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Vehicular Network-Aware Route Selection Considering Communication Requirements of Users for ITS

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***Abstract*—Increasing demands of mobile users on communication and new types of devices, such as sensors, machines, and vehicles, impose high load on cellular networks. Since requirements are expected to rise in a near future, new ways for cellular network offloading are needed. A promising solution for vehicles and vehicular users is to offload data to vehicular networks. To maximize offloading of the cellular networks, the vehicles can be navigated through areas characterized with more available communication capacity. Hence, we propose a novel scalable traveling route selection algorithm determining the route according to a traveling time and available throughput of both cellular and vehicular networks. While the maximum tolerated traveling time is defined by the vehicular users, an estimation of available throughput is based on a vehicular movement prediction. The proposed route selection algorithm is able to offload cellular network by up to 17% and time spent without required quality of connection can be reduced by 65%. At the same time, the traveling time is prolonged only negligibly in comparison with state-of-the-art algorithms.**

***Index Terms*—Cellular networks, Intelligent Transportation System (ITS), navigation, offloading, route selection, vehicular networks.**

I. Introduction

In RECENT years, wireless networks face significant increase in data transmission caused by high demands of users on throughput. Especially, cellular networks are expected to be highly overloaded in near future due to new emerging services [1]. Rapid growth of communication requirements can also be seen in the field of Intelligent Transportation Systems (ITSs), where an increasing amount of interconnected vehicles in combination with higher demands of on-board users on communication affect wireless networks. For example, 80% of the vehicular users are interested in services such as a vehicle health report [2]. Furthermore, it is expected that, in the near future, the number of on-board users streaming audio will increase from current 38% to 89% and Internet surfing will be used by 71% instead of current 14% [2]. This indicates that the requirements of passengers on communication capacity will rise significantly.

For communication of the vehicles, a concept of vehicular ad-hoc networks (VANETs) can be exploited. The physical and medium access control layers of VANETs are defined by the IEEE 802.11p standard. The IEEE 802.11p together with the IEEE 1609 protocol is called the wireless access in vehicular environments (WAVE) standard. The primary aim of VANETs is to enable communication-based automotive safety applications through sharing traffic information (TI). The information can be shared either between the vehicles (V2V) or between the vehicles and an infrastructure (V2I), where the infrastructure is represented by road side units (RSUs).

Internet traffic of on-board users carried through an existing cellular network infrastructure can be offloaded to VANETs since the vehicular network capacity is currently underutilized. A concept exploiting VANETs to provide Internet connection to the users in the vehicles is known as a service-oriented VANETs [3]. The service-oriented VANETs can reduce load of the cellular networks by transmission of data generated by the users in the vehicles via the vehicular networks (if connection is available). In addition, the connection via VANET is free of charge, thus, it is convenient for the vehicular users also. However, an overexploitation of the service-oriented VANETs can result in the same overloading problem as in case of the cellular networks.

A feasible solution for the cellular network offloading can be seen in a redirection and navigation of some vehicles with respect to their communication requirements. An algorithm for an efficient redirection of vehicles based on a reactive route selection exploiting static information on signal-to-noise ratio (SINR) of both cellular and vehicular networks is presented in our previous work [4]. However, neither the load of cells nor the available capacity of cells are taken into account in [4]. Neglecting such information may lead to the navigation via routes providing high channel quality, but with very limited capacity of the RSU or a cellular base station (eNB) as these may serve many users. On the other hand, the redirection of the vehicles based only on the network capacity and communication requirements of the vehicles and the vehicular users disregarding other route-related parameters (such as route passing time) can significantly prolong the traveling time in comparison with the fastest possible route (FPR).

The main objective of this paper is to offload the cellular networks by smart selection of traveling route to navigate vehicles with consideration of a predicted load of the communication networks. To that end, we propose a novel dynamic centralized proactive route selection algorithm denoted as vehicular network-aware route selection algorithm (VaRSA). This VaRSA leads to maximization of the time spent by the on-board users connected to VANET instead of the cellular networks. Besides, the VaRSA results in lowering of the communication cost for the users, while quality of service (QoS) experienced by them is not affected. The main extension of our prior work [4] consists in a proactive estimation of the future load of the RSUs and eNBs. The estimation is based on the movement prediction

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of all vehicular users and on an estimation of the requirements of vehicular users on the network throughput. This information is then exploited for a determination of available throughput at all feasible routes of the vehicle's movement and also for the selection of the most suitable route considering the users requirements on communication. At the same time, the VaRSA respects the user's requirements on the traveling time. It means any prolongation of the traveling time is negligible and only within limits defined by the users.

To prove the efficiency of our proposed algorithm, we also assess an impact of the speed prediction inaccuracy. Moreover, we thoroughly evaluate an impact of the number of vehicles and the throughput required by the users on the performance of the proposed algorithm. To that end, we enhance the simulation model presented in [4] by realistic movement of the vehicles in Manhattan-like area for VaRSA. The improved model accurately simulates behavior of vehicular users on road (acceleration/deceleration, turning) taking into account other vehicles, intersections, etc.

Note that all terms *route*, *routing*, *path*, and *traffic* in this paper are related to *movement and traveling of the vehicles*, not to the communication. On the other hand, the term *network* denotes only *wireless communication network*. Also notice that we focus on V2I scenario in this paper while V2V scenario is left for future research.

This paper is organized as follows. Section II gives an overview on related work in the area of a proactive route selection, predictive algorithms suitable for vehicles, and methods for offloading of cellular network. Section III outlines a set of assumption for the proposed scheme, thoroughly describes our proposal, and classifies services available for vehicles and onboard users. Sections IV and V provide the description of simulation models and simulation results, respectively. Section VI summarizes major conclusions and outlines future research directions.

II. Related Works

To find an appropriate route, route selection algorithms (known as navigation or route planning algorithms) are incorporated into ITS [5]–[8]. The route selection algorithms can be classified according to three criteria. The first criterion classifies the route selection algorithms to static and dynamic. Whereas the static approach selects the route based only on a fixed road topology regardless the current TI, the dynamic route selection reflects the current traffic state and changes route accordingly. The static route selection is able to find the route without a necessity to transfer additional information and, thus, without any additional connection cost. However, the static route selection may also incur a hunting phenomenon, which results in overloading main roads with large number of navigated vehicles (see [5]).

The second criterion determines whether the route selection is autonomous (also called distributed) or centralized. In case of the autonomous route selection, each vehicle is in charge of its own route selection. In contrast, the centralized route selection is performed in a centralized service center. The main disadvantage of the autonomous route selection is that it can result in the Braess effect [6] (i.e., the situation when an autonomous addition of a new route to the topology impairs the overall performance of the whole traffic system). Although the vehicles have to communicate with the centralized service center, the centralized route selection can eliminate a negative effect of selfish decision [7] and leads to a higher performance and a lower traffic cost for all involved vehicles [8].

The third criterion divides the route selection algorithms to a proactive and a reactive. The reactive route selection uses only a historical or real-time TI and assumes that the traversal time remains stable for a whole journey. This could lead to a suboptimal route selection since the situation on the road can change rapidly. A dynamic rerouting can help to avoid this problem; however, it can also lead to further deterioration of the route selection quality in case of frequent changes [9]. In contrast to the reactive algorithms, the proactive algorithms exploit a traffic prediction for an estimation of a future state resulting in more efficient route selection. According to Li *et al.* [10], a precise route toward destination point (DP) can be proactively predicted in about 78%–99% cases. At the same time, the exact time spent in a given section of the route can also be proactively predicted in more than 70% instances. Therefore, the proactive prediction is seen as a very promising approach for the route selection.

An overview of the short-term vehicular movement prediction is given in [11]. The existing work on traffic prediction can be classified into two categories: parametric and nonparametric [12]. The parametric methods include prediction models based on historical average and smoothing techniques, regression [13], autoregressive integrated moving average [14], or Kalman filter [15]. In contrast, the nonparametric prediction models use nonparametric regression [16], neural networks [17], [18], machine learning [19], fuzzy logic [20], or artificial intelligence [21]. One of the most precise predictions of the future traffic state is done through a link traversal time as described in [22]. The link traversal time represents the time spent by the vehicle in a specific road section. According to Wahle *et al.* [23], the link traversal time is more useful for the prediction than the real-time TI and can result in uniform distribution of the traffic.

However, the traffic prediction algorithms mentioned above do not consider an origin point (OP), a destination point, or a route planned from the OP to the DP. Therefore, the inaccuracy in estimation of the link traversal time is also influenced by an error in the prediction of the vehicles destination and in the prediction of the selected route. It leads to a deterioration of the prediction accuracy, as shown in [10]. In contrast, if the route selection system with centralized architecture is exploited, the OP and the DP as well as planned route between them is known in advance, since most of the drivers do not change the already selected route during the journey [24]. In [24], He *et al.* exploit knowledge of the OP and the DP by the centralized route selection algorithm with a prediction of position of other vehicles to select the shortest possible route. For prediction of the link traversal time, the authors consider the driving time together with the time of waiting at intersections. A dynamic navigation protocol for the time efficient route selection is also introduced in [25]. As in the previous case, the route selection algorithm exploits knowledge of the OP and the DP together with information on already visited route segments in order to predict the future traffic at each possible route. A participatory system navigating drivers in a balanced way, denoted as Themis, is introduced in [26]. The Themis coordinates traffic and proactively alleviates congestions according to the estimated travel time and a popularity score computed using the information learned from other vehicles in the system. It leads to more continuous and balanced traffic without congestions.

None of the previous works exploits prediction of the vehicles position for the cellular network offloading or for improvement of the communication throughput. An overview of a technical solution and challenges for the offloading of vehicular communication to Wi-Fi networks are presented in [27]. In [28], an offloading of the cellular network by using an opportunistic vehicular ad hoc networks for a noncritical application has been proposed. The predictive method for the offloading cellular network communication of the vehicular users is introduced in [29]. The proposed method is based on historical information such as tracks with timestamps, radio frequency fingerprints, and link and network-layer addresses of visible access points. In [30], procedures exploiting a mobility prediction and prefetching to enhance the offloading of the traffic from the cellular network for both delay-tolerant and delay-sensitive traffic have been proposed. In [31], the short-term mobility prediction based on a fog-of-war model is exploited for the decision on which data can be buffered in the RSUs and transmitted to the vehicle once it reaches area of the RSU instead of transmission via the cellular network. Although the cellular network could be offloaded, the algorithms does not exploit prediction for an efficient route selection with awareness of the communication quality required by the users in the vehicle.

We estimate load of both the cellular network, represented by Long-Term Evolution-Advanced (LTE-A), and the vehicular network, represented by WAVE, in every place and in each future moment during the journey. The load estimation is based on an expected future position of the vehicles obtained by a vehicular traffic prediction algorithm [24] and an estimation of requirements of the vehicular users on the network throughput. With respect to the available capacity of both LTE-A and WAVE networks, a new route selection algorithm considering the requirements of users on throughput and a maximum tolerated prolongation of journey is proposed.

III. Proposed Vehicular Network Aware Route Selection Algorithm

In this section, the concept of VaRSA is introduced. First, we list the assumptions taken into account by the proposed VaRSA. Next, the database exploiting SINR fingerprints, denoted as long-term average SINR map (LASM) is introduced. The LASM, originally presented in [10], is extended by a prediction of available capacity of both vehicular as well as cellular networks. Despite the vehicular and cellular networks are represented by WAVE and LTE-A, respectively, in this paper, the same approach can be applied to any other cellular and vehicular networks. Finally, the core of the proposed VaRSA is thoroughly described.

Fig. 1 shows the system architecture of the proposed centralized route selection algorithm. The main part of the general centralized route selection architecture is represented by a centralized route selection entity (CRSE). The core function of the CRSE is to provide an efficient route selection for all involved vehicles based on a combination of current and predicted TI. Note that for our algorithm, an extension of the conventional centralized architecture consists only in adding the LASM with ability to perform prediction.

A. Assumptions

Before detailed introduction of our approach, we define a set of realistic system level assumptions that has to be fulfilled to take advantage of the proposed VaRSA algorithm. All assumptions are commonly considered in many studies of future ITS or even practically implemented. Following assumptions are considered.

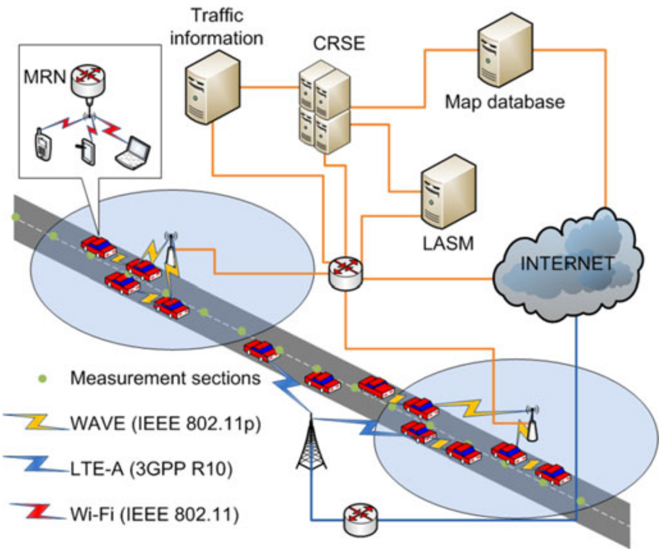

Fig. 1. System architecture.

1) All vehicles using the proposed route selection algorithm are equipped with a satellite navigation, such as GPS or GLONASS, to determine their position.
2) Vehicles are equipped with vehicular network interface, such as WAVE [32], which enables to receive/report current TI from/to other vehicles in the vicinity or from/to the RSUs. We also assume that each vehicle can access LTE-A, if available.
3) Each vehicle can serve as a mobile relay node providing the Internet connection for the on-board users instead of direct connection of individual on-board users to LTE-A. For this purpose, a short-range communication technology, such as Wi-Fi, can be exploited on inner interface of the vehicle [33], [34]. Note that the throughput required by the vehicle is composed of demands of the on-board users and requirements of the vehicle itself.
4) The Internet connection for the on-board users via the RSUs is intended primarily for the vehicles using any centralized route selection algorithm (not limited only to the proposed one). The vehicles using an autonomous route selection algorithm can exploit the Internet connection via the RSUs only if the network resources are available and only until these are not required by other vehicles using any centralized route selection algorithm. Such restriction is applied since the future load of the RSUs is estimated via the prediction of the vehicles position over time, but the future position of the vehicles exploiting the autonomous route selection is not known. Note that the vehicles using an autonomous route selection algorithm can still share common vehicular TI, such as reporting values from sensors and receiving current TI via the RSUs without any restriction.
5) The delivery of emergency messages (i.e., unexpected traffic situations, such as sudden roadblock or request for help in case of an accident) is of the highest priority and it has to be processed in a very short time. Therefore, a

TABLE I
NOTATIONS OF PARAMETERS USED IN THIS PAPER

Parameter	Description
F	Utility function
$T^W/T^L/T^O$	Time interval during which a vehicle experiences sufficient channel quality to WAVE/to LTE-A/time without sufficient QoS
$\Omega/\Phi/\Theta$	Weights of the FPR/WAVE connection/avoidance of insufficient QoS
γ_i^W/γ_i^L	SINR perceived by the vehicle from the strongest WAVE RSU in ith measurement section/from the strongest eNB in ith measurement section; averaged values stored in LASM
$\widehat{C}_x^W/c_v^W$	Maximum capacity offered by xth RSU/capacity required by vth vehicle connected to WAVE
$\widehat{C}_y^L/c_v^L$	Maximum capacity offered by yth eNB/capacity required by vth vehicle connected to LTE-A
$c_{j,i}^W/c_{j,i}^L$	Estimated available capacity of WAVE/LTE-A in ith measurement section of jth path
τ_r	Total throughput required by guided vehicle
Π	Set of measurement sections composing a route of the vehicle between the OP and the DP
$T^{\mathrm{MIN}}/T^{\mathrm{MAX}}$	Minimum predicted travel time between the OP and the DP/maximum tolerated travel time between the OP and the DP

flooding algorithm sending the emergency message to all available network interfaces, is applied.

B. Prediction of Available Capacity for Route Selection

For easy following of the description of the proposed algorithm, we summarize all used parameters in Table I.

The prediction of available capacity is based on information from the LASM database. The LASM, introduced in [4], stores an average SINR from all RSUs, γ_i^W, and eNBs, γ_i^L, at each measurement section similarly to well-known approach of fingerprints (see, for example, [35]). In line with [35], we assume that the distance between two measurement sections is 5 m. In this paper, the concept of LASM is further extended by a prediction of the future available capacity in each measurement section in a time instant t. For the prediction of the vehicles' future position, we exploit the centralized algorithm defined in [24].

For the WAVE network, the required capacity of the users in the vth vehicle, c_v^W, depends on γ^W experienced by the vehicle from its serving RSU. Total available capacity of the x-th RSU that can be offered to the users in the vth vehicle at the time t is calculated as follows:

$$c_x^W(t) = \widehat{C}_x^W - \sum_{v\in U} c_v^W(t) \tag{1}$$

where $\widehat{C}_x^W$ is the maximum capacity that the xth RSU is able to provide, U is the set of vehicles connected to xth RSU, and c_v^W represents the capacity required by the vth vehicle connected to the serving RSU (via WAVE) at the time t. Note that a part of total available capacity of each RSU is reserved for a common TI and emergency messages. According to Baiocchi *et al.* [36], the common TI is in orders of $40-50$ kb/s and it is included in c_v^W. The maximum capacity of WAVE network available in the ith measurement section (ms$_i$), c_i^W, is derived from $c_x^W(t)$ [as defined in (1)] and the SINR level of the serving RSU in the ms$_i$, γ_i^W is determined as mentioned in [37] and [38].

For the LTE-A network, the capacity required by the vth vehicle, c_v^L, is related to the number of resource blocks (nrb_v^L) available for the users at the serving eNB and known γ^L. The γ^L is transformed to the number of bits per resource block (n_b) knowing modulation and coding scheme, as shown in [39] and [40]. Then, the required capacity is defined as $c_v^L(t) = nrb_v^L(t) \times n_b(t)$. Based on the capacity required by other vehicles, the total available capacity provided by the yth eNB at the time t is calculated as

$$c_y^L(t) = \widehat{C}_y^L - \left(\sum_{v\in V} c_v^L(t)\right) - \Psi(t) \tag{2}$$

where $\widehat{C}_y^L$ is the maximum capacity that the yth eNB is able to provide, V is the set of vehicles connected to the yth eNB, c_v^L is the capacity required by the vth vehicle connected to the yth eNB at the time t, and $\Psi(t)$ represents the capacity required by the nonvehicular users connected to the serving eNB at the time t.

The maximum available capacity of the eNB in the ms$_i$ (c_i^L) is calculated based on the total available capacity $c_y^L(t)$ provided by the serving eNB in the time when the vehicle is passing through the ms$_i$ and γ_i^L, as mentioned in [39] and [40]. Although there exist many route prediction algorithms for general mobile users, such as destination and mobility path prediction [41], their accuracy is lower than in case of the vehicular user following preselected route to known DP. Since we do not need to know the exact position of other mobile users, we estimate only their average requirements Ψ using long-term (e.g., days) statistical profile, as described in [42].

Note that the prediction of vehicles' position and requirements can be done not only for the vehicles that exploit the proposed VaRSA algorithm, but also for other vehicles using other centralized route selection algorithms. However, if the vehicle does not use any centralized route selection algorithm, the prediction of available capacity (especially for RSUs) cannot be done accurately. Therefore, the connection of vehicles not using any centralized route selection to the RSUs is intended for transfer of TI. User data can be transmitted via the RSUs only in case of available resources.

C. Proposed Route Selection Algorithm

In this section, the proposed VaRSA is introduced. In the first step of the VaRSA, the navigated vehicle sends the OP and the DP together with the required type of communication service to the CRSE. This information is delivered within the route selection request (RSR) message (see Algorithm 1, line 1). After the CRSE receives the RSR message, it calculates the duration of the FPR between the OP and the DP, T^{MIN}. T^{MIN} is derived from a map database and the predicted traffic situation, as described in [24] (line 2). Note that the process of finding the FPRs is similar for all commonly used centralized route selection algorithms.

After the calculation of T^{MIN}, this time is sent back to the navigated vehicle (line 3). Based on the preference of the users in navigated vehicle, the maximum tolerated time (T^{MAX}) of the journey is selected and sent back to the CRSE (line 4). Note that the setting of T^{MAX} according to the users preference leads to a significant reduction of the possible routes only to the set R^{MAX}. The setting of T^{MAX} also results in a substantial reduction of the proposal's complexity since T^{MAX} reduces the number of possible routes between the OP and the DP.

After the CRSE receives the T^{MAX}, all possible routes between the OP and the DP with the travel time shorter than the

T^{MAX} form the set R^{MAX}, i.e.,

$$R^{\mathrm{MAX}} = \{\Pi_1, \Pi_2, ..., \Pi_j, ..., \Pi_N\} \tag{3}$$

where each route is composed of n_j measurement sections

$$\Pi_j = \{\mathrm{ms}_{j,1},\ \mathrm{ms}_{j,2}, ..., \mathrm{ms}_{j,i}, ..., \mathrm{ms}_{j,n_j}\}. \tag{4}$$

Each $\mathrm{ms}_{j,i}$ in (4) is characterized by three parameters: traversal time $T_{j,i}$, SINR level of the strongest RSU γ_i^W, and SINR level of the strongest eNB γ_i^L. The traversal time $T_{j,i}$ represents the time spent by the vehicles in the $\mathrm{ms}_{j,i}$. The SINR levels for each measurement section are stored in the LASM and the capacity available in a specific time to users in both WAVE and LTE-A networks is calculated, as described in Section III-B. The total time spent by the vehicle on the route Π_j is expressed as

$$T_j^T = \sum_1^{n_j} T_{j,i}. \tag{5}$$

Based on the available capacity of WAVE in a single $\mathrm{ms}_{j,i}$ and the throughput required by the navigated vehicle, the total time when the required throughput of WAVE is available for the route Π_j can be calculated as

$$T_j^W = \sum_1^{n_j} T_{j,i}, \qquad \{T_{j,i} | c_{j,i}^W > \tau_r\} \tag{6}$$

where τ_r represents the throughput required by the navigated vehicle including the on-board users throughput and $c_{j,i}^W$ is the available capacity of WAVE in the $\mathrm{ms}_{j,i}$ in the time when the navigated vehicle is passing the $\mathrm{ms}_{j,i}$ (derived in Section III-B).

Analogously to T_j^W, the total connection time to LTE-A for the route Π_j is expressed as

$$T_j^L = \sum_1^{n_j} T_{j,i}, \qquad \{T_{j,i} | c_{j,i}^L > \tau_r \wedge c_{j,i}^W < \tau_r\} \tag{7}$$

where $c_{j,i}^L$ is the available capacity of LTE-A within the $\mathrm{ms}_{j,i}$ in the time when the navigated vehicle is passing this particular $\mathrm{ms}_{j,i}$ (also described in Section III-B).

Note that since the main aim of the proposed algorithm is to offload the cellular network, the connection via WAVE is preferred. It means if both networks (i.e., WAVE and LTE-A) are able to provide the required throughput τ_r in particular $\mathrm{ms}_{j,i}$, the time interval $T_{j,i}$ is included only in T_j^W.

Besides the places where WAVE or LTE-A are available, the vehicle can be also in the location when neither WAVE nor LTE-A are able to fulfill QoS requirements of the vehicles and the on-board users. The time when the insufficient QoS below required level is offered is defined as (line 17)

$$T_j^O = T_j^T - \left(T_j^W + T_j^L\right). \tag{8}$$

To select the most suitable route for the vehicle considering QoS, we define a utility function F_j. The F_j is computed for each route from set R^{MAX} as (line 18)

$$F_j = \Omega\left(T_j^T\right) + \Phi\left(T_j^T - T_j^W\right) + \Theta\left(T_j^O\right) \tag{9}$$

where $\Omega \in \langle 0, 1\rangle$ represents the weight representing the preference of the FPR, $\Phi \in \langle 0, 1\rangle$ indicates the weight representing

Algorithm 1: WAVE-aware route selection algorithm.

1: Vehicle sends OP/DP and weights to CRSE through RSR
2: CRSE calculates T^{MIN} based on map database and predicted traffic situation
3: CRSE sends T^{MIN} back to vehicle
4: User/vehicle selects T^{MAX} and sends it back to CRSE
5: set R^{MAX} is formed (3)
6: **for** 1:each route forming set R^{MAX} **do**
7:     **for** 1:all mss of route Π_j **do**
8:       $c_{j,i}^W$ is calculated
9:     **if** $c_{j,i}^W > \tau_r$ (6) **then**
10:       $T_j^W = T_j^W + T_{j,i}$ (6)
11:      **else** $c_{j,i}^W$ is calculated
12:       **if** $c_{j,i}^W < \tau_r \& c_{j,i}^L > \tau_r$ (7) **then**
13:        $T_j^L = T_j^L + T_{j,i}$ (7)
14:       **end if**
15:      **end if**
16:     **end for**
17:     $T_j^O = T_j^T - \left(T_j^W + T_j^L\right)$ (8)
18:     $F_j = \Omega\left(T_j^T\right) + \Phi\left(T_j^T - T_j^W\right) + \Theta\left(T_j^O\right)$ (9)
19: **end for**
20: **Route with the lowest F is selected**

the preference of WAVE connection, and $\Theta \in \langle 0, 1\rangle$ is the requirement on avoidance of insufficient QoS. All weights can be set manually by user or automatically according to the requirements on communication (as explained in Section IV-B). The weights are independent and can be set autonomously from each other. If the FPR is the only criterion, as in conventional route selection, the weights are set to $\Omega = 1$, $\Phi = 0$, and $\Theta = 0$. Then, the route with the minimal total traveling time T_j^T is selected. If the only objective is to maximize the time in WAVE coverage T_j^W, the weights are set to $\Omega = 0$, $\Phi = 1$, and $\Theta = 0$. In this case, the users targets to minimize data connection cost as WAVE is free of charge. If only avoidance of insufficient QoS is preferred, the weights are set to $\Omega = 0$, $\Phi = 0$, and $\Theta = 1$. In this case, the users prefer to ensure possibility of communication during the travel disregarding available technologies. At the end, the route with the lowest F_j is selected as the preferred one.

IV. Simulation Setting

In this section, a simulation environment and performance evaluation settings are defined. First, the detailed description of the simulation model for the vehicular traffic is provided. Then, we explain the setting of weights of the proposed algorithm for the performance evaluation and we present state-of-the-art algorithms considered for comparison of the performance. Last, the performance metrics are described.

A. Simulation Models

For the performance evaluation, we develop a MATLAB simulator suitable for a modeling of the vehicular movement within the environment covered by two cooperating wireless networks. The MATLAB simulator exploited in this paper is an extended version of a simulator used in [4]. The simulation area is composed of six vertical and six horizontal streets with a length of 5 km (see Fig. 2). The total width of the streets is 16 m including

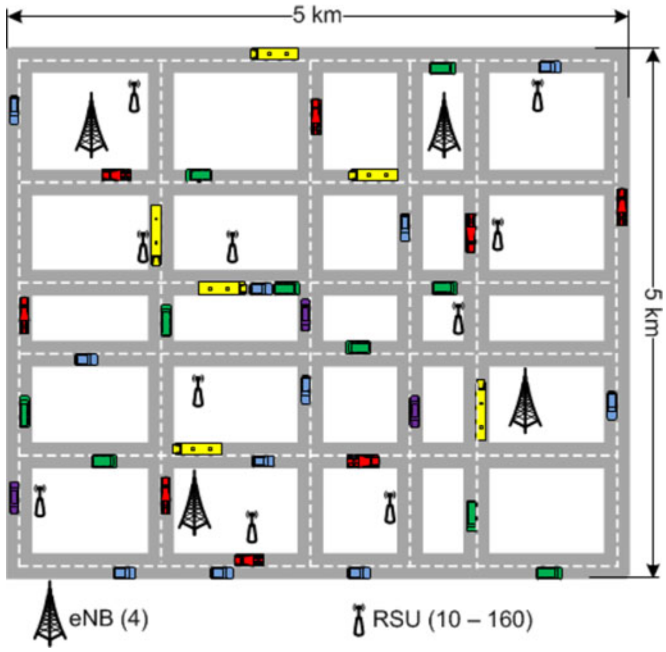

Fig. 2. Illustrative example of simulation environment for ten RSUs in the system.

TABLE II
LIST OF SIMULATION PARAMETERS

Parameter	Value (default)
Number of vertical/horizontal streets	6/6
Size of simulation area [km × km]	5 × 5
Length of vehicles [m]	5–15
Maximum acceleration/mean acceleration [m/s^2]	6/3
Maximum/mean speed [m/s]	18/12
Frequency band WAVE/LTE-A [GHz]	5.9/2
Frequency bandwidth WAVE/LTE-A [MHz]	10/100
Transmission power of RSUs/eNBs [dBm]	20/32
Height of RSUs / eNBs [m]	1.8/32
Noise level WAVE/LTE-A [dBm/Hz]	−174
Number of simulation drops	100
Number of RSUs	10–160
Number of vehicles	400–1600
Required throughput [Mb/s]	1–15

footpaths. The vehicles move within the street in both directions in the middle of the lane corresponding to the vehicle direction.

All used simulation parameters are summarized in Table II. In the simulation, there are 400–1600 moving vehicles representing low- and high-density vehicular traffic, respectively, and generating background load for both LTE-A and WAVE networks. Such span express network load deviation. For each vehicle, unique OP/DP and dynamic movement characteristics, such as maximum acceleration, average speed, etc., are selected randomly with normal distribution based on parameters listed in Table II. The movement characteristics are generated randomly to represent individual driving style of each driver/vehicle. Moreover, the dynamic movement characteristics are restricted by physical limits of the vehicles in terms of acceleration, deceleration, and maximum speed of vehicle. The behavior of vehicles is similar to a real traffic pattern as the vehicles take traffic environment into account. It means that the vehicles smoothly and uniformly accelerate on the direct path as well as gradually and uniformly decelerate in front of intersections or close to a queue of other vehicles. Mean acceleration of the vehicles is 3 m/s^2 while mean deceleration is 1 m/s^2. Also a fluent pass through the intersection is considered. It means if the vehicles are going straight, their acceleration rises more rapidly than if they are turning. During the turning, the vehicle moves through the intersection with a constant speed. Moreover, the density of vehicles in a given segment influences the possibility to pass through this street segment. After the vehicle arrives into the final DP, it is removed from the simulation environment since it has no longer impact on traffic situation (user cannot exploit WAVE and connects to LTE-A). Simultaneously, a new vehicle with new random characteristics is placed in a random position in the simulation area. During the simulations, we assume that 50% of all background vehicles use VaRSA with random setting of weights. Rest of the background vehicles always selects the FPR. In a real situation, the FPR is chosen by the drivers using common navigation systems or by the drivers familiar with the neighborhood as these are able to select the shortest possible path by themselves.

In the simulation environment, two types of the base stations are deployed. The position of four eNBs providing the LTE-A connection is fixed for all simulation drops. Contrarily, the number and positions of the RSUs providing WAVE connection are variable and ranges between 10 and 160 RSUs. The path loss of WAVE is modeled as a combination of free space path loss model with two-ray ground path loss model, as suggested in [37]. The SINR level and the throughput for WAVE is derived from [38] and [43] for all vehicles by assuming adaptive modulation. For LTE-A, the Okumura-Hata path loss model for urban scenarios [44] is used. We assume that handover from LTE-A to WAVE and vice versa is seamless and no addition delay influences total throughput as the time of handover can be predicted [45]. Since we focus on heavily loaded cellular network and high requirements of users, we assume that, on average, 85% of capacity of each eNB ($\widehat{C}_y^L$) is occupied by the nonvehicular users ($\Psi \approx 0.85 \times \widehat{C}_y^L$). Note that we assume 100 MHz bandwidth (i.e., 1 mil resource blocks/s per one antenna [46]) and 8×8 multiple-input multiple-output (MIMO). The requirements of each third vehicle are generated by lognormal distribution with mean value of 3 Mb/s while the rest of the vehicles requests only 100 kb/s for TI.

For the performance evaluation, a particular navigated vehicle is monitored in the map. For maximization of the number of possible routes between the OP and the DP (without detour), one of the intersections in the corners is randomly selected as the OP of the navigated vehicle. The DP is selected according to the OP in the opposite corner of the simulation environment. It means 252 possible routes exist between the OP and the DP. The difference between individual routes consists in different travel times and in different coverages of WAVE and LTE-A. During the simulation, the most appropriate route for the navigated vehicle is selected according to the predefined weights (Ω, Φ, and Θ). Based on [4], the upper bound of the traveling time extension T^{MAX} is set to $1.15 \times T^{\mathrm{MIN}}$. In order to obtain valid and representative results, 100 simulation drops are run and then averaged out. In each drop, all characteristics of the background vehicles including their OPs and DPs and new unique positions of all RSUs are randomly generated.

B. Evaluated Algorithms

The proposed VaRSA algorithm is compared with the algorithm selecting the FPR, denoted as FPR, based on prediction of traffic situation according to [24]. Then, we also compare the proposed improvement with our former work, which targets to maximize time when the vehicles are connected via WAVE [4]. This algorithm is denoted as route selection maximizing time in WAVE and labeled in figures as MTW. As shown in [4], the MTW significantly outperforms other competitive algorithms in terms of time spent by vehicles connected to WAVE. Thus, we do not include additional algorithms to keep clarity and readability of figures and results.

One of the main advantage of the proposed VaRSA algorithm is its scalability enabled by setting of weights (Ω, Φ, and Θ). All weights can reach value between 0 and 1. Nevertheless, not all combinations corresponds to a realistic situation. For evaluation, we define three combinations of weights in order to represent following conventional services: TI service, background used data (BUD), and real-time used data (RtUD).

TI service represents common information related to road traffic and vehicle state, such as speed of vehicle, outside humidity, temperature, traffic level, and other parameters, collected by sensors in the vehicle. These data are transmitted by all vehicles connected to the network. Traffic data collected in the system serve as a source of information for other vehicles and for precise route selection and/or for avoidance of traffic congestions. LTE-A connection is prohibited to be used for this type of service, since it can lead to additional loading of LTE-A network by data generated by vehicles. Since this information can be transferred anytime later, there is no need to find a different route for the vehicle ensuring its timely delivery. Thus, in case of no other user data transmission, the weight for the FPR Ω is set to 1 and weights of Φ and Θ are set by default to 0. By substituting these weights to (9), the F_j for VaRSA-TI can be rewritten as

$$F_j^{TI} = T_j^T \tag{10}$$

BUD service represents a delay-tolerant (i.e., non-real-time) applications, such as e-mails, chat, synchronization, web browsing, or similar applications, which do not need real-time interaction of users. In comparison to TI, delivery of user data is necessary for BUD. Therefore, if WAVE connection is not available for predefined period required by the application, the vehicle initiates connection to LTE-A if its available capacity is sufficient [31]. If not, the network with higher available capacity is exploited. To that end, the weights for the fastest possible path, Ω, and preference of WAVE, Φ, are set to 1 while the preference for avoidance of low QoS, Θ, is set to 0. Using these weights in (9), the F_j for VaRSA-BUD is as follows:

$$F_j^{\mathrm{BUD}} = 2 \times T_j^T - T_j^W. \tag{11}$$

RtUD service represents delay sensitive real-time applications, such as video streaming or audio/video calls that require continuous connection without drops. This type of service typically need throughput from hundreds of kb/s to several Mb/s. A reliable delivery of real-time service is necessary similar to that in the case of BUD. In addition, the connection must be reliable with time without sufficient QoS must be minimized. Consequently, if there is no WAVE connection with sufficient throughput, the connection to LTE-A network is selected. If even LTE-A is not able to serve the vehicle with sufficient QoS, the network with higher available capacity is selected. In this case, all weights are set to 1. Hence, the utility function F_j for VaRSA-RtUD is given by

$$F_j^{\mathrm{RtUD}} = 2 \times T_j^T - T_j^W + T_j^O \tag{12}$$

The default setting used in VaRSA if at least one on-board device utilizes wireless communication is BUD. In case there are no requirements on data communication, TI is selected. Finally, RtUD is chosen if a real-time application is already running at the time when the route to the DP is being selected. If a real-time application is launched during the way already selected according to either BUD or TI service, new route to the DP is chosen by initiating VaRSA as described in Algorithm 1 with weights set for RtUD. On the other hand, if the route is selected with respect to RtUD service but this service is no longer exploited during travel, the planned route remains the same and no replanning of route is performed. This eliminates continuous switching of route due to change of varying service requirements imposed by the on-board users [8].

Since the transmission of emergency messages is exceptional and unpredictable, we do not consider this type of services for simulation. Nevertheless, in case of the emergency situation, a flooding algorithm that sends the emergency message to all available network interfaces would be applied in real networks.

C. Performance Metrics

Setting and modification of weights (Ω, Φ, and Θ) allows the proposed VaRSA to find the most appropriate route between the OP and the DP for different types of applications. Since each setting of weights focus on different goals, we evaluate the fulfilment of each setting in terms of:

1) Ratio of time spent by vehicles connected via WAVE to total duration of route (ϕ) is given as

$$\phi_j = \frac{T_j^W}{T_j^T} \times 100\%. \tag{13}$$

Maximization of ϕ is the main objective of VaRSA set for BUD (VaRSA-BUD).

2) Ratio of time spent on the route without sufficient QoS of connection to total duration of route (θ) is given as

$$\theta_j = \frac{T_j^O}{T_j^T} \times 100\%. \tag{14}$$

Minimization of θ is the main goal of VaRSA-RtUD.

3) Prolongation of journey (ω) is given as

$$\omega_j = \frac{T_j^T - T^{\mathrm{MIN}}}{T^{\mathrm{MIN}}} \times 100\%. \tag{15}$$

Minimization of ω is the main objective of VaRSA-TI.

Since accuracy of the prediction of vehicles position can influence estimated load of cell and, it can also influence selection of route. Therefore, inaccuracy of prediction and its impact on the performance of the proposed algorithm is analyzed. The inaccuracy in prediction of vehicles position is implemented in simulations as inaccuracy of speed prediction. The prediction accuracy reachable in real network can be typically below 3% according to Cheng *et al.* [27], but we analyze even higher inaccuracies up to 10% to prove efficiency for worse cases. If the speed is underestimated (negative values), the real speed is higher than the estimated one. In this case, the journey is shorter

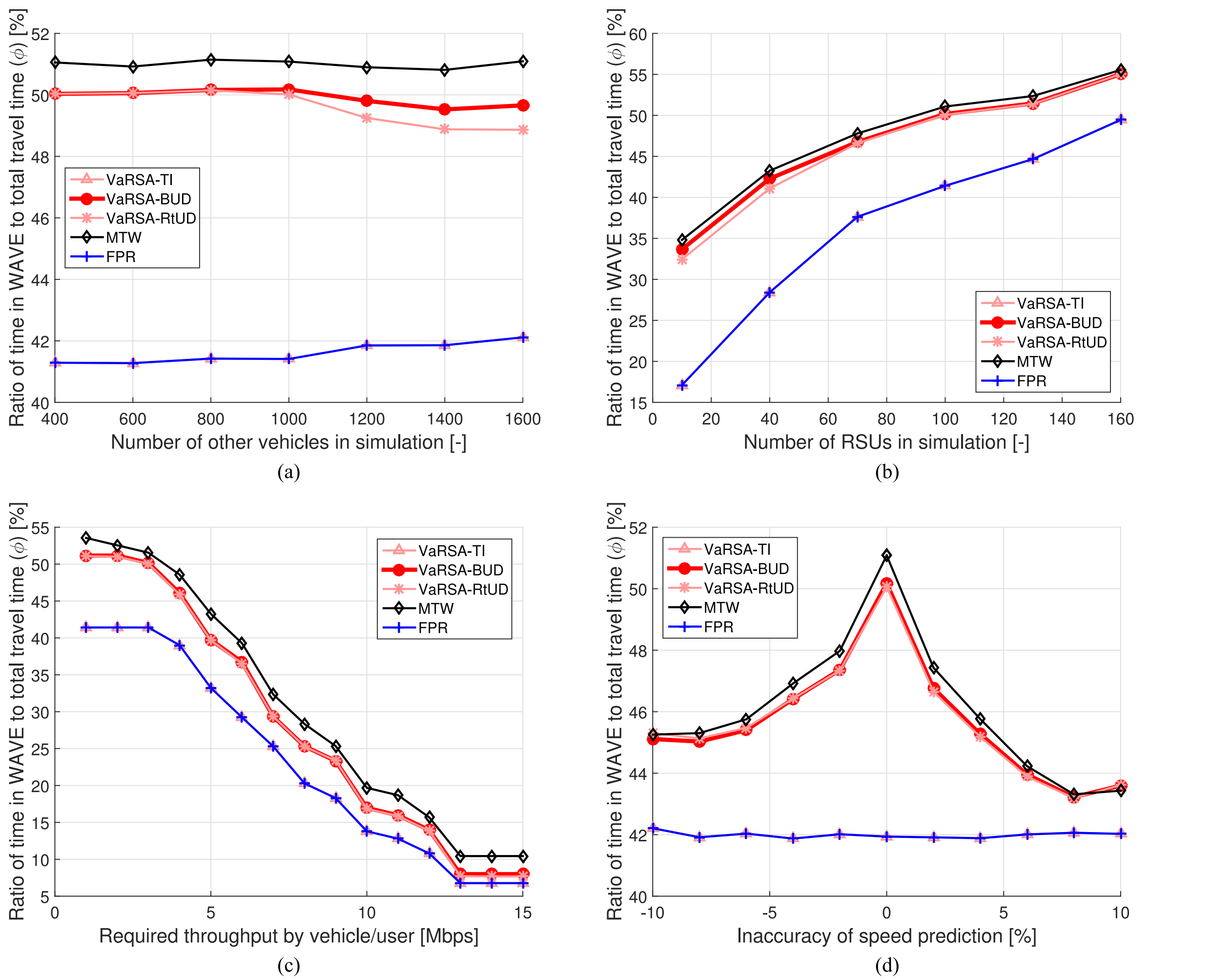

Fig. 3. Ratio of time when vehicles are connected via WAVE to total travel time (ϕ): (a) depending on number of vehicles; (b) for different number of RSUs; (c) for different required throughputs; and (d) for different inaccuracies.

than expected. On the other hand, if the speed is overestimated, the journey is longer than expected duration. Note that in default setting, no inaccuracy of position prediction is considered.

V. Simulation Results

In this section, evaluation of the proposed VaRSA for different weights and its comparison with FPR and MTW is presented. The section is split into four parts according to the evaluated aspects. Following three sections (Sections V-A–V-C) show performance VaRSA from perspective of three different metrics (i.e., ϕ, θ, and ω). Section V-D provides joint discussion of all simulation results. Note that default setting of simulation (unless specified otherwise) is: 100 RSUs, 1000 vehicles, 3 Mb/s (for navigated vehicle).

A. Ratio of Time Spent in WAVE to Total Travel Time

In this section, we focus on maximization the ratio of time spent in WAVE, represented by weight ϕ. This objective corresponds to VaRSA-BUD as defined in Section IV. Other two services (VaRSA-TI and VaRSA-RtUD) are also depicted in Fig. 3 to prove that even unsuitable selection of weights do not leads to worse performance comparing to conventional algorithms. The proposed VaRSA-BUD shows ϕ very close to the MTW in all cases and, thus, ϕ is significantly extended in comparison with conventional FPR. Note that even if the maximization of ϕ is not the main objective of VaRSA-RtUD, it shows similar results as VaRSA-BUD.

Fig. 3(a) depicts the dependence of ϕ on total number of vehicles (load deviation) in simulation. The number of vehicles influences ϕ negligibly for VaRSA-BUD and MTW as T^T as well as T^W are slightly prolonging with higher number of vehicles because of more busy traffic [see relation between T^W and T^T in (13)]. The VaRSA-BUD reaches ϕ similar to the MTW (difference is lower than 1.3% in all cases). In contrast, for FPR (and VaRSA-TI), ϕ is slightly rising with the number of vehicles. Although ϕ for FPR (and VaRSA-TI) is slightly rising, the proposed VaRSA-BUD introduces gain of at least 7.5% when compared to both FPR even for 1600 vehicles. As shown in Fig. 3(b), the ϕ rises significantly with the number of RSUs. This is due to the fact that WAVE coverage is improving with additional RSUs in the area and vehicles can spend more time connected to WAVE (i.e., higher T^W is observed). The highest ϕ is reached by MTW (35% for 10 RSUs) while the lowest ϕ is observed for FPR (only 17% for 10 RSUs). Notice that with

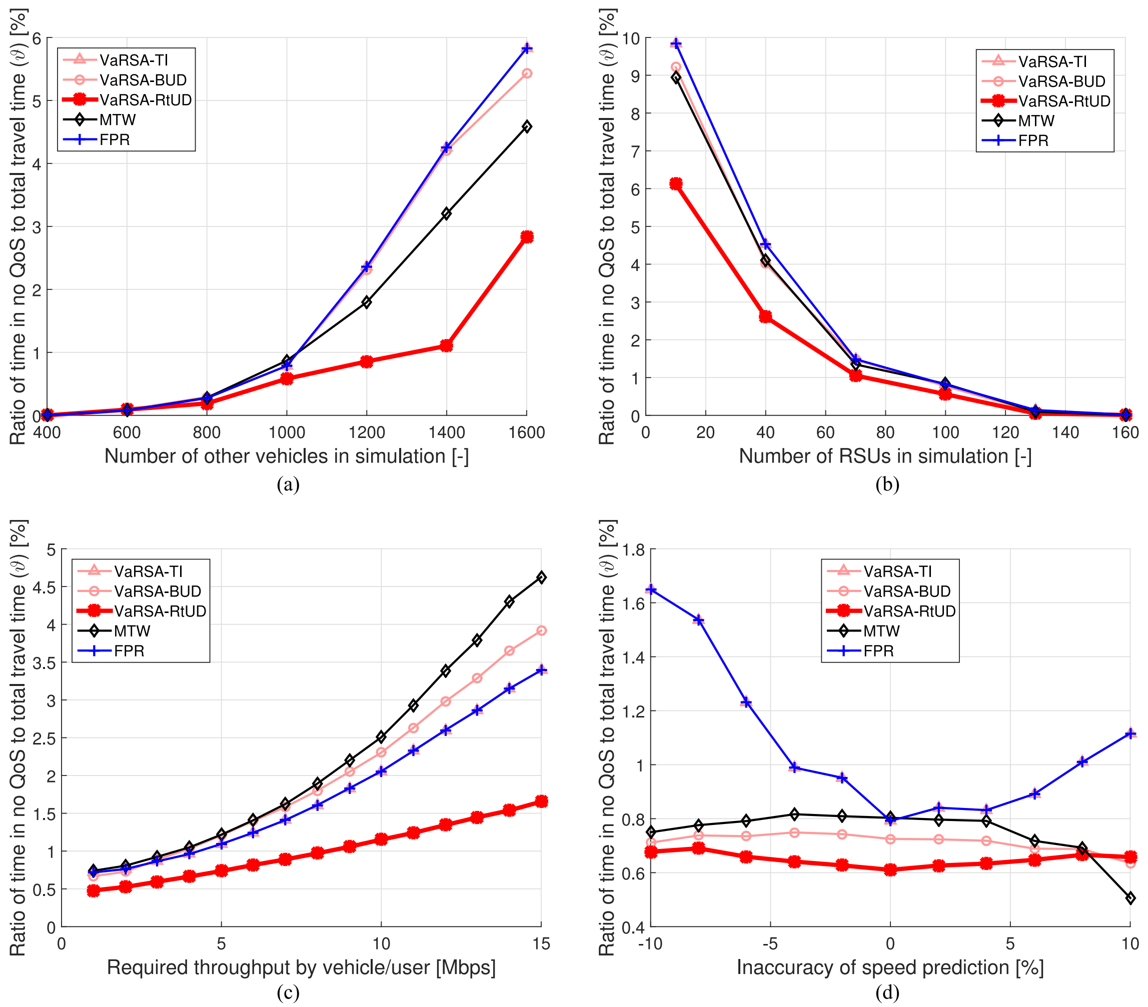

Fig. 4. Ratio of time when requirements for data transmission from vehicular users are not satisfied (no QoS) to total travel time (θ): (a) depending on number of vehicles; (b) for different number of RSUs; (c) for different required throughputs; (d) for different inaccuracies.

rising number of RSUs, the difference between all algorithms is slightly decreasing as WAVE becomes less loaded with high number of RSUs.

With increase in users throughput requirements [Fig. 3(c)], WAVE is no longer able to provide sufficient QoS and vehicles have to connect to LTE-A network more often. However, even for high throughput requirements, VaRSA-BUD is still able to extend ϕ by more than 10% in comparison to FPR while the difference between MTW is kept lower than 3%. In Fig. 3(d), it can be seen that the speed estimation inaccuracy results in lower time in WAVE due to inaccurate information on available throughput for path selection. The proposed algorithm as well as MTW are influenced in a similar way by the prediction inaccuracy. Even if the inaccuracy of prediction is 10%, ϕ for VaRSA-BUD is still higher than for FPR.

B. Ratio of Time Without Satisfied QoS to Total Travel Time

In this section, we focus on minimization the ratio of time spent without sufficient QoS, represented by weight θ. This objective is represented as VaRSA-RtUD. Disregarding the simulation configuration (i.e., the number of vehicles, number of RSU, required throughput, or inaccuracy), the lowest θ is observed for the proposed VaRSA-RtUD in the most of cases. Fig. 4(a) demonstrates that higher number of vehicles generates higher number of requirements which cannot be fully satisfied. Consequently, θ is increasing for all algorithms as well. However, VaRSA-RtUD shows significantly lower θ than other algorithms. For the highest number of vehicles (1600 vehicles), the FPR doubles θ comparing to VaRSA-RtUD. As Fig. 4(b) presents, higher number of RSUs in the simulation results in lower θ for all compared. This is due to the fact that T^W is prolonged, as shown in Fig. 3(b), while additional RSUs can serve more requests so T^O is reduced. The proposed VaRSA significantly outperforms all compared algorithms for all densities of RSUs. The gain is notable especially for low density of RSU. For example, VaRSA-RtUD reduces outage by 4% comparing to FPR if 10 RSUs are deployed in simulation area.

Fig. 4(c) depicts that rising throughput requirements of users leads to increasing θ for all algorithms. This is a result of the fact that higher requirements of users on throughput are harder to satisfy by WAVE or by LTE-A. Note that conventional FPR, again, reaches nearly twice higher θ and MTW even nearly three times higher θ than VaRSA-RtUD for high throughput requirements. It shows suitability of VaRSA even for heavily loaded scenarios. As in all previous cases, VaRSA-RtUD reaches the

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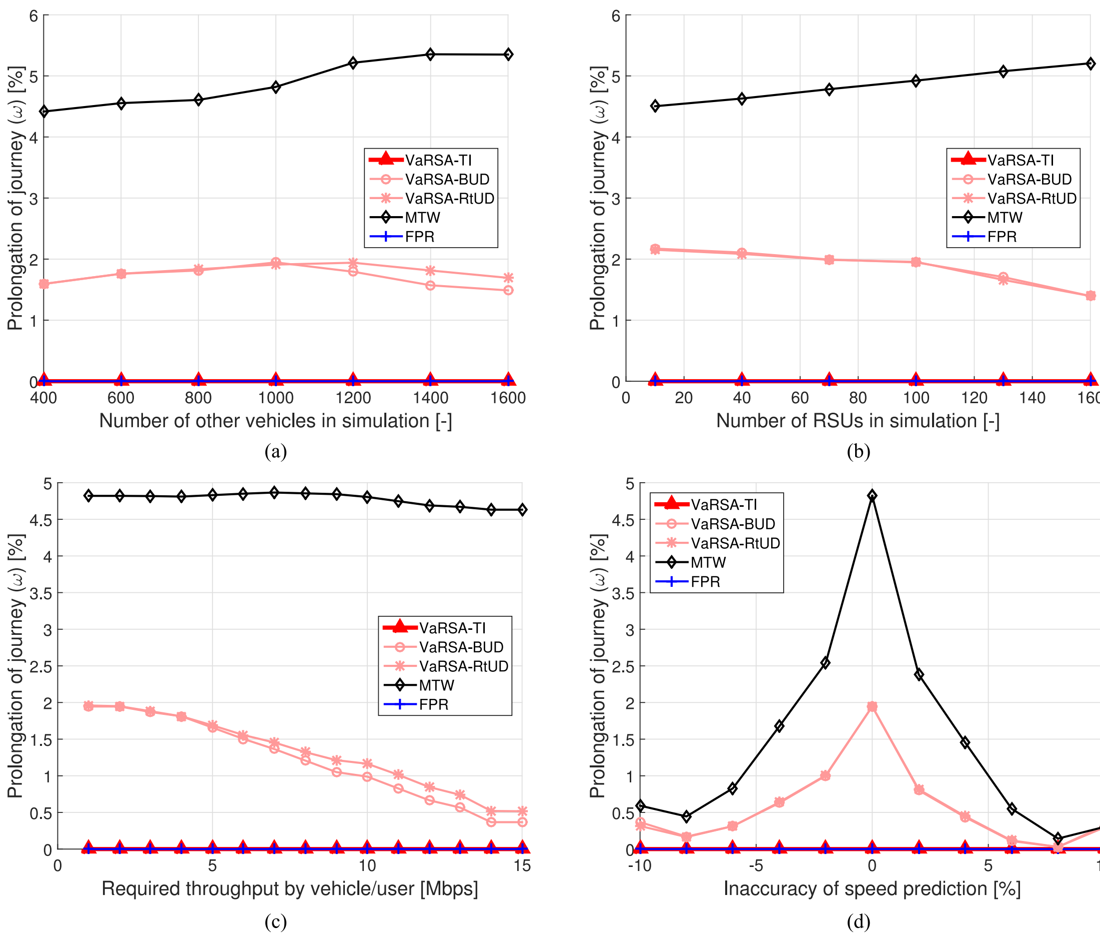

Fig. 5. Prolongation of total travel time with respect to the FPR (ω): (a) depending on number of vehicles; (b) for different number of RSUs; c) for different required throughputs; and (d) for different inaccuracies.

lowest θ for all levels of required throughputs. Fig. 4(d) indicates that VaRSA-RtUD is able to maintain the lowest θ even in case of speed prediction inaccuracy. Moreover, the θ of VaRSA-RtUD is nearly independent on inaccuracy of prediction. In case of FPR, minimum θ is reached for no inaccuracy and it is rising with inaccuracy.

C. Prolongation of Total Travel Time

For users preferring the fastest route, the prolongation of journey is the most important weight. Minimization of journey prolongation, represented by ω, is the main objective of VaRSA-TI. As could be expected, no prolongation of journey is caused by FPR and VaRSA-TI algorithms, since these two algorithms always select the route with the minimum T^{MIN}. In contrast, MTW shows always the highest prolongation ω. Note that the prolongation caused by MTW is more than twice higher than for the proposed algorithm for BUD and RtUD services. In Fig. 5(a), the dependence of ω on the number of vehicles in simulation is depicted. No prolongation is observed for FPR and for VaRSA-TI for all densities of vehicles. Even for VaRSA-BUD and VaRSA-RtUD in journey prolongation remains very low (less than 2%) comparing to MTW, which prolongs journey by 4.4% for 400 vehicles and 5.2% for 1600 vehicles. With rising number of RSUs [depicted in Fig. 5(b)], the prolongation of total travel time is decreasing for VaRSA-BUD and VaRSA-RtUD. Higher number of RSUs in simulation causes improvement in coverage of whole simulation area; thus, the faster routes are also covered and the travel time can be shortened. On the other hand, ω is slightly rising with the number of RSUs for MTW and it becomes nearly four times higher than in case of VaRSA-BUD and VaRSA-RtUD for 160 RSUs.

As can be seen in Fig. 5(c), the higher requirements on throughput lead to significant shortening of ω for VaRSA-BUD and VaRSA-RtUD while ω is nearly constant for MTW. With rising throughput requirements of vehicular users, the number of routes able to satisfy such requirements decreases, as shown in Figs. 3(c) and 4(c). Therefore, the advantage of VaRSA is lowering and selected route is more similar to the fastest route. Finally, Fig. 5(d) illustrates the dependence of ω on inaccuracy of speed prediction. Results show the maximum prolongation for MTW, VaRSA-BUD, and VaRSA-RtUD in case of no inaccuracy of speed prediction. The reason is that the offloading of cellular network caused by prolongation of time T^{W} requires only slight prolongation of whole journey. In case of inaccuracy, the ratio of time in WAVE ϕ is lowered [see Fig. 3(d)] and therefore with rising of inaccuracy, the gain of VaRSA is suppressed. However, as Fig. 5(d) shows, the ω for VaRSA algorithm is always lower than MTW.

D. Results Discussion

As the presented results prove, the proposed VaRSA is able to fulfill requirements of vehicular users for all types of typical services easily by setting weights (Ω, Φ, and Θ).

For users who require no data transmission, VaRSA selects the fastest route disregarding coverage of LTE-A or WAVE. Therefore, no prolongation comparing to the FPR is observed (shown as VaRSA-TI). In case of delay tolerant applications exploited by users on board (VaRSA-BUD setting), only negligible prolongation of journey (less than 2% of the total travel time) is observed by the user. On the other hand, users are less often without connectivity to one of both networks. Moreover, up to 17% of travelling time the data traffic can be offloaded from cellular network to free of charge WAVE comparing to FPR. The ratio of time spent by vehicles connected to WAVE is nearly the same as in the case of MTW while the prolongation of journey is reduced to less than half by the proposed VaRSA for BUD services. If users require high-quality real-time connection (VaRSA-RtUD setting), the ratio of time when vehicles are connected to WAVE is prolonged significantly (at least by 6.5%) while the minimum ratio of time spent with insufficient QoS is suppressed to roughly half and two-thirds of time experienced without required QoS for the FPR and MTW algorithms, respectively. Even in this case, prolongation of journey is negligible (below 2%) and reduced by at least 60% comparing to MTW.

Note that not only values equal to 0 or 1 can be selected as weights. For example, if weight of fastest possible path, Ω, is set to 0.5 while other two parameters Φ and Θ are set to 1, the prolongation of journey ω and the ratio of time in WAVE ϕ of selected route can be higher than in case of Ω equal to 1 while ratio of time in no QoS θ can be reduced. This applies also for setting of other weights. However, particular influence depends on number of available paths and their concrete characteristics.

Presented results show that the proposed algorithm is able to offload cellular network by the efficient redirecting of a part of the vehicles to the areas with sufficient throughput. The proposed algorithm reduces the probability of network congestions and higher QoS is experienced by the users. This enables a variety of services, such as online car health reporting or online uploading of videos from on-board cameras. Besides the vehicle-related services, the on-board users can also exploit entertainment services, such as video or music streaming or online gaming.

VI. Conclusion

In this paper, the novel route selection algorithm VaRSA considering users requirements on data transmission and availability of WAVE and LTE-A has been proposed. For efficient route selection, the proposed algorithm exploits traffic forecast based on traversal time prediction in combination with knowledge of capacity of base stations. Based on known future position and throughput requirements of vehicles, the load of RSUs and eNBs when the vehicle reaches their area of coverage is estimated and throughput available for new user is determined.

As the simulation results show, the proposed route selection algorithm is able to serve users preferring free of charge connection to WAVE network as well as users who require high quality services or want to select the fastest route possible. Such diversity is enabled by selection of weights according to different demands of users. Consequently, the time spent by vehicles connected to WAVE can increase up to 17% comparing to fastest route while the quality of connection is maintained on the highest achievable level and prolongation of total travel time is negligible (less than 2%). Thus, the proposed algorithm outperforms all compared route selection algorithms. Since the algorithm exploits prediction of vehicles movement, it is the most suitable for environment with autonomous vehicles without drivers. However, it can be naturally used by vehicles with drivers as well.

A future extension is to improve QoS for on-board users while a prolongation of the total travel time and the load of cellular network will be reduced exploiting the V2V connection between vehicles. The proposed algorithm, its real limits, and impact of weights will be also tested in a real environment.

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