessed and the selected decision-making algorithm can be adjusted accordingly. The training of a decision-making algorithm was done with offline measurements, because outliers and other deficiencies can be removed before decision-making. VHO decision-making mechanisms were based on the following factors.

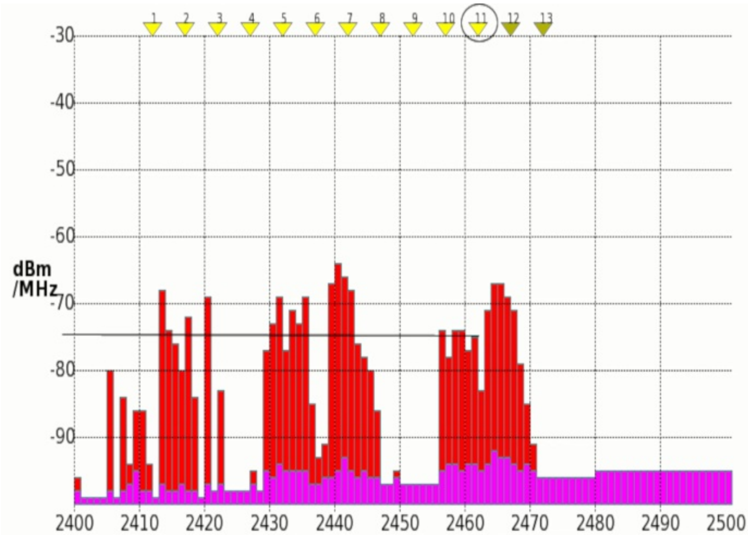

Fig. 6. Interference level for different WLAN channels as shown by CORAL

– *Reference*, Radio Access technology is selected automatically by the connected wireless module
– *Signal Strength*, Vertical handover is based on measured signal strength and coverage prediction results.
– *Proactive*, Vertical handover is done using a machine learning algorithm assisted with network planning and location information. (see chapter III A and B)

The driving route and relevant landmarks are depicted in Fig. 7. The drive test started from Digitalo building, went around it, passed the water tower, and continued down a small hill towards Micronova building. At the lowest location, the car was turned around and driven the same route back to Digitalo. The aim was to test whether WLAN APs in Digitalo as well as the AP installed on top of the water tower connected to CORAL were accessible from a moving car. The route was driven back and forth in order to study whether there are differences in entering and leaving cell boundaries. The turning at the lowest location was selected so that a NLOS condition occurred at the closest base station. In this experiment, we used DNAs (commercial network operator) UMTS and GSM networks, and our own WLAN access point installed at the water tower. The signal strength is indicated with colors. Warm color indicates high received signal level and cold color a low one. In the picture, blue color is indicating areas where surrounding buildings and terrain are shadowing the connection between a base station and the car. From the measurement, we observed that a measured signal strength value depends on the drive direction and serving cell boundaries. The network tends to keep a user connected to a serving base station as long as possible (even if not feasible). Therefore, we also measured signal strengths

Fig. 7. Measurement route with signal strength colours

of neighbouring cells. Similar drive tests were also carried out using another operators network (Sonera) in order to study multi-operator aspects.

When a wireless module was making VHO decisions (reference case), the terminal stayed the throughout whole measurement in the UMTS network even though the used traffic load (QoSMeT control traffic) could have been serviced by the other available networks. This case is shown in Fig. 8 A. In order to study the use of learning algorithms in VHO, we used service type specific constraints to classify the training and testing data. A classifier assigns the most suitable network for each measurement sample. The reference with 100 % reliability is shown in Fig. 8 B. The color indicates the active network - green color is UMTS, blue WLAN, and red GSM. When the measurement car turned around Digitalo, the velocity was so low that connection to Digitalos WLAN APs was possible. In areas where the communication link from car to a GSM base station was shadowed, the terminal switched to UMTS.

The classified training data (see chapter III A.) was used to train all six selected machine learning algorithms. The outcome of training was validated with test data obtained from the drive test and the reliability percentages were computed. The latter one indicates how many correct decisions were made by the trained algorithm. In addition, Self-Organized Map (SOM) classification algorithm was also tested. The achieved reliability percentage was 88 % with the same training and testing data.

In this trial measurement, the best algorithm (SVM) reached 95.6 % reliability. Although this seems good, the algorithm did make tens of wrong decisions. The sequence of wrong decisions was often bursty indicating that the decision-making algorithm was hesitating between two or more alternatives. This hesitation caused unnecessary ping-pong effects. To alleviate this problem, a minimum threshold time was added to the decision-making logic.

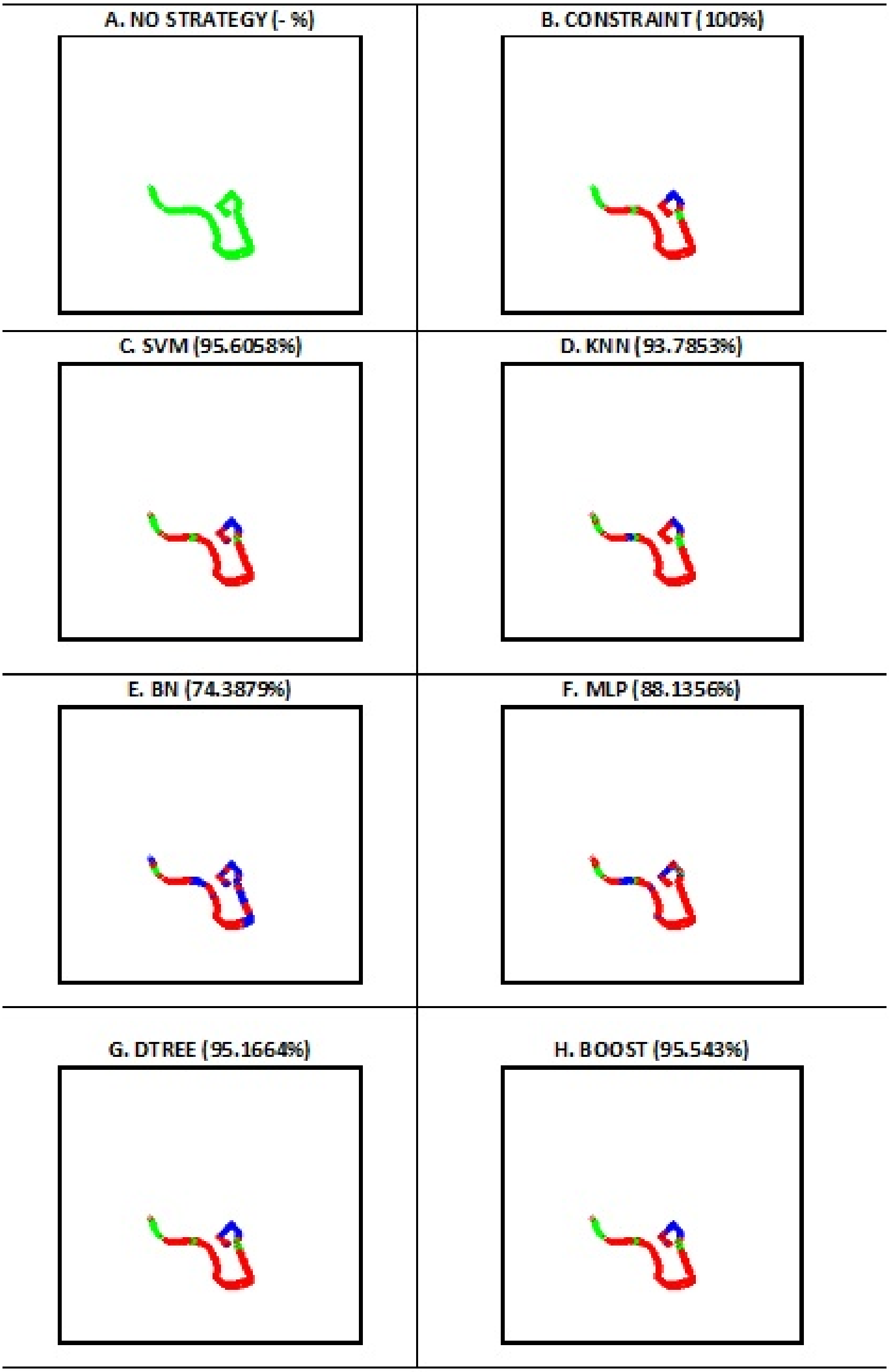

Fig. 8. Performance of learning algorithms in decision making

Based on the trial, we learned that the problem is not purely in the decision-making algorithms. It is more in the data we give them. If the data does not contain clear and systematic indicators to guide the algorithm, then it is possible for the algorithm to make too many incorrect decisions. In the worst cases, the reliability dropped even under 50 %. The measurement data collected from operational networks contain more outliers and deficiencies, which need to be removed before the training. The training in a laboratory environment is easier, because external interference can be isolated and network loads can be controlled in a step-by-step manner. It appeared that in operational networks, more sophisticated learning algorithms, like MLP, have more problems with incorrect training data than the simpler ones. The simple SVM algorithm gave the best results, which indicated that it was more robust and immune to unusual deviations in data.

5 Future Work

In the future, we are planning to test learning algorithms with a mobile terminal running several types of applications. So far, we have focused on a single application (web browsing, video streaming, data downloading with UDP or TCP/IP). The objective is also to integrate adaptive video coding to the HET-Q testbed in order to give video streaming applications opportunity to choose between a vertical handover and an adaptation of video streaming quality. In addition, the aim is to extend the testbeds applicability to support M2M (machine-to-machine) communication for indoor applications. Moreover, we found out that the same learning algorithms used for vertical handovers can also be utilized to automate network coverage tuning with steerable antenna solutions [2] and real-time measurements.

6 Conclusions

This paper describes the implemented testbed and the preliminary results obtained from using learning algorithms for the proactive handover decision-making in heterogeneous networks. The decision-making utilizes real-time PHY/MAC information, application level QoS, network planning information, users movements as well as cognitive radio parameters. The testbed utilizes several learning algorithms.

It was found out that the idea of utilizing learning based decision-making algorithms is plausible for terminal to select the suitable network based on networks load conditions. However, training of learning algorithms turned out to be challenging. Lack of clear patterns as well as outliers and deficiencies in the data tend to decrease the performance of the learning algorithms. Hence, the training of the algorithm is crucial and needs to be done with caution. The results obtained from the field trials confirm that learning algorithms are potential especially for real-time streaming applications in heterogeneous network benefiting from foresighted VHO decisions.

Acknowledgement. This work was performed within the ITSE (Intelligent Telecommunication Systems with Enhanced cognitive processing) project funded by VTT. The work is a follow-up to the prior work carried out in the IST-TALOS [10](Transportable Autonomous patrol for Land bOrder Surveillance system).

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