VECOS: A Vehicular Connection Steering Protocol

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***Abstract*—Due to their worldwide deployment, 3GPP mobile networks, particularly Long-Term Evolution (LTE), are gaining a lot of momentum, as are LTE-connected vehicles. While one may envision an LTE-connected vehicle as a nicely designed vehicle with sophisticated equipment, a conventional vehicle with a person using an LTE-enabled smartphone or tablet on board can be logically qualified for an LTE-connected vehicle. Maintaining an acceptable quality of service (QoS)/quality of experience (QoE) of LTE services for a user on board a moving vehicle is a challenging problem. One approach for that is to anticipate QoS/QoE degradation and to exploit the different radio access technologies, such as WiFi, that may be available at an LTE-connected vehicle or, in general, at an LTE-enabled user equipment (UE) on board the vehicle. For this purpose, this paper introduces a complete framework that proactively defines QoS/QoE-aware policies for LTE-connected vehicles (UE devices) to select the most adequate radio access out of the available access technologies (e.g., WiFi and LTE) that maximizes QoE throughout the mobility path. The policies are communicated to the users following 3GPP standards and are enforced by the UE devices. They take into account the service type, the mobility feature, and the traffic dynamics over the backhauls of the different available accesses. Two different models were proposed to model the network selection process. The first model is based on multiple-attribute decision making (MADM) techniques, whereas the second model is based on the Markov decision process (MDP). Moreover, the network selection process is modeled using a time-continuous Markov chain, and the performance of the proposed framework (VECOS) is extensively evaluated through NS2-based simulations considering the case of two wireless access technologies, namely, WiFi and cellular networks. The obtained results illustrate that in comparison with conventional vertical handoff mechanisms whereby WiFi is always selected whenever it becomes available, the proposed framework ensures better QoS and achieves better QoE throughout the time of the received service and the mobility path of the user, even in the case of errors in the prediction of the user's mobility.**

***Index Terms*—Markov chains, Markov decision process (MDP), network selection, quality of experience (QoE), wireless local area network (WLAN), 4G.**

I. Introduction

INTERNET-CONNECTED vehicles, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) communications constitute a promising market for the launch of a plethora of applications on the move, ranging from comfort and infotainment applications to onboard active safety applications [1], [2]. Smart vehicles are therefore envisioned to be equipped with different access types, to interconnect among themselves, and to connect to mobile networks. In this paper, we mainly consider vehicles with the right equipment and capacity to connect to a mobile network [e.g., Universal Mobile Telecommunications System (UMTS), Long-Term Evolution (LTE), etc.], in addition to their IVC/RVC-oriented IEEE wireless local area network (WLAN) interfaces. It shall be noted that a conventional vehicle with a passenger, equipped with a smartphone/tablet (i.e., incorporating both LTE and WiFi technologies) on board, could easily qualify for such envisioned smart vehicles.

On the other hand, broadband mobile IP connectivity will not be serviced only via mobile access technologies such as UMTS and LTE. This is mainly due to the fact that no mobile operator would economically be able to invest into only these mobile access technologies and their relevant mobile core networks to accommodate peak hours of emerging bandwidth-intensive mobile applications, particularly due to the fact that the average revenue per user (ARPU) are getting stagnant given the trend toward flat-rate business models. Operators are thus investigating cost-effective methods for accommodating the increasing mobile network traffic with minimal investment into the existing mobile infrastructure [6]. In this vein, due to their better indoor coverage and cost effectiveness, mobile operators are deploying large-scale WLAN networks for mobile services. These WLAN networks are either owned and administrated by the mobile operators or rented and exploited through partnerships with a third party (e.g., MERAKI providing "100% cloud-managed WiFi"). It shall be noted that these public WiFi hotspot networks have been deemed as a viable way to selectively offload significant amounts of mobile IP traffic and to ultimately alleviate congestion at macro networks [5], [7]. This is mainly interesting in case of dense-urban high-traffic load areas, such as an enterprise building or a downtown business district. With this regard, many carriers (e.g., Softbank, NTT DoCoMo, AT&T, and Verizon) are already installing thousands of WiFi hotspots to be used for offloading traffic, originated by smartphones, from their cellular networks [8], [9]. T-Mobile is even looking at transiting its cellular voice services, Voice over LTE (VoLTE) to an IP multimedia subsystem (IMS)-based WiFi calling client, implemented on its smartphones [24]. Other operators such as KDDI adopt Worldwide Interoperability for Microwave Access (WiMAX) for traffic offload.

However, the first drawback behind adopting WiFi hotspots for data offload is that although the vast majority of user equipment (UE), such as smartphones, tablets, and netbooks,

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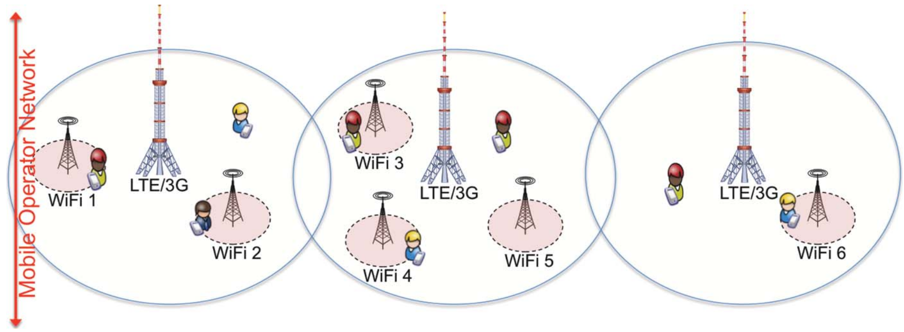


Fig. 1. Envisioned mobile network architecture.

have an embedded WiFi modem, its usage for data offload depends on customer willingness/consent, involves user interaction, and involves manual intervention from the users. Indeed, when a mobile user intends to perform a bandwidth-intensive application, such as downloading a YouTube video, the mobile user needs to be instructed, via a pop-up message, to turn on his/her WiFi radio to perform the task, and after the completion of the task, the user needs to be instructed again to turn off the WiFi radio to save battery life. While, with current standards, this scenario is difficult to automate by carriers in case of WiFi-based traffic offload due to the lacking mechanisms, ongoing standardization activities are, as explained in Section II, aiming for the automatic enabling of WiFi-based data offload.

With the integration of WiFi into the global coverage of a mobile operator, the resultant mobile network architecture is as shown in Fig. 1, whereby many areas of a city are covered with WiFi, LTE, and/or other access types. Mobile operators may confidently use WiFi as a backup network for their networks if and only if the WiFi backhaul network, or the fixed broadband connection, ensures a level of quality of service (QoS) similar to that provided by cellular networks. WiFi would indeed become a step down in performance in scenarios whereby a potential number of users simultaneously connect to WiFi while the communication path, in the backhaul [e.g., to the Digital Subscriber Line Access Multiplexer (DSLAM) or to other relevant potential nodes] is congested or is about to get severely congested. Therefore, the level of congestion on the backhaul link, intuitively along with the WiFi radio link quality, is a crucial determinant for the insurance of the quality of mobile services provided at WiFi. A solution to the backhaul segment may deceptively appear simple by increasing the backhaul capacity, e.g., on busiest sites, i.e., by having the mobile network operator overprovision the dedicated resources (e.g., maximum bandwidth) at DSLAMs or other relevant nodes through well-defined service-level agreements (SLAs) with the Internet Service Provider (ISP). However, resource overprovisioning is certainly not a cost-efficient solution. Economic constraints of such a solution become apparent particularly in developing markets, whereby wireless access fees are amazingly less expensive than those of cable or DSL [9]. An agile admission control framework that anticipates QoS/quality of experience (QoE) degradation and proactively defines QoS/QoE-aware policies for LTE-connected vehicles (UE devices) to select the most adequate radio access out of WiFi and LTE (or any other available wireless access technology), for a particular application, taking into account the application type, the mobility feature (e.g., speed, user mobility entire/partial path, and user final/intermediate destination), and the traffic dynamics over the backhauls of the different available access technologies (i.e., LTE and WiFi), as well as enable IP flow mobility between the networks associated with the different access technologies (e.g., WiFi and macro LTE networks), would be of vital importance. The design of such framework, while minimizing impact, if any, on current 3GPP specifications, and the evaluation of the proposed framework define the focus of this paper. An abridged version of this paper can be found in [27].

The remainder of this paper is structured as follows. Section II highlights the relevance of this work to the state-of-the-art in the context of vertical handover schemes, wireless network selection, and LTE-connected vehicles. The key design philosophy and distinct features that were incorporated in the proposed scheme, i.e., vehicular connection steering (VECOS) protocol, are described in Section III. Section IV introduces the analytical model used for the network selection process. In addition to presenting and discussing the analytical results, Section V portrays the simulation philosophy, in addition to defining various details for the setting of parameters. It also presents the simulation results and compares among different network selection methods. This paper concludes in Section VI with a summary recapping the main advantages and achievements of VECOS.

II. Related Work

In today's wireless networking domain, diverse wireless technologies are utilized for sharing data and providing data services. Among the available technologies, the leading example is the widely deployed 3GPP cellular networks, including the UMTS and LTE, to which many operators have already shown commitments. Internetworking VANETs with 3GPP mobile systems or connecting vehicles directly to 3GPP networks have been also gaining a great deal of momentum over the past few years. In [3], the NG Connect program is considering direct communication of cars to the LTE network. In [4], Benslimane *et al.* introduced a heterogeneous integration of VANET and 3G networks using mobile gateways (i.e., vehicles), achieving significant reduction in the overall frequency of handoff occurrences at base stations and important savings in the scarce resources of the access network.

On the other hand, due to the huge mobile traffic volumes that are far beyond the original mobile network capacity, mobile operators are also considering other radio access technology (RAT; e.g., WiFi) networks to offer mobile IP connectivity, which is in addition to their underlying 3GPP networks. The availability of several wireless access technologies to connect vehicles (e.g., highly mobile UE devices) to the Internet introduces the need to have efficient network selection mechanisms when UE is invoking vertical handovers.

Indeed, the emergence of heterogeneous networks has given rise to a number of vertical handover schemes. Yang *et al.* [14] proposed the Customer Surplus function to deal with non-real-time transmission. In this protocol, users first survey their network interfaces and determine the list of available access networks. They subsequently predict the transfer rate of each available network, taking the average of the last five data transfers and then derive completion times. After that, they compute the predicted utility, which is the relationship between the budget and the user's flexibility in the transfer completion time. Finally, for each candidate network, users compute consumer surplus, which is the difference between utility and cost charged by the network, and they choose the best one to request for connection. It can be noticed that this scheme works fine in non-real-time traffic but not for real-time multimedia services, which are the most popular nowadays. To handle handoff, Liu *et al.* [15] proposed the Profit function, where each handoff is associated with a profit that is decided by a target function with two parameters, namely, bandwidth gain and handoff cost. Parameters used in the calculation of the gain include 1) access networks along with their maximum bandwidth provided to a single user as well as capacity utilization, 2) application's maximum requirement on bandwidth, and 3) access networks' bandwidths used by a mobile node for handoff. Then, the authors defined a handoff cost as data volume lost due to handoff delay; it corresponds to the volume of data that could have been transmitted during the handoff delay. Thus, the profit is a difference between gain and cost. At each handoff epoch, mobile node compares profit from each network and chooses the profit that yields maximum profit. This scheme takes only bandwidth-related parameters into account. However, solely considering bandwidth cannot guarantee good QoE for multimedia applications. Deploying multiattribute decision making (MADM), Wilson *et al.* [16] proposed an algorithm based on a fuzzy logic controller (FLC) to evaluate fitness ranking of candidate networks. They differentiate decision making into three phases, namely, preselection, discovery, and decision making. The preselection phase takes criteria from user, application, and network to eliminate unsuitable access networks from further selection. The authors implemented a discovery phase based on fuzzy logic control; they "fuzzify" crisp values of the variables network data rate, signal-to-noise ratio (SNR), and application requirement data rate into grade of membership in fuzzy set. Then, these membership functions are used as input to the predefined logic rule base. Finally, overall ranking is obtained through "defuzzification" with the weighted-average method. It shall be noted that fuzzy logic control gives good results in the case of few metrics. However, if the number of metrics increases, the system may become highly complex and may give erroneous results. The proposed schemes covered many aspects and have taken into account several parameters. However, it is interesting and advantageous to take into consideration QoE (a crucial quality factor) when making a decision, as in [17]. For more research work on vertical handover in wireless heterogeneous networks, see [21].

To facilitate the implementation of a vertical handover between 3GPP and WiFi networks and assist UE devices in selecting the optimal radio access out of many available access technologies, current discussion within 3GPP with regard to whether WLAN can be considered as a "trusted non-3GPP" or "nontrusted non-3GPP" access. For an efficient interworking between WLAN and LTE, many operators and vendors are in favor of qualifying WLAN as a trusted non-3GPP. There are also ongoing standards activities on enabling seamless WLAN-based offload versus nonseamless WLAN-based offload [10] and on location-based selection of gateways for seamless WLAN-based offload. While the access network discovery and selection function (ANDSF) was initially designed for the selection between 3GPP and non-3GPP accesses such as WLAN [11], further standards work considers the extension of ANDSF functionalities to the selection of packet data network (PDN) connection from within the 3GPP domain and enabling UE devices to steer IP flows among the available PDN connections (operator policies for IP interface selection (OPIIS) [12]). Other ongoing standards activities focus on defining metrics for the identification of a data flow/application [13] to enable per-IP-flow offload. Some of the envisioned metrics are domain name and application unique ID, and others, such as throughput, content size, and behavioral statistics, may also be considered. Based on the identification of the application type, an operator may enforce policies that would force a UE to steer the relevant flow via WiFi or LTE.

The network selection or vertical handover procedure proposed in this paper is based on the mobility feature of a vehicle and its prediction, and the load dynamics of the backhaul network of the available accesses and their prediction. Regarding the former, in [18], Nadembega *et al.* have proposed a scheme for the prediction of the entire or partial moving path of a vehicle, supported by the prediction of the final destination or intermediate points along the path based on historical data, contextual knowledge, and spatial conceptual maps [19]. The two papers also present a brief overview on existing mobility modeling and prediction methods that can be of use in this work. Regarding the reflection of traffic dynamics of access backhaul networks in an admission control operation, a QoS/QoE predication-based admission control for deciding on handovers and flow mobility between a macro network and a small-cell network has been proposed in [20].

The network selection process has to consider attributes and criteria defined by the operator as well as the user. Criteria defined by the user aim at maximizing his/her QoS (e.g., data rate and latency) and minimizing the communication cost. Criteria defined by the network operator are mainly related to network resource optimization (e.g., network utilization and load balancing between wireless networks). Sometimes, there is a conflict among these criteria; for instance, increasing user data rate may impact load balancing between networks. Several

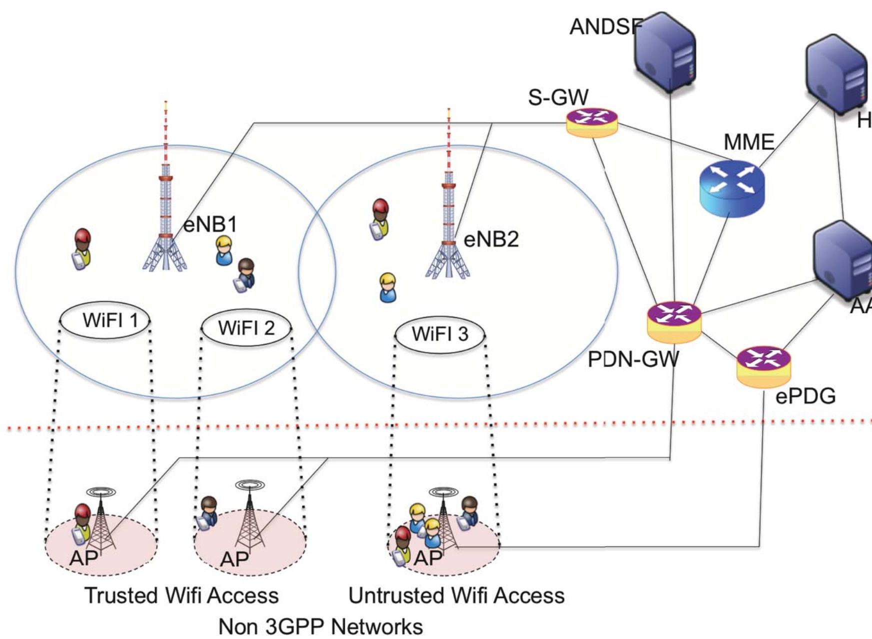


Fig. 2. Considered network architecture.

solutions have been proposed based on mathematical models or empirical solutions to find a tradeoff between user and operator requirements. Most of these solutions do not consider QoE as a criterion for users and are based on an instantaneous sample of the criteria values to take the decision. On the one hand, it is generally agreed that QoS is not enough to model the user satisfaction; on the other hand, using instantaneous values is not efficient as these values do not reflect the long trend evolution of the criteria, which may result in wrong decisions. VECOS tackles these issues by including the measured QoE in the RAT selection/decision process. Rather than using the instantaneous values, VECOS predicts these values, capturing the long trend evolution of these values. Combining mobility and QoE prediction permits to create for each UE a list of APs to connect to in order to reduce exchanged messages and reduce the handover procedure, while maximizing user's QoE.

III. Vehicular Connection Steering (VECOS)

The envisioned network architecture along with its main components are portrayed in Fig. 2. The mobile network consists of a number of wireless domains, each comprising a number of access points (APs) using the same or different wireless access technologies (i.e., 4G networks). In the proposed VECOS framework, we used a centralized approach at the mobile operator domain to assist the UE devices to discover available access networks and to select the best network access following policies defined, *a priori* or dynamically/on demand, by the mobile operator and enforced by UE devices, in a transparent manner to users. In addition, we simulated the deployment of a number of monitoring agents over the entire mobile network, to assess the QoE experienced by users at each AP within the urban wireless domains. We enhanced the ANDSF (or similar equipment) with new functionalities (see Fig. 3) by implementing the following modules:

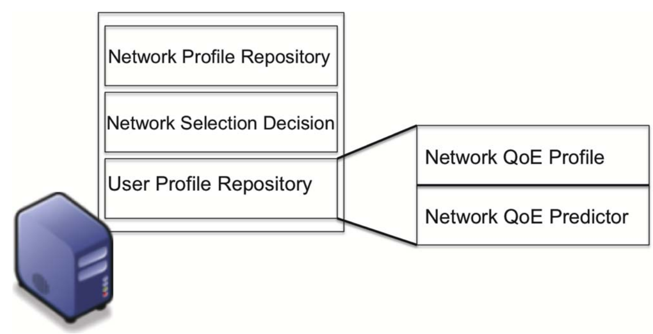


Fig. 3. Proposed additional components to ANDSF or alike node.

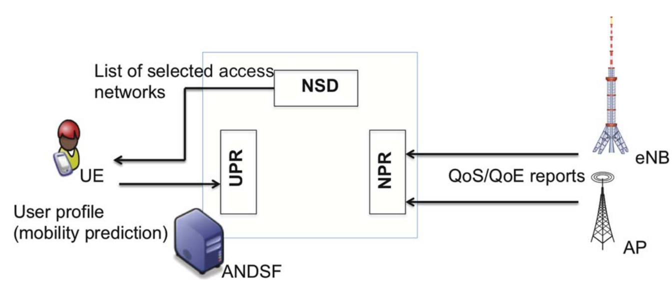


Fig. 4. Frames range affected by the loss of key frames (single layer case).

- network profile repository (NPR), which contains an updated profile of each wireless network composing the mobile domain. Further, NPR is composed by two other units: NPR and network QoE predictor (NQP);
- user profile repository (URP), which contains a repository for updated profiles of users;
- network selection decision (NSD), which implements the algorithm that selects the best network access to fulfill certain policies.

Fig. 4 plots the major interactions that take place between the network, the UE, and ANDSF. The network (consisting of the

TABLE I
GLOSSARY OF USED VARIABLES AND THEIR DEFINITIONS

Variable	Definition
Ω	User satisfaction level (a score from ω_{min} to ω_{max})
ω_{min}	Lowest (poor service) perceived quality
ω_{max}	Excellent perceived quality
ω_i	A score indicated by user i
θ_i	A duration for which user i was connected to an access network
λ_i	Average throughput achieved by user i while being connected to an access network
AP_k	Access Point k
$S_p(\theta_p, \lambda_p)$	Predicted user satisfaction depending on the predicted duration θ_p and the predicted throughput λ_p
$\phi(j)$	Correlation between the predicted link bandwidth and the actual one measured during period $\Delta(j)$
$\Delta(j)$	Time period j
$S_a(j : j < k)$	Actual measured user satisfaction during a number of previous periods $\Delta(j)$
$\Psi(j)$	Correlation between predicted user satisfaction and the actual one measured during a time period $\Delta(j)$
AP^{list}	Sorted list of APs likely to be visited by the UE
M	TOPSIS alternatives (options)
L	TOPSIS alternatives/criteria
$x_{i,j}$	Score of option i with respect to criterion j
D(mxm)	Matrix constructed with score $x_{i,j}$
$r_{i,j}$	A non-dimensional attribute
w_j	Weight of alternative j
A^+	TOPSIS ideal solution
A^-	TOPSIS negative solution
S^+	TOPSIS Ideal alternative
S^-	TOPSIS negative alternative
C_j	TOPSIS ideal solution
q_w	QoE at the WiFi cell
q_m	QoE at the macro cell
K	Number of decision epochs in the MDP model
γ	Discount factor
δ^*	Optimal policy
R_1	Radius of WiFi cell
R_2	Radius of macro cell (3G/LTE)
Γ_1	Residence time in WiFi cell
Γ_2	Residence time in macro cell
N	Number of WiFi cells
vel	UE velocity
$E[Q_m]$	Mean QoE perceived in the macro cells
$E[Q_w]$	Mean QoE perceived in the WiFi cells

different available access technologies, e.g., eNB and WLAN) provides periodic reports on average QoS/QoE experienced by users to the NPR unit of ANDSF. Using the 3GPP's S14 interface, the UE communicates the user profile to the UPR unit of ANDSF. In return, the NSD unit of ANDSF recommends to the UE a list of accesses ordered following a suitable logic. For the sake of the readability of this paper, Table I provides a glossary of the different variables used in this paper along with their definitions.

A. QoE Prediction

QoE is defined in [21] as "the overall acceptability of an application or service, as subjectively perceived by the end user." QoE is different from QoS network indicators in terms of bandwidth, loss rate, and jitter, which are not sufficient to get a precise idea about the visual quality of a received video sequence. QoE instead focuses on the overall experience of a user. QoE is obtained through mean opinion score (MOS). MOS scales from 0 to 5 or 0 to 10, i.e., 5 or 10 for maximum quality and 0 for very bad quality. Information on user satisfaction is explicitly collected from users when they hand out from an access network. Users that are requested to score their satisfaction level can be selected randomly or following a defined logic such as only users that received a particular service/application type or video or only users that have been connecting to an access network for a time exceeding a specific threshold. Users may be given incentives for scoring the service. A user's satisfaction level can be, for example, a score from $\omega_{\min}$ to $\omega_{\max}$, with $\omega_{\max}$ indicating an excellent perceived quality and $\omega_{\min}$ indicating a poor service. Satisfaction levels can be collected from a randomly selected group of users, for instance, using short message service (SMS), through a web portal or through a dedicated application. There may be different ways for computing the average user satisfaction level using any function that takes the following metrics as inputs, namely, the score ω_i indicated by a customer i, the duration θ_i during which the user was connected to an access network, the types of applications/services received by the customer, and the average throughput λ_i achieved by the customer while being connected to an access network. The user satisfaction indicators ($\omega_{\min}$, $\omega_{\max}$, θ_i, λ_i) values are then reported to a QoE profiling unit at the ANDSF (or another relevant node) to build/update the user satisfaction profile for the different APs AP_k. We recall that the NPR consists of two units, namely, NQP and network QoE predictor (NQPr). Based on the received user satisfaction indicator, the NQP entity builds/updates the QoE profile of each access network available in the wireless

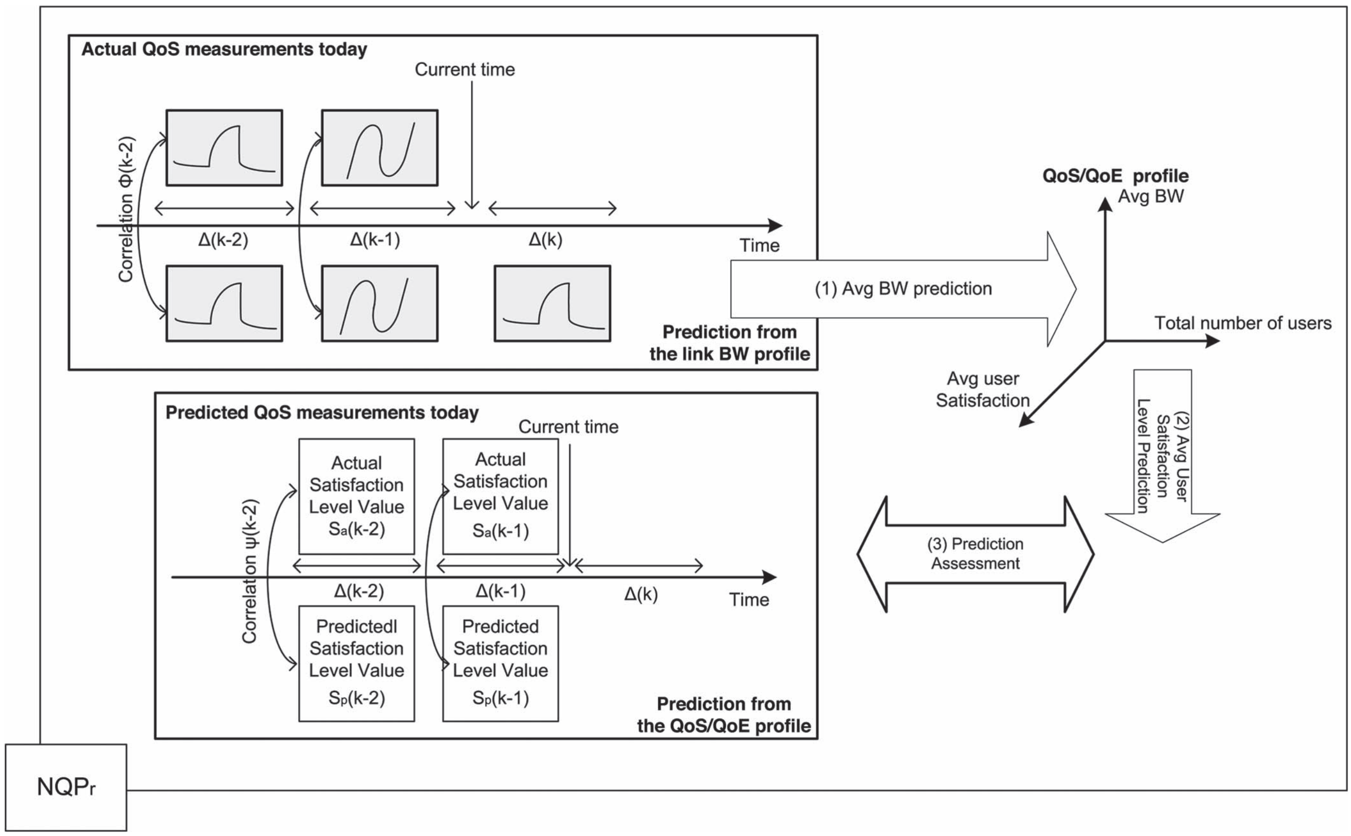


Fig. 5. QoE prediction process.

domain. NQPr implements a QoE predictor similar to that defined in [21], using any suitable learning technique (e.g., neural networks and fuzzy techniques) that translates QoS indicators such as available bandwidth and time of connection into user satisfaction. NQPr predicts the average user satisfaction from the relevant QoE statistical profile available at NQP. Indeed, according to the network profile available at NQP, the learning function establishes a relation between user satisfaction $(\omega_{\min}, \omega_{\max})$ and the time duration, as well as user throughput (θ, λ). Thus, the predicted user satisfaction $Sp(\theta_p, \lambda_p)$ depends on the predicted time duration θ_p and the predicted available throughput λ_p for a specific time window. The learning algorithm is constantly enhanced, by assessing the prediction accuracy (see Fig. 5). A value predicted for a time slot $[T_{k-1}; T_k]$ is compared against real values, effectively measured during the specific time slot, and correlation between the two values is assessed. The correlation between the predicted link bandwidth value and the actual value measured during a time period $\Delta(j)$ is denoted by $\Phi(j)$. The system assesses this prediction by comparing the predicted user satisfaction values $Sp(j; j < k)$ and the actual satisfaction values $Sa(j; j < k)$ measured during a number of previous time periods $\Delta(j; j < k)$. The correlation between the predicted user satisfaction value and the actual value measured during a time period $\Delta(j)$ is denoted by $\Psi(j)$. The learning algorithm is then constantly improved to reduce the difference between $\Phi(j)$ and $\Psi(j)$. For more details on the procedure of predicting QoE and how to correlate QoS information to QoE metrics, see [21] and [31].

B. Mobility Prediction and Context Uploader

UPR, which was first introduced in [23], consists of four units, i.e., Context Repository Service (CxRS), Context Gathering Service (CxGS), Context Aggregation Service (CxAS), and Context Distribution Service (CxDS). At regular times, CxGS gathers context information from users. Contextual information may also include users' personal information and preferences provided by the user when she first subscribes to the service and user's mobility patterns predicted by a mobility predictor (MP) entity implemented at terminals. Indeed, in the envisioned network architecture, UE devices comprise two new tools: MP and context uploader. The MP makes estimates of the users' mobility features, by using, for instance, models developed in [18] and [19], and notifies them to the CxGS unit of ANDSF. After this operation, UPR at ANDSF is informed of the list of APs that the UE is most likely going to be connected to during the service time.

C. Overall Process

Fig. 6 shows the overall process of network selection used in the proposed VECOS solution. When a user (of a UE) initiates a particular service, the UE first checks its table of operator policies provided by the mobile operator through ANDSF. If the policies indicate that the UE needs to first consult ANDSF for the access selection for this particular service/application, it accordingly contacts ANDSF, providing ANDSF with further information on its mobility features (i.e., predicted by models

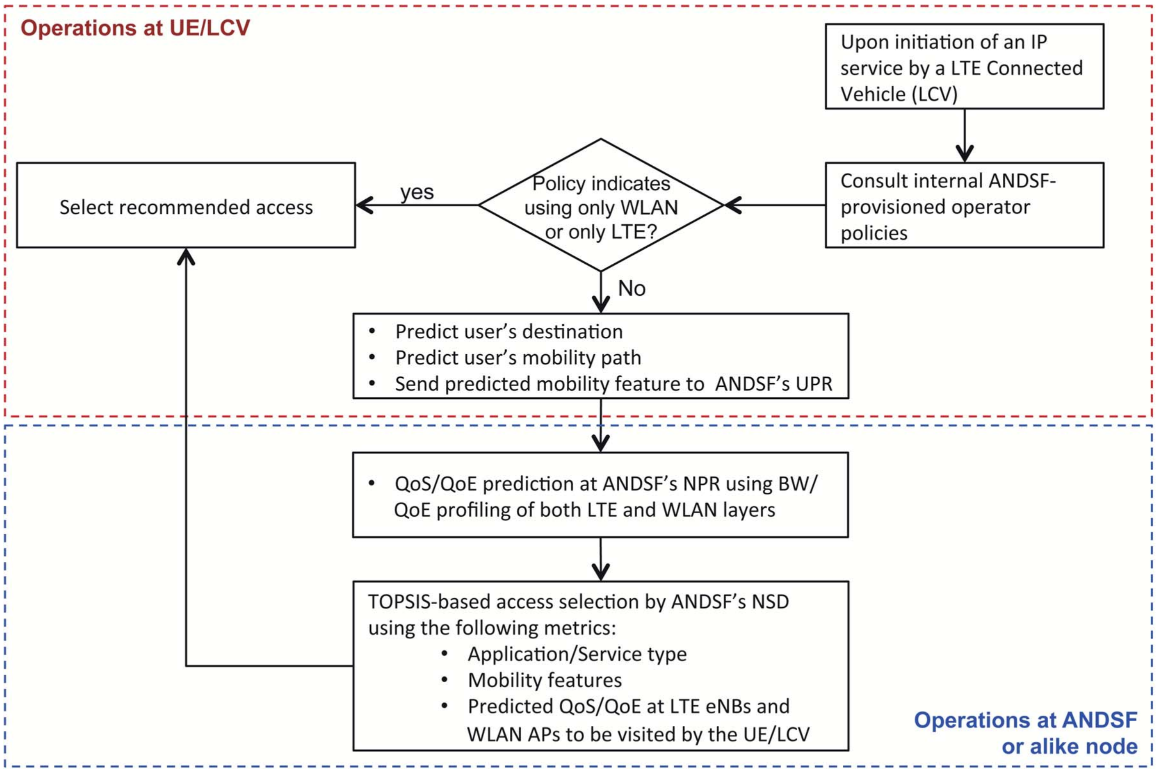


Fig. 6. Proposed VECOS protocol for vehicles connected to LTE (or to other suitable mobile access technology).

similar to those in [18] and [19]). Based on the user's mobility profile and following the UE-AP encounter model devised in [25], ANDSF sorts out a list of APs AP^{list} from both the WLAN and LTE layers that are likely to be visited by the UE, as well as the relevant time and duration of encounter with each AP. For each AP AP_k from within the list AP^{list}, the predicted QoE profile is loaded from NQPr. This gives rise to a matrix as shown in Fig. 7. In Fig. 7, we denote by R and S the total number of the different eNBs and WLANs the vehicle is predicted to encounter, respectively, during a time window of interest (e.g., expected duration of service or predetermined period of time). During this time window of interest, the vehicle encounters z different combinations of eNBs and WLANs, each for a time period $\Delta_i\{1 \leq i \leq z\}$, defining the duration of the encounter between the vehicle and the ith set of eNB and WLAN (e.g., in Fig. 7, Δ_2 denotes the duration of the encounter between the vehicle and the set of eNB_1 and $WLAN_2$). From the QoE statistical profile, available and constantly updated at ANDSF's NPR and using a suitable time-series model [22], [25], a model of QoE distributed over time is formed for each AP of each access type, as shown in Fig. 5. In the figure, S_{pq} and S_{xy} denote the perceived QoE averaged over a number of days and during the qth and yth time intervals, at eNB_p and $WLAN_x$, respectively. For each period of time $\Delta_i\{1 \leq i \leq z\}$, ANDSF compares the minimum values of QoE predicted to be perceived by users during the time interval $[t_0 + \sum_{j=1}^{i} \Delta_j; t_0 + \sum_{j=1}^{i+1} \Delta_j]$ and that is for each access type. It is important to note that user satisfaction or QoE is not the only criterion considered by the NSD entity, but other criteria defined by user and network operator (such as maximizing user QoE, reducing network cost, maximizing security, supporting high mobility, etc.) are considered. Similar to [17], we formulate the network selection problem by using the MADM theory. The MADM approach can be applied by using different algorithms. In this paper, we assume that NSD is employing the technique of order preference by similarity to ideal solution (TOPSIS), which outperforms other techniques [26] such as simple adaptive weighting (SAW) and minimal distance utopia point (MDUP), to select the optimal access network. Having said that, it shall be noted that any suitable MADM solution may be used for NSD in VECOS.

D. Network Selection Based on TOPSIS

Network selection may be considered as a complex problem, involving several tasks that need to be carried out in order for a user, a network operator, or both to take a decision. The TOPSIS approach (or any MADM-alike solution) consists of four steps. Each step forms a distinct process. These steps are as follows.

1) Selection of the decision criteria: This step involves the identification of all parameters that should be considered during the decision process.
2) Collection of values for the selected criteria: For all parameters selected during the first step, the performance of each alternative (i.e., normalized values of the parameters) is collected through the candidate access networks.
3) Criteria weights: The weights for the selected set of parameters are then specified. Weights indicate the importance that each parameter has in the final decision.
4) Ranking of the alternatives: Based on the input of the previous two steps, the ranking of the alternatives is performed, and a decision can be made.

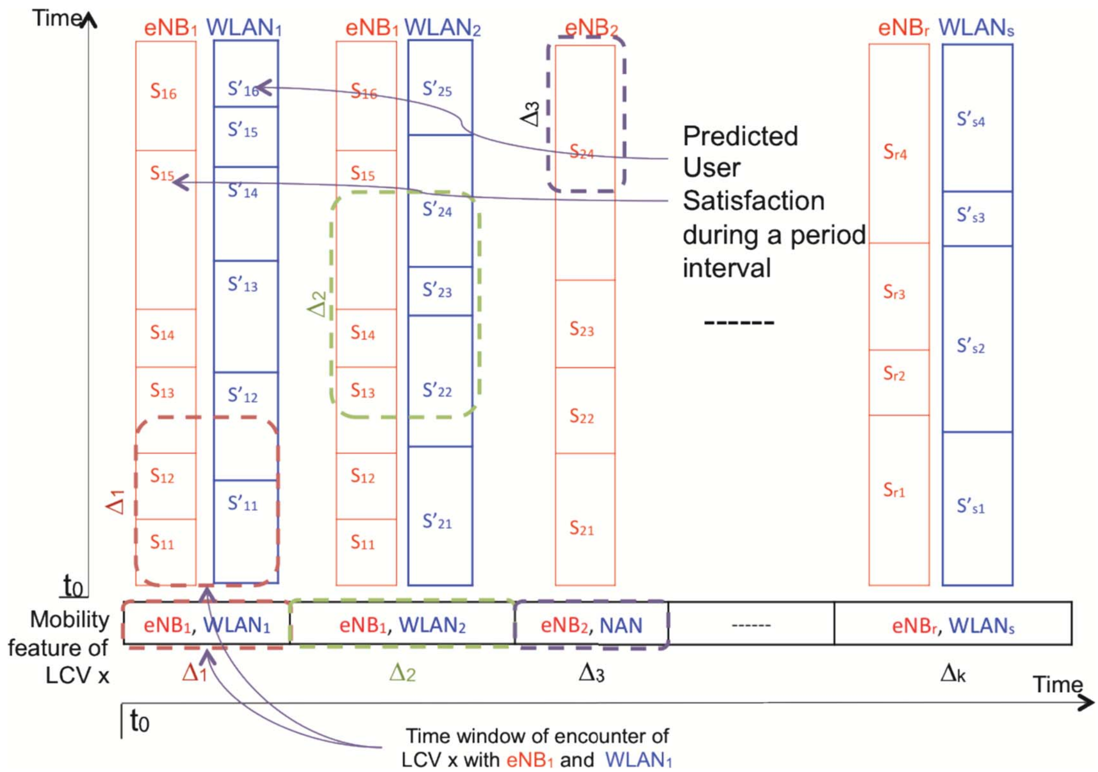


Fig. 7. Envisioned matrix for comparing QoE to be perceived at different APs of different access types a vehicle would encounter during a time window of interest.

The TOPSIS method assumes two artificial alternatives as hypotheses: ideal alternative that has the best level for all attributes considered and negative ideal alternative that has the worst attribute values. TOPSIS selects the alternative closest to the ideal solution and furthest from negative ideal alternative. TOPSIS assumes the availability of m alternatives (options) and l attributes/criteria, as well as a score for each option with respect to each criterion. We denote by $x_{i,j}$ the score (attribute) of option i with respect to criterion j. In our case, m represents the available access networks (3G, WLAN), whereas l represents the criteria number (such as QoE, security, mobility, connection cost, etc) to be considered in the network selection process. Thus, a matrix $D(mxn)$ is constructed with the scores $x_{i,j}$. The data of this matrix are normalized to transform each attribute $x_{i,j}$ to a nondimensional attribute $r_{i,j}$ as follows:

$$r_{i,j} = \frac{x_{i,j}}{\sqrt{\sum_{i=1}^{m} x_{i,j}^2}}. \tag{1}$$

Indeed, it is important to have nondimensional attributes, as we deal with different kinds of metrics. The obtained new matrix is called the normalized decision matrix. This matrix is again transformed to a weighted normalized decision matrix by multiplying each column by its associated weight. Depending on the provided service and the user requirements, the metric m may not have the same importance. Thus, we assign each attribute a weight such as the sum of all weights is equal to one. An element of the new matrix is

$$v_{i,j} = w_{i,j} r_{i,j}. \tag{2}$$

It should be noted that a decision D taken at a time instant t remains valid for a period Δ during which the vehicle encounters a set of eNB and WLAN. Now, TOPSIS can construct the ideal and the negative solutions. The ideal solution A^+ is constructed as follows:

$$A^+ = \{v_1^*, v_2^*, \ldots, v_i^*\} \tag{3}$$

$$v_j^+ = \begin{cases} \max_i(v_{i,j}), & \text{if } j \in J \\ \min_i(v_{i,j}), & \text{if } j \in J' \end{cases} \tag{4}$$

where J denotes the set of benefit attributes or criteria (more is better), and J' is the set of negative attributes or criteria (less is better). The negative ideal solution A^- is built as follows:

$$A^- = \{v_1^-, v_2^-, \ldots, v_i^-\} \tag{5}$$

$$v_j^- = \begin{cases} \min_i(v_{i,j}), & \text{if } j \in J \\ \max_i(v_{i,j}), & \text{if } j \in J'. \end{cases} \tag{6}$$

For each alternative, a separation measure (denoted as S^+ for the ideal alternative and S^- for the negative alternative) is computed as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{l} \left(v_{i,j} - v_{i,j}^+\right)^2}, \qquad \text{for } i = 1, \ldots, m \tag{7}$$

$$S_i^- = \sqrt{\sum_{j=1}^{l} \left(v_{i,j} - v_{i,j}^-\right)^2}, \qquad \text{for } i = 1, \ldots, m. \tag{8}$$

Since the separation measures are computed, the relative closeness to the solution is calculated as follows:

$$C_i = \frac{S_i^-}{\left(S_i^+ + S_i^-\right)}, \qquad 0 < C_i < 1, \quad \text{for } i = 1, \ldots, m. \quad (9)$$

The ideal solution is the one whereby C_i has the value closest to one. Once the list of recommended APs is decided for each encounter time $\Delta_i\{1 \leq i \leq z\}$, ANDSF communicates this list of APs to the UE/vehicle that enforces it during the service time. It is worth mentioning that NSD applies the TOPSIS procedures only for the predicted time duration Δ, where there is more than one AP in the AP^{list} list. For the other periods, the default AP is chosen as the point of attachment. It is worth noting that in the proposed VECOS framework, we consider mainly four criteria for the MADM model, namely, QoE, cost, security, and mobility.

1) QoE is the most important criterion in VECOS, as our aim is to maximize user QoE. It is therefore given the highest weight.
2) Cost represents the cost of communication for the operator. WLAN has the highest score as it allows network operators to offload some of the traffic through WiFi with low cost (i.e., saving resources of the mobile core network).
3) Security shows the capacity of each network to secure the communication. It is obvious that cellular networks are more secure than WiFi networks.
4) Mobility represents the possibility to move in the network without the need to do frequent handovers. Of course, cellular networks have the highest score as a cell coverage area is much larger than that of a WiFi cell.

E. Network Selection Based on MDP

Having described how we can use MADM, and particularly TOPSIS, we now focus on modeling the network selection process of VECOS using MDP. In this model, we assume that the decisions on whether to use a macrocell or a WiFi cell (if both are available) are done every t s (i.e., decision epochs $= t$ s). The set of decision epochs is denoted as $T = \{1, 2, 3, \ldots, K\}$. Intuitively, when only one RAT is available, no decision optimization takes place. To retrieve an optimal policy for deciding to which RAT a UE has to attach, we define an MDP that associates with each state an action, corresponding transition probabilities, and rewards. Let s_t be the process describing the evolution of the system state. Let S denote the state space. A state s is composed by the type of the network currently used by the UE (i.e., 1 for WiFi and 2 for macrocell), the current QoE perceived at the macrocell (denoted by q_m) and the QoE perceived at the WiFi cell (denoted by q_w). Therefore, a formal representation of a state s, at an instant t, is in the form of $(b, q_m, q_w)\,(b \in 1, 2)$. We denote by $A = (a_1, a_2)$ the vector describing the actions available to ANDSF at each decision epochs. Action $a_1 = 1$ is used if the UE has to connect to a WiFi cell, whereas $a_2 = 2$ is employed if the UE has to connect to the macrocell. It is important to note that if a UE is attached to a WiFi cell and the selected action by the MDP model is a_1, then the UE has to remain connected to the same network. The same logic is to consider in the macrocell case.

The information regarding the perceived QoE for each network at instant t is available at ANDSF through the QoS/QoE mapper, which constantly tracks the users' satisfaction values. For a given action a, an instantaneous reward $r(s, s', a)$ is associated with a transition from state s to another state s'. The corresponding formal representation of the discrete-time MDP process is $(S, A, (A_s, s \in S), p(s'|s, a), r(s, s', a))$, where $p(s'|s, a)$ denote the transition probability from state s to state s', if action a is chosen. Since the state transition depends on the current state and action but not on the previously visited states, this system is then Markovian. Given a current state $s = (b, q_m, q_w)$ and the chosen action is a, the probability to be in state $s' = (b', q'_m, q'_w)$ is given by

$$p(s'|s) = \begin{cases} p\left(q'_m|q_m\right) p\left(q'_w|q_w\right), & \text{if } a = b' \\ 0, & \text{else} \end{cases} \quad (10)$$

where

$$p\left(q'_m|q_m\right) = \begin{cases} p_{em}, & \text{if } q'_m = q_m \\ 1 - p_{em}, & \text{if } q'_m \neq q_m \end{cases} \quad (11)$$

$$p\left(q'_w|q_w\right) = \begin{cases} p_{ew}, & \text{if } q'_w = q_w \\ 1 - p_{ew}, & \text{if } q'_w \neq q_w. \end{cases} \quad (12)$$

The probabilities $p(q'_m|q_m)$ and $p(q'_w|q_w)$ represent the probability that the predicted QoE in the macrocell, respectively WiFi cell, changes if an action a is chosen. Therefore, they depend on the QoE prediction precision done by the QoE prediction module at ANDSF. The QoE prediction tool estimates/predicts QoE with error probabilities equal to p_{em} and p_{ew} for the macrocells and WiFi cells, respectively. A policy δ is mapping between a state and an action and can be denoted as $a_t = \delta(s_t)$, where $t \in K$. Accordingly, a policy $\delta = (\varrho 1, \varrho 2, \varrho 3, \ldots, \varrho K)$ is a sequence of decision rules to be used at all decision epochs. In this paper, we restrict ourselves to only deterministic policies, as they are simple to implement [29]. For each decision epoch, ANDSF notes the selected network as specified by the chosen action by MDP. For each transition between states, a reward is obtained. This reward corresponds to the predicted QoE (q') at the destination cell. In addition, a constant cost is added to the reward function associated to action a_2, which selects the macrocell. As for the MADM solution, the cost of using a macrocell is higher than that of a WiFi cell. Accordingly, the reward function is obtained as follows:

$$r(s, s', a) = \begin{cases} q'_w, & \text{if } a = 1 \\ q'_m - Cst, & \text{if } a = 2 \end{cases} \quad (13)$$

where Cst denote the cost of using a macrocell. Given a discount factor $\gamma \in [0, 1)$ and an initial state s, we define the total discounted reward for a policy $\delta = (\varrho 1, \varrho 2, \varrho 3, \ldots, \varrho K)$ as follows:

$$v_\gamma^\delta = \lim_{N \to \infty} E_\gamma^\delta \left\{ \sum_{t=1}^{N} \gamma^{t-1} r_t \right\} = E_\gamma^\delta \left\{ \sum_{t=1}^{\infty} \gamma^{t-1} r_t \right\}. \quad (14)$$

Qm\Qw	1	2	3	4	5
1	1	1	1	1	1
2	1	1	1	1	1
3	2	1	1	1	1
4	2	2	1	1	1
5	2	2	2	1	1

(a)

Qm\Qw	1	2	3	4	5
1	1	1	1	1	1
2	1	1	1	1	1
3	1	1	1	1	1
4	2	1	1	1	1
5	2	2	1	1	1

(b)

Qm\Qw	1	2	3	4	5
1	1	1	1	1	1
2	1	1	1	1	1
3	2	1	1	1	1
4	2	2	1	1	1
5	2	2	2	1	1

(c)

Fig. 8. Optimal policies for the network selection process given by the MDP. (a) $Cst = 0.5$, $p_{em} = 0$, and $p_{ew} = 0$. (b) $Cst = 1$, $p_{em} = 0$, and $p_{ew} = 0$. (c) $Cst = 1$, $p_{em} = 0.1$, and $p_{ew} = 0.4$.

To derive the value of the discount factor γ, we follow the same model as in [32]. We assume that K (number of decision epochs or the connection termination time for a UE) is following a geometrical distribution with mean $1/(1-\gamma)$.

Let $v(s)$ denote the maximum discounted total reward, given the initial state s. That is, $v(s) = \max_{\delta \in \Phi} v^{\gamma}(s)$.

From [30], the optimality equations are given by

$$v(s) = \max_{\delta \in \Pi} \left\{ r'(s, s'a) + \sum_{s' \in S} \gamma p(s'|s, a) v(s') \right\}. \tag{15}$$

The solutions of the optimality equations correspond to the maximum expected discounted total reward $v(s)$ and the optimal policy $\delta^*(s)$. It is worth mentioning that the optimal policy $\delta^*(s)$ indicates the decision as to which network the UE is to be attached, knowing state s. There are several algorithms that can be used to resolve the optimization problem given by the above optimality equations. Value iteration and policy iteration are two noticeable examples.

We used a MATLAB implementation of the value iteration algorithm [30] to derive the optimal policy for different configurations (changing the cost value Cst and the probability of having errors in the QoE prediction). We consider that the connection termination time has an average of 50 min ($\gamma = 0.98$). Fig. 8 shows the construction of the optimal policies for three different configurations as follows.

- Conf. 1: A low cost is incurred for using the macrocell, and the prediction precision is accurate.
- Conf. 2: A relatively high cost is incurred for using the macrocell, and the prediction precision is accurate.
- Conf. 3: A relatively high cost is incurred for using the macrocell, and there are errors in the prediction.

In the third configuration, we consider more errors in predicting the QoE of WiFi cells than in the case of macrocells. This is to reflect the high fluctuations in WiFi cell behavior due to the use of a distributed mechanism (CSMA/CA) at the MAC layer.

The horizontal axis (i) denotes the current QoE perceived at the WiFi cell (q_w), whereas the vertical axis (j) shows the current QoE perceived in the macrocell (q_m). The intersection between i and j represents the action ($a = 1$ choose WiFi cell, $a = 2$ choose the macrocell). Note that the same policy result is obtained regardless of the currently used network. Except for case 3, we observe that the choice of the WiFi cell connection

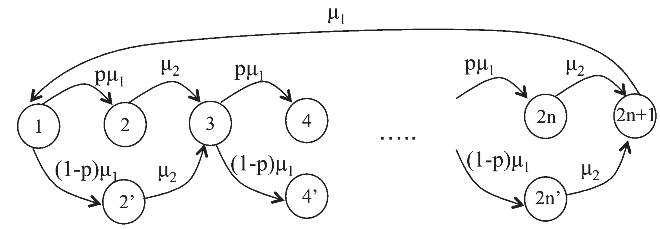


Fig. 9. Associated CMTC.

is recommended for practically all the states, where q_w is equal to or greater than $q_m + 1$. This is logical as the MDP process tries to maximize the maximum discounted reward function, which depends on user QoE and the cost of using the macrocell connection. However, when the prediction of user QoE in the WiFi cell is less accurate than that in the macrocell, the optimal decision recommends using the macrocell rather than WiFi. For instance, in the state (5, 3), the optimal policy recommends using the WiFi cell in the second configuration and the macrocell in the third configuration. Again, for the state (5, 3), we observe that the optimal policy differentiates between the first and second configurations. This is due to the fact that reducing the cost leads the optimal policy to recommend using the macrocell rather than the WiFi cell as this increases user QoE.

IV. Analytical Model

Here, we derive an analytical model to evaluate the impact of the network selection process on the VECOS framework. We consider the network model in Fig. 2, whereby a connected car is traveling an area covered by 3G or LTE macrocells, and within the coverage of each macrocell, n WiFi cells are deployed. We consider that WiFi cells have circular coverage areas with a radius R_1. No overlapping is assumed between WiFi cells, and the distance between any two neighboring cells is the same.

Despite the fact that in reality a macrocell may have hexagonal coverage, in this work, we assume circular coverage areas for macrocells. We denote by R_2 the radius of a macrocell coverage. Indeed, this assumption is rational as UE devices cross cells in a linear fashion (vehicle mobility). We assume that a UE is connecting to a remote service throughout its movement. Let $X(t)$ denote the type of cell a UE is connected to at instant t. The residence time in each cell is assumed to follow an exponential distribution with parameters Γ_1 and Γ_2 for the macrocells and WiFi cells, respectively. The decision epoch corresponds to situations when a UE detects a WiFi connection. In this case, the system $\{X(t), t \geq 0\}$ forms a continuous-time Markov chain (CMTC) with the state space $S = \{1, 2, 2', 3, 4, 4', \ldots, 2n, 2n', 2n+1\}$, as shown in Fig. 9. The odd states (except state $2n+1$) represent the decision epochs, where there is a need to take a decision to switch to WiFi or to remain connected to the macronetwork. We model this according to a probability p. In VECOS, the network selection process (TOPSIS and MDP) dynamically defines this probability at each decision epoch. The transition rate (μ_1) from odd states (except state $2n+1$) to pair states depends on the residence time in the macronetwork and the probability to handoff to a WiFi cell or not. The transition rate (μ_2) from pair states to odd states depends only on the residence time duration in the WiFi cell. In fact, after deciding to switch to a WiFi cell or to remain connected to the macronetwork, the next state represents the case where only a 3G/LTE connectivity is available.

Let $\pi_s = \lim_{t\to\infty} Prob[X(t) = s], s \in S,$ be the stationary probability distribution of $X(t)$. The balance equations to derive the stationary probability are given as follows:

$$\begin{cases} \mu_1\pi_1 = \mu_1\pi_{2n+1} \\ \mu_2\pi_2 = p\mu_1\pi_1 \\ \mu_2\pi_2' = (1-p)\mu_1\pi_1 \\ \ldots \\ \mu_1\pi_k = \mu_2\pi_{k-1} + \mu_2\pi_{k-1}' \\ \mu_2\pi_{k+1} = p\mu_1\pi_k \\ \mu_2\pi_{k+1}' = (1-p)\mu_1\pi_k \\ \ldots \\ \mu_2\pi_{2n} = p\mu_1\pi_{2n-1} \\ \mu_2\pi_{2n}' = (1-p)\mu_1\pi_{2n-1} \\ \pi_1 + \sum_{i=1}^{n}(\pi_{2i} + \pi_{2i+1} + \pi_{2i}') = 1. \end{cases} \tag{16}$$

After resolving the equation system, we obtain

$$\begin{cases} \pi_1 = \pi_{2n+1} = \frac{1}{2+n+n\frac{\mu_1}{\mu_2}} \\ \pi_{2i} = p\frac{\mu_1}{\mu_2}\frac{1}{2+n+n\frac{\mu_1}{\mu_2}} \\ \pi_{2i'} = (1-p)\frac{\mu_1}{\mu_2}\frac{1}{2+n+n\frac{\mu_1}{\mu_2}}. \end{cases} \tag{17}$$

The residence time of each cell is obtained as follows:

$$\Gamma_1 = \left(\frac{2R_2}{vel} - \frac{2nR_1}{vel}\right)\frac{1}{n+1} \tag{18}$$

$$\Gamma_2 = \frac{2R_1}{vel} \tag{19}$$

where vel denotes the velocity of the considered UE. It is worth noting that Γ_1 represents the residence time during which the UE is connected by default to the macrocell network (e.g., no WiFi is available). Since the distance between WiFi cells is equal, this duration is the same for other time periods when only the macro connection is available. Thus, there are $(\mathrm{n}+1)$ periods of Γ_2 duration, when only the macrocell connectivity is available. Hence, the transition rates, μ_1 and μ_2, are equal to $1/\Gamma_1$ and $1/\Gamma_2$. Since the NQPr entity is able to predict the user QoE of each cell, we can estimate the average QoE perceived by a mobile user as follows:

$$E[Q] = \left(\sum_{i=0}^{n-1}(\pi_{2i+1} + \pi_{2i}) + \pi_{2n+1}\right)E[Q_m] + \left(\sum_{i=0}^{n-1}\pi_{2i+2}'\right)E[Q_w] \tag{20}$$

where $E[Q_w]$ and $E[Q_{macro}]$ denote the average QoE in the WiFi cells and in the macrocell, respectively. Here, we assume that all WiFi cells have the same average QoE, and all macrocells ensure the same QoE. By replacing the obtained values of π, we obtain

$$E[Q] = \left(\frac{1}{3n + n\frac{(n+1)R_1}{R_2 - nR_1}}\right)\left(2 + n + np\frac{n+1}{R_2 - nR_1}\right)E[Q_m] + \frac{(1-p)n(n+1)R_1}{R_2 - nR_1}E[Q_w]. \tag{21}$$

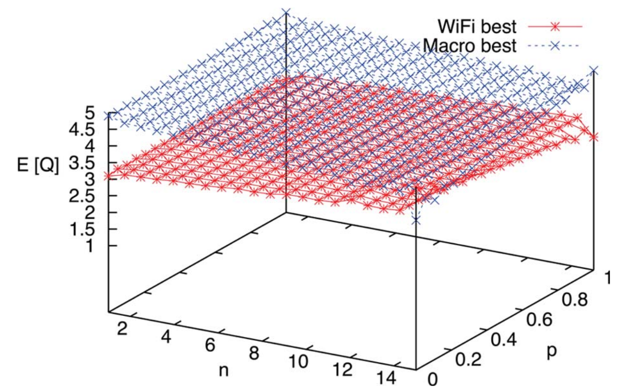


Fig. 10. Average QoE for different numbers of WiFi cells and different values of probability p.

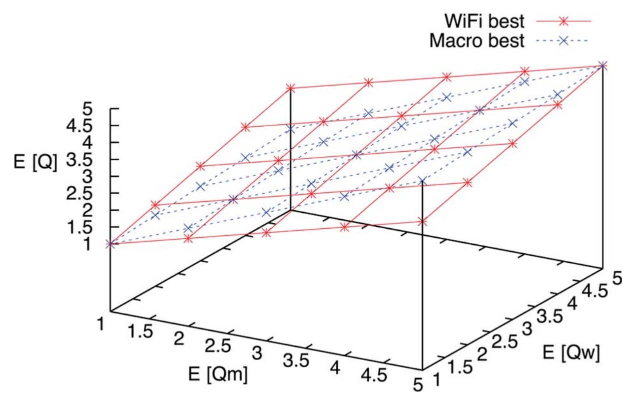


Fig. 11. Average QoE for different MoS values of both 3G and WiFi.

V. Performance Evaluation

A. Numerical Results

By resolving the systems presented in the previous section, we can evaluate the performance of the proposed solution in terms of average QoE perceived by a user during his mobility. Without any specific purpose in mind, we set $R_1 = 100$ m and $R_2 = 2000$ m. Furthermore, unless otherwise specified, we set the average user velocity to 10 m/s.

Fig. 10 shows the average QoE for different numbers of deployed WiFi cells (density) (n) and for different values of the probability p. We envisioned two cases, namely, the case whereby the macrocell ensures the best QoE ($E[Q_m] = 5$ and $E[Q_w] = 3$) and another case whereby WiFi cells ensure the best QoE ($E[Q_m] = 3$ and $E[Q_w] = 5$). We observe that when WiFi cells ensure better QoE, increasing the number of WiFi cells increases the average QoE. However, in the first case, when the macrocell ensures better QoE, increasing the number

TABLE II
ENVISIONED SIMULATION SCENARIO

3G1 (10%)	3G1 (20%)	3G1 (20%)	3G1 (20%)	3G1 (50%)	3G2 (30%)	3G2 (30%)	3G2 (30%)	3G2 (30%)	3G2 (30%)	3G2 (30%)
	WLAN1 (80%)		WLAN2 (30%)	WLAN3 (50%)	WLAN4 (30%)		WLAN5 (110%)		WLAN6 (50%)	
0-30 s	30-120 s	120-170s	170- 270s	260- 360s	350- 450s	450-540s	540- 620s	620- 670s	670– 770s	770- 900s

TABLE III
EXAMPLE OF CRITERIA SCORING

Technology	QoE(MoS)	Cost	Security	Mobility
WLAN	Measured/predicted (x_1/10)	High	Low	Low
3G	Measured/predicted (x_2/10)	Low	High	High

of WiFi cells has a negative impact on the overall QoE. On the other hand, as expected, the probability of remaining in the macrocell or offload traffic through WiFi cells has an important impact on the average QoE. Depending on which cell type ensures better QoE, the probability p increases or decreases the users' QoE. This shows the importance of the proposed network selection process to select the appropriate probability to maximize the average QoE. Therefore, the TOPSIS approach can ensure the always-best connection principle by adequately selecting probability p. In Fig. 11, we set the number of WiFi cells (n) to 10, which represents a medium density of WiFi cells. We varied the values of $E[Q_m]$ and $E[Q_w]$ MoS values of 3G and WiFi, respectively. We considered two values for p: 1) $p = 0.2$, which gives priority to the WiFi cells; and 2) $p = 0.8$, which gives priority to the macrocell. We notice that $E[Q]$ is convex to both $E[Q_m]$ and $E[Q_w]$. It, however, increases more rapidly when increasing $E[Q_m]$. This behavior is expected as most of the time, the UE is connected to the macrocell. Accordingly, we can clearly assess that ensuring high QoE in the macrocell is critical if the network operator wants to increase the user QoE, particularly in areas with a low density of WiFi cells.

B. Simulation Model

To evaluate the performance of VECOS in a more realistic way, we use the network simulator, i.e., NS2, with the NIST add-on [24]. This specific module includes several wireless access technologies and implements vertical handover by using the IEEE 802.21 standards. Note that details on the 3G implementation details in NS2 are available in [28]. We consider a scenario whereby a UE randomly moves in the range of different available access networks composed by 3G and WiFi cells, as depicted in Table II. Unlike the analytical model, the WiFi cells are overloaded in different ways to reflect different QoE values. Furthermore, the probability of selecting a network is not static; it is rather derived using either the TOPSIS or the MDP module as detailed in the previous section. It is worth noting that the network selection process of VECOS does not rely on the LTE-physical information. Using 3G instead of an LTE simulation model shall therefore have no impact on any of the fundamental observations made about VECOS. The simulations are run for 900 s, which is a duration long enough to ensure that the system has reached its stability. Through the simulations, the UE receives a video stream encoded with a constant bit rate (CBR) at 320 kb/s. The UE moves at an average speed of 10 m/s visiting different areas covered by 3G only or by both 3G and WiFi. The residual times of the UE at each area along with the load of each cell are shown in Table II. For instance, between $t = 170$ s and $t = 270$ s, the UE is visiting an area covered by a 3G cell with 20% of load and a WiFi cell with 30% of load. Here, the load represents the ratio of the bandwidth used by active connections to the maximum cell bandwidth.

C. Network Selections Process: TOPSIS Versus MDP

As previously stated, VECOS uses either TOPSIS or MDP for network selection. Table III shows an example of the TOPSIS criteria scoring used by ANDSF. It is worth mentioning that only QoE needs to be assessed by NQPr, whereas users' policies or ANDSF's define the other parameters. The scores of security, mobility, and cost are given in a generic way. The final score used in TOPSIS has to express the requirement defined in Table III. For instance, security could be scored with three values: 3 for a highly secure network, 2 for a medium secure network, and 1 for a loosely secure network. Mobility could have a binary value, e.g., 1 when the network allows mobility, 0 otherwise. Cost could be the price for 1 kbit of data. For the TOPSIS implementation of VECOS, we considered these scores for the three attributes: 3/3 for high requirement, 2/3 for medium, and 1/3 for low. We recall that TOPSIS handles nondimensional scores, by applying a normalization process before dealing with the network selection procedure. Clearly, the choice of the criteria's value is empirical and depends on the preferences of the operator or the entity managing the network selection process. Furthermore, the weight vector associated with each attribute is defined as follows: $W_1 = (0.7, 0.15, 0.05, 0{,}1)$; the highest weight is given to the QoE criterion, as the first goal of VECOS is to ensure high user experience, and the second criterion is the cost of the connection. With an aim to compare between TOPSIS and the three MDP

TABLE IV
SELECTED NETWORKS FOR THE SCENARIO OF TABLE II

TOPSIS	$\{3G_1, 3G_1, WLAN_2, 3G_1, WLAN_4, 3G_2, 3G_2, 3G_2, WLAN_6, 3G_2\}$
MDP conf. 1	$\{3G_1, 3G_1, WLAN_2, 3G_1, WLAN_4, 3G_2, 3G_2, 3G_2, WLAN_6, 3G_2\}$
MDP conf. 2	$\{3G_1, 3G_1, WLAN_2, WLAN_3, WLAN4, 3G_2, 3G_2, 3G_2, WLAN_6, 3G_2\}$.
MDP conf. 3	$\{3G_1, 3G_1, WLAN_2, 3G_1, WLAN_4, 3G_2, 3G_2, 3G_2, WLAN_6, 3G_2\}$

configurations introduced in Section III-E, Table IV shows the selected networks for the scenarios of Table II. Except for MDP conf. 2, the obtained results show that all solutions select the same network for each time interval. This is attributable to the fact that MDP conf. 2 privileged using WLAN over 3G as this latter reduces the expected discounted reward due the cost incurred when using 3G. Furthermore, both MDP and TOPSIS recommend the same networks to use. The only case where the two schemes exhibit a different behavior is when the cost incurred by using 3G is proportionally higher in comparison to the gain obtained by QoE. Accordingly, VECOS is always able to select the appropriate network access that constantly maximizes user's QoE.

D. Results

As a comparison term with VECOS, we use a cost-based handover decision mechanism, selecting always WLAN as the preferred point of attachment to the network whenever it becomes available. This mechanism is obtained when considering the connection cost as the most important criterion (with highest weight) for selecting the access network. The presented results of VECOS are those obtained when TOPSIS or MDP (conf. 1) are used as the network selection method associated with the configuration of Table II and the weight vector W1. Unless otherwise stated, the prediction of the mobility features of the UE is initially assumed to be accurate. This assumption is made to avoid any possible confusion between degradation in performance due to inaccuracy in mobility path prediction and performance degradation due to the selection of the loaded AP. In other simulation scenarios, we vary the length of a user's mobility path that the system can predict. For instance, we consider a scheme that can predict the whole trajectory of a mobile user or just a part of the trajectory. This shall cope with the possible inaccuracy in the mobility path prediction.

Fig. 12 plots the instantaneous UE's data download rate during the simulation. In comparison to the default handover decision mechanism, VECOS exhibits better performance, and that is due to the fact that it favors APs with the lowest load along the predicted mobility path of a UE. In contrast, the default scheme always adopts the same order of preference, penalizing sometimes the user satisfaction as there are periods (e.g., $t = 20$ s to $t = 120$ s, $t = 520$ s to $t = 620$ s) when data rates potentially available at 3G are higher than those offered by WLAN, i.e., due to high contention in the WLAN cell. In case of VECOS, we also remark degradations in the UE's data rate. These degradations mainly occur during the actual handover operation from WiFi to 3G.

Figs. 13 and 14 plot the end-to-end delays and packet loss rates experienced by the UE during the course of the simulation. These figures support the general observation made from

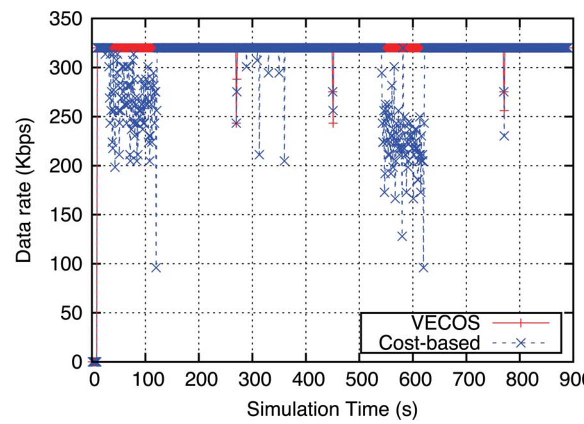


Fig. 12. Instantaneous data download rate during the simulation time.

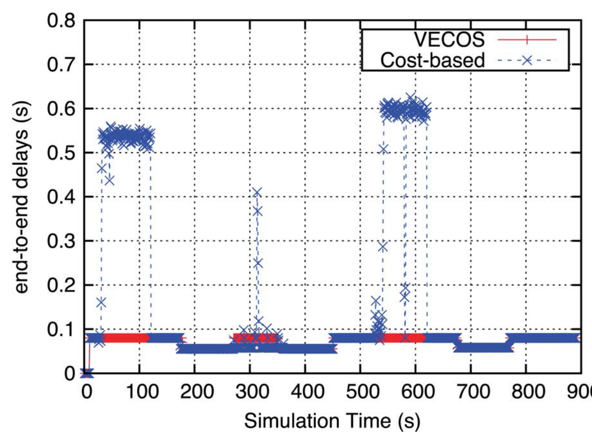


Fig. 13. Instantaneous end-to-end delay during the simulation time.

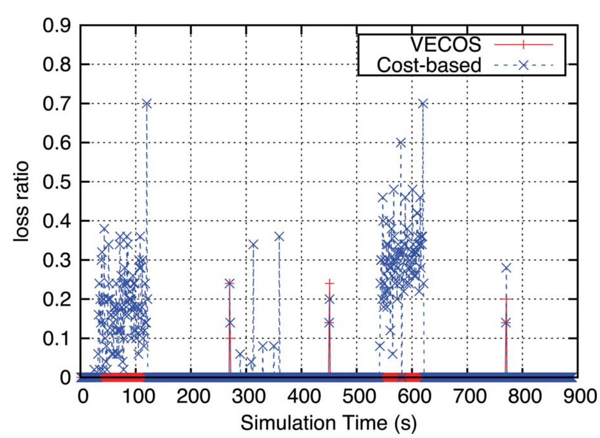


Fig. 14. Instantaneous loss rate during the simulation time.

Fig. 12. The degradation of the data download rate seen in Fig. 12 is mainly due to the high loss rate resulting from the high contention in the WLAN cell. In fact, most of the packets are dropped at the AP queue, since the probability to access

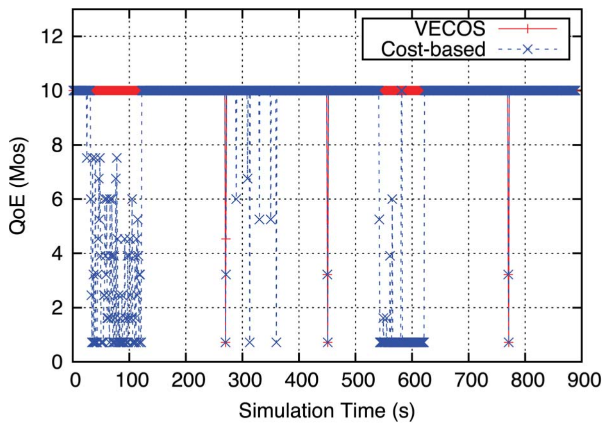


Fig. 15. Instantaneous loss rate during the simulation time.

the channel is low. Furthermore, VECOS maintains lower end-to-end delays throughout the simulation time, whereas these delays are higher when the default mechanism is used. For instance, it reaches 0.7 s in case of the default mechanism, mainly when the WLAN cells are working under high loads. To further evaluate the impact of packet loss and end-to-end delays on user QoE, we draw in Fig. 15 the instantaneous user QoE in terms of the MOS. The MOS is a value between 0 and 10, representing the quality as perceived and given by users to a service. The values 10 and 0 represent the highest video quality and the worst video quality, respectively. These scores were obtained by the pseudo subjective quality assessment (PSQA) tool [20], which is an automatic QoE evaluation tool for multimedia services based on the random neural network. It learns the nonlinear relationship between parameters impacting the service quality and the user perceived QoE. It shall be noted that the PSQA version used in the simulations is dedicated to video quality evaluation. Fig. 15 clearly shows that the user's QoE heavily and frequently degrades in case of the default handover mechanism. These degradations correspond to the time periods when the packet loss and end-to-end delays are high. In contrast, the figure shows that the VECOS scheme maintains high values of MOS throughout the entire simulation.

To investigate the impact of the criterion weight of TOPSIS on VECOS performance, we modify the weight vector W. We refer to the version employing weight vector W_1 by VECOSv1 and VECOSv2 to the version using a new weight vector W_2 defined as follows: $W_2 = \{0.4, 0.4, 0.05, 0.15\}$. VECOSv2 is giving the same weight to the QoE and Cost criteria. Therefore, the selected networks are $\{3G_1, 3G_1, WLAN_2, WLAN_3, WLAN_4, 3G_2, 3G_2, 3G_2, WLAN_6, 3G_2\}$, where $WLAN_3$ is used instead of $3G_1$ as in case of VECOSv1. It shall be noted that VECOSv2 performance is also obtained with MDP (conf. 2) since the cost of using a 3G connection is increased in comparison with VECOSv1.

Table V shows the performance of VECOSv1, VECOSv2, and the cost-based network selection scheme in terms of user's QoE (MOS). The two versions of VECOS exhibit nearly the same performance, noting a slightly better MOS achieved by VECOSv1. However, VECOSv2 considerably reduces the cost as it substitutes a 3G connection with WLAN.

TABLE V
QoE-BASED COMPARISON OF VECOS WITH COST-BASED NETWORK SELECTION SOLUTION

	VECOSv1	VECOSv1	Cost-based
Max. MOS	10	10	10
Average MOS	9.9943	9.9392	8.213
Variance MOS	0.485	0.502	13.2735

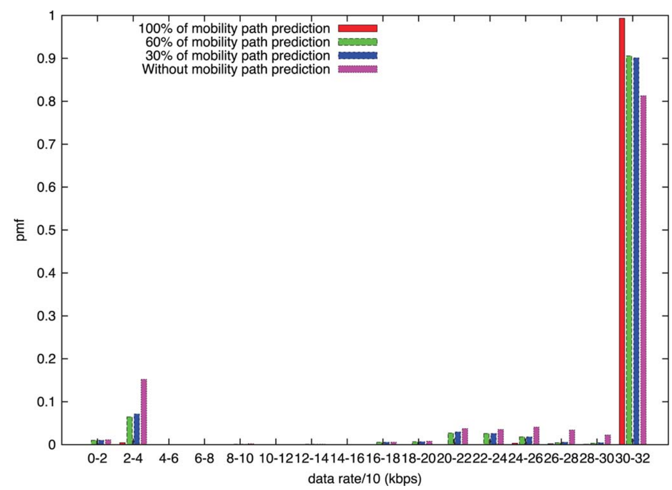


Fig. 16. PMF of the UE's data download rate for different values of the mobility prediction accuracy.

To evaluate the impact of errors in the mobility prediction, we plot in Fig. 16 the probability mass function (PMF) of the data download rate achieved by the UE in four scenarios: 1) when VECOS is used and the mobility path is fully predicted with accuracy; 2) when VECOS is used and only 60% of the mobility path is predicted; 3) when VECOS is used and only 30% of the path is predicted; 4) and when the default handover mechanism is used, intuitively with no path prediction. Note that the VECOS results are those based on Table II configuration (VECOSv1). As expected, predicting the entire path of the UE allows achieving the best performance. In fact, when the path is fully predicted, the probability that the UE achieves 320 Kb/s is around 0.9. However, the lower the prediction accuracy, the lower the data rate obtained by the UE. For instance, the UE achieves 320 kb/s with a probability of 0.85, 0.83, and 0.7 in the case of 60%, 30%, and 0% of prediction accuracy, respectively. The same trend in performance is also experienced in terms of end-to-end delay, packet loss, and QoE, as shown in Figs. 17–19.

It worth mentioning that predicting the entire path, associated to TOPSIS formulation for network selection, ensures high QoE for users, with a MOS almost equal to five throughout the simulation (as seen in Fig. 19). Indeed, according to the configuration of TOPSIS (see Table III), the vehicle is always connected to the best network that maximizes the user's QoE.

VI. CONCLUSION

Stemming from 1) the observation that mobile operators are deploying different access technologies in addition to their current 3GPP technologies and 2) the expected popularity of LTE-connected cars or simply the wide usage of smartphones

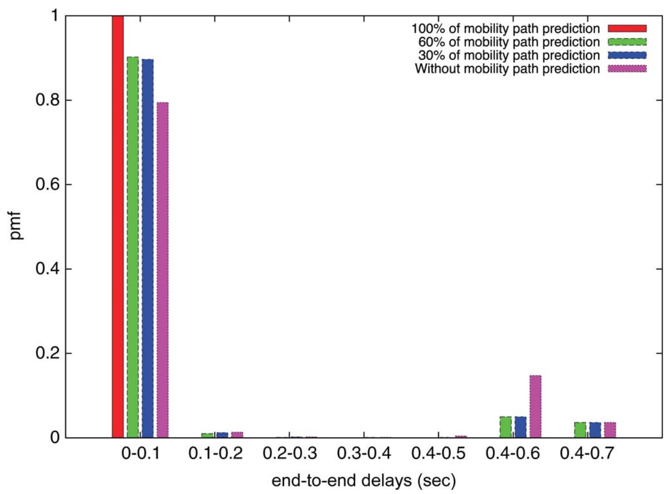


Fig. 17. PMF of the UE's end-to-end delays for different values of the mobility prediction accuracy.

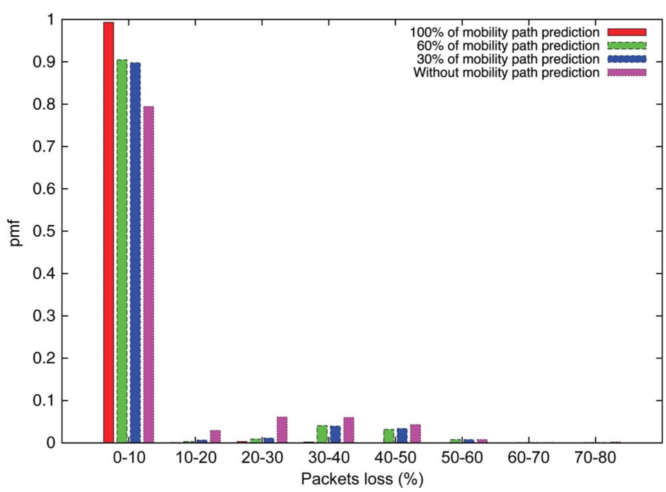


Fig. 18. PMF of the UE's packet loss for different values of the mobility prediction accuracy.

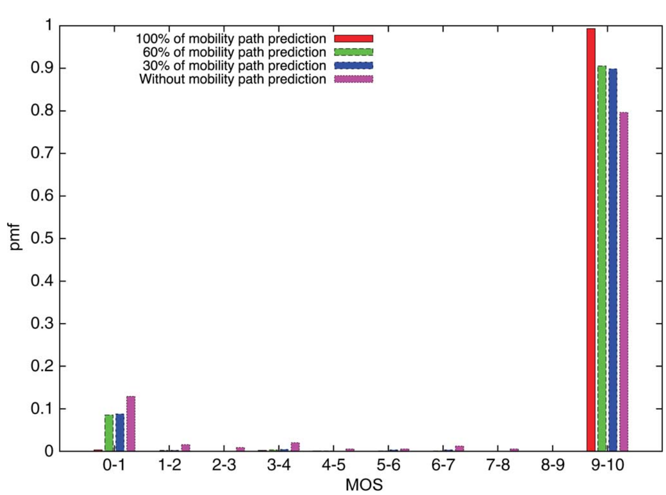


Fig. 19. PMF of MOS for different values of the mobility prediction accuracy.

onboard vehicles, this paper has been motivated by the need for a framework that proactively defines QoE/QoS-aware policies for LTE-connected vehicles to select the most adequate radio access out of the different available access technologies. The selection of radio access technologies takes into account the service type, the mobility feature of users, and the traffic dynamics over the backhaul networks of the available access technologies. The proposed framework defining a complete protocol dubbed VECOS encompasses different modules to be deployed at the network control plane as well as at UE. The proposed modules assist in predicting the UE mobility features, predicting the available throughput backhaul network and translating this information into a user satisfaction factor (QoE) and implementing a network selection mechanism. VECOS enables a mobile operator to establish the list of APs a user of a UE is likely going to visit during a time window of interest and to predict the mean satisfaction level the user is likely going to experience at each AP when connected to the AP. Based on these assessments, the mobile operator provides guidelines to the UE on which the AP is to connect to and when ensuring the highest QoE for the user. These guidelines are enforced by the UE using adequate tools. The performance of VECOS was evaluated through simulations and compared against a baseline cost-based vertical handover scheme. The obtained results demonstrated the better performance of VECOS. They also illustrated the impact of the mobility prediction accuracy on the overall performance of VECOS.

Admittedly, a number of challenges could be associated with real-life implementation of VECOS. For example, always carrying out the prediction of QoE and/or mobility with high accuracy can be a challenge. We have shown in the MDP model the impact of errors in the prediction on the proposed policy. Effectively, predicting QoE in WiFi cells is very challenging due the underlying CSMA/CA algorithm. However, we have proved, through simulation results, that VECOS still exhibits good performance even in the presence of some errors in the mobility and QoE prediction. In this vein, it shall be noted that the accuracy of such predictions can be largely improved, with time, using suitable probabilistic/learning-based schemes (e.g., [33] and [34]). Another challenge associated with VECOS pertains to the scalability of the solution, as RAT selection is done for each UE. This can be alleviated by limiting VECOS to only specific types of users (e.g., VIP users, users paying for VECOS recommendation as a service, users receiving a specific service/application, users traveling over a specific region, etc.).

As for the real-life implementation of VECOS, the network-relevant features of VECOS can be implemented at ANDSF that has been standardized in 3GPP since Release 8. Many vendors do offer ANDSF as highly stable products. The role of ANDSF is in line with the spirit of VECOS, as it recommends to UE the radio access type to connect to for a specific PDN connection and/or IP flow. Plugins relevant to ANDSF at UE are also standardized and available in pre-Release 8 UE. With these plugins, a UE is able to receive policies from ANDSF and enforce them at the UE level. VECOS will be using ANDSF to communicate the QoE-aware policies, defined by the mobile network operator, and will be using these plugins to read the policies and enforce them at the UE level. All in all, we do believe that the implementation of VECOS in LTE-connected cars is straightforward and can be achieved with minimal impact on existing 3GPP standards.

REFERENCES

[1] T. Taleb, A. Benslimane, and K. Ben Letaief, "Towards an effective risk-conscious and collaborative vehicular collision avoidance system," *IEEE Tran. Veh. Technol.*, vol. 59, no. 3, pp. 1474–1486, Mar. 2010.

[2] T. Taleb *et al.*, "A stable routing protocol to support ITS services in VANET networks," *IEEE Trans. Veh. Technol. J.*, vol. 56, no. 6, pp. 3337–3347, Nov. 2007.

[3] ALU's LTE Connected Car Project. [Online]. Available: http://www.alcatel-lucent.com/blog/tag/ng-connect

[4] A. Benslimane, T. Taleb, and R. Sivaraj, "Dynamic clustering-based adaptive mobile gateway management in integrated VANET-3G heterogeneous wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 3, pp. 559–570, Mar. 2011.

[5] T. Taleb, K. Samdanis, and F. Filali, "Towards supporting highly mobile nodes in decentralized mobile operator networks," in *Proc. IEEE ICC*, Ottawa, ON, Canada, Jun. 2012, pp. 5398–5402.

[6] Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2009–2014, Feb. 2010, White Paper.

[7] "Mobile Traffic Growth + Cost Pressures = New Solutions?" New Mobile, Jan. 2010.

[8] N. Gohring, "KDDI offloads traffic on cellular network through Wi-Fi," IDG News Service, Jul. 2011. [Online]. Available: http://www.networkworld.com/news/2011/070111-kddi-offloads-traffic-on-cellular.html

[9] "RAN Congestion: Breaking the 3G/4G Bottleneck," Heavy Reading 4G/LTE Insider, vol. 2, no. 2, Mar. 2011.

[10] 3rd Generation Partnership Project (3GPP), "Study on S2a mobility based on GTP and WLAN access to EPC," Sophia-Antipolis, France, 3GPP Specifications TR 23.852, 2011.

[11] 3rd Generation Partnership Project (3GPP), "Architecture enhancements for non-3GPP accesses," Sophia-Antipolis, France, 3GPP Specifications TS 23.402, 2011.

[12] 3rd Generation Partnership Project (3GPP), "Operator Policies for IP Interface Selection (OPIIS)," Sophia-Antipolis, France, 3GPP Specifications TR 23.853, 2011.

[13] 3rd Generation Partnership Project (3GPP), "Data identification in Access Network Discovery and Selection Function (ANDSF) (DIDA)," Sophia-Antipolis, France, 3GPP Specifications TR 23.855, 2012.

[14] X. Yang, J. Bigham, and L. Cuthbert, "Resource management for service providers in heterogeneous wireless networks," in *Proc. IEEE WCNC*, Mar. 13–17, 2005, vol. 3, pp. 1305–1310.

[15] X. Liu, V. Li, and P. Zhang, "Joint radio resource management through vertical handoffs in 4G networks," in *Proc. IEEE GLOBECOM*, Nov./Dec. 2006, pp. 1–5.

[16] A. Wilson, A. Lenaghan, and R. Malyan, "Optimizing wireless access network selection to maintain QoS in heterogeneous wireless environments," in *Proc. WPMC*, Sep. 18–22, 2005, pp. 8–13.

[17] K. Piamrat, A. Ksentini, C. Viho, and J. M. Bonnin, "QoE-aware vertical handover in wireless heterogeneous networks," in *Proc IWCMC*, Istanbul, Turkey, Jul. 2011, pp. 95–100.

[18] A. Nadembega, A. Hafid, and T. Taleb, "A path prediction model to support mobile multimedia streaming," in *Proc. IEEE ICC*, Ottawa, ON, Canada, Jun. 2012, pp. 2001–2005.

[19] A. Nadembega, T. Taleb, and A. Hafid, "A destination prediction model based on historical data, contextual knowledge and spatial conceptual maps," in *Proc. IEEE ICC*, Ottawa, ON, Canada, Jun. 2012, pp. 1416–1420.

[20] T. Taleb and A. Ksentini, "QoS/QoE predictions-based admission control for Femto communications," in *Proc. IEEE ICC*, Ottawa, ON, Canada, Jun. 2012, pp. 5146–5150.

[21] K. Piamrat, A. Ksentini, J.-M. Bonnin, and C. Viho, "Radio resource management in emerging heterogeneous wireless networks," *Comput. Commun.*, vol. 34, no. 9, pp. 1066–1076, Jun. 15, 2011.

[22] T. Taleb, A. Hafid, and A. Nadembega, "Mobility-aware streaming rate recommendation system," in *Proc. IEEE GLOBECOM*, Houston, TX, USA, Dec. 2011, pp. 1–5.

[23] *The Network Simulator NS2 NIST Add-On: IEEE 802.21 Model*, Nat. Inst. Std. Technol., Adv. Network Technol. Div., Washington, DC, USA, 2007.

[24] IMS, Not VoLTE, is the Future of Voice With T-Mobile, Phone Scoop, Philadelphia, PA, USA, Feb. 28, 2012. [Online]. Available: http://www.phonescoop.com/articles/article.php?a=9976

[25] T. Taleb, S. Cherkaoui, and E. D. Ngangue Ndih, "On supporting mobile peer to mobile peer communications," in *Proc. IEEE ICC*, Ottawa, ON, Canada, Jun. 2012, pp. 596–600.

[26] F. Bari and V. Leung, "Multi-attribute network selection by iterative TOPSIS for heterogeneous wireless access," in *Proc. IEEE Consum. Commun. Netw. Conf.*, Las Vegas, NV, USA, Jan. 2007, pp. 808–812.

[27] T. Taleb, A. Ksentini, and F. Filali, "Wireless connection steering for vehicles," in *Proc. IEEE GLOBECOM*, Anaheim, CA, USA, Dec. 2012, pp. 56–60.

[28] EURANE-Enhanced UMTS Radio Access Networks for ns2. [Online]. Available: http://eurane.ti-wmc.nl

[29] M. Puterman, *Markov Decision Process: Discrete Stochastic Dynamic Programming*. Hoboken, NJ, USA: Wiley-Interscience, 1994.

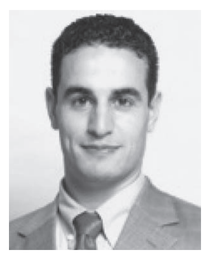
[30] INRAs Matlab MDP Toolbox. [Online]. Available: http://www.inra.fr/mia/MDPtoolbox

[31] A. Ksentini and T. Taleb, "QoE-oriented adaptive SVC decoding in DVB-T2," *IEEE Trans. Broadcast.*, vol. 59, no. 2, pp. 251–264, Jun. 2013.

[32] E. Steven-Navarro, Y. Lin, and V. Wong, "An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks," *IEEE Tran. Veh. Technol.*, vol. 57, no. 2, pp. 1243–1254, Mar. 2008.

[33] D. Gundlegard and J. M. Karlsson, "Handover location accuracy for travel time estimation in GSM and UMTS," *IET Intell. Transp. Syst.*, vol. 3, no. 1, pp. 87–94, Mar. 2009.

[34] Y. Liang, Y. SiXing, H. Weijun, and L. ShuFang, "Spectrum behavior learning in cognitive radio based on artificial neural network," in *Proc. MILCOM*, Baltimore, MD, USA, Nov. 2011, pp. 25–30.



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