Optimal exploitation of sparsely localised traffic data for modelling traffic flow in road networks

Stephen Robinson
School of Mathematics and Physics, Queen's University Belfast, Belfast, United Kingdom
Salissou Moutari
School of Mathematics and Physics, Queen's University Belfast, Belfast, United Kingdom

ABSTRACT: Traffic flow data are generally collected using induction loops. Therefore, to capture traffic dynamics along road sections, a very fine mesh of induction loops is required. However, due to their higher cost of installation and maintenance, induction loops are installed only at some specific areas, namely around road intersections and slip roads. The most optimal exploitation of the sparsely localised data collected via the induction loops installed within a road network, is to combine a prediction model (e.g., a machine learning model), trained using these collected data, with a macroscopic model of traffic flow also known as continuum model. The prediction model enables to forecast the traffic demand and supply downstream and upstream the intersection, respectively, whereas the macroscopic model of traffic flow will be used to capture traffic dynamics, namely the space-time nonlinear features, along the sections of the road non-equipped with induction loops. In this study, we present an application of such approach, where an artificial neural networks model and the well-known Lighthill, Whitham and Richards model (LWR model) are used as prediction and continuum models, respectively. The investigated road network includes parts of the highways A12-A120, A120, A12 and A14 in East Anglia (England, United Kingdom).

1. INTRODUCTION

Due to the rapid growth of traffic density, road traffic will continue to be a major social and economic problem. However, because of a wide range of constraints such as physical space, financial resources, environmental concerns, the traditional approach, which consists of expanding infrastructures of highways, has proven to be no longer viable. Currently, one of the most promising alternatives to ease traffic conditions on highways consists of an optimal utilization of the existing highways' infrastructures via Intelligent Transport Systems (ITSs). The effectiveness of an ITSs, in improving traffic conditions on highways depends highly upon the efficiency of its operational model. Accurate and timely forecasting of traffic volume is an essential aspect for an effective management of traffic congestion via ITSs. Most of the current research activity around ITSs management focuses on traffic flow forecasting models based essentially on historical observations including statistical models e.g. (Smith et al., 2002) and Artificial Intelligence models such as Bayesian networks e.g. (Sun et al., 2006), artificial neural networks e.g. (van Lint et al., 2005), etc. Due to their ability to capture the stochastic and complex nonlinearity of time series as well as their ability to run in a parallel computing environment, ANN prediction models have shown a considerable potential for use in ITS applications, where real-time control is essential in improving the capacity of transportation systems.

However, like most traffic forecasting models based on historical observations, the ANN approach is suitable for estimating the traffic flow rate at a location, in a road network, where historical observations are available. Generally, traffic flow data are collected by means of inductive loops and these can only be installed locally. Therefore, a very close mesh is required to capture traffic dynamics along sections of highways. Due to the higher cost of installation and maintenance of inductive loops, it would be cost-effective to install them only at some specific areas in the road network, e.g., around intersections, and then use an appropriate method to derive the traffic states in the non-equipped areas, i.e., along sections of highways. Thanks to their ability to reproduce and capture appropriately the space-time nonlinear features of traffic flow, continuum models of traffic flow based on conservation laws appear to be a natural way to model traffic flow along sections of highways, and therefore they offer some alternatives to address the difficulties inherent to the use of forecasting methods based on historical observations including the ANN approach.

The purpose of the study presented in this paper is to introduce an integrated framework for traffic flow simulation in road networks, which is based on a coupling of a continuum model of traffic flow e.g. (Lighthill and Whitham, 1955), (Richards, 1956) with the ANN approach e.g. (Rumelhart et al. 1986). The proposed framework aims to offer an alternative traffic flow modeling approach, which takes advantages of both continuum traffic modeling, and the ANN approach. The core idea is to use the ANN approach to estimate traffic volume at some specific locations on highways, in particular at the entry(ies) and exit(s) of intersections, while traffic dynamics along sections of highways is modeled using a continuum type model. As such, the ANN approach enables a dynamic routing procedure for traffic flow assignment at junctions while the continuum model guarantees the conservation of the number of vehicles as well as the correct propagation of irregularities along sections of highways.

2. MACROSCOPIC MODELS

This section is dedicated to a brief presentation of the models, to be used in this study, namely the continuum model introduced in (Lighthill and Whitham, 1955), (Richards, 1956) and the ANN approach (Rumelhart et al. 1986).

2.1. *Continuum model*

Based on hydrodynamic analogy, continuum models of traffic flow describe traffic flow in terms of fluid behavior. This point of view is more concerned with the overall average behavior of traffic flow rather than the interactions between individual vehicles; thereby it involves macroscopic variables such as the average traffic density, the average velocity, and the traffic flow rate. Continuum models of traffic flow, e.g. (Lighthill and Whitham, 1955), (Richards, 1956), (Aw and Rascle, 2000), (Kerner, 2004), are governed by mass conservation equations which are either derived from car-following models e.g. (Gazi et al., 1961), (Herman and Prigogine, 1971), or based on perturbations of the isentropic gas dynamics models. The first macroscopic model of vehicular traffic flow was introduced in the fifties, independently, by Lighthill and Whitham (Lighthill and Whitham, 1955) and Richards (Richards, 1956). This model, which is commonly referred to as the LWR model, consists of the following single continuity equation:

$$\frac{\partial}{\partial t}\rho(x,t) + \frac{\partial}{\partial x}q(x,t) = 0, \qquad (1)$$

where $\rho = \rho(x, t)$ and $v = v(x, t)$ denote the average density and the average velocity of cars, respectively at location x and time t, whereas $q(x, t) = \rho(x, t)v(x, t)$ denotes the traffic flow-rate. However, since equation (1) involves simultaneously two variables ρ and v, therefore a suitable closure relation which for example expresses the flow-rate q as a function of the density ρ is required to complete the model. A such closure relation is generally obtained by reproducing the typical behaviour of the experimentally observed flow-density relationship, through which the flow-rate q can be expressed as a function of the density ρ, i.e., $q = f(\rho)$. This flow-density relationship is often referred to as the fundamental diagram. Let $\rho_{\max}$ denote the maximum density of vehicles allowed along a road section (e.g., when cars are parked bumper to bumper). Generally, the function $f(\rho)$ is required to be monotonically increasing from $\rho = 0$ up to a certain density value $\sigma \in (0, \rho_{\max})$, monotonically decreasing for $\rho \in [\sigma, \rho_{\max}]$, and

$$f(\rho) = \rho v_e(\rho), \qquad (2)$$

$$\text{where} \quad v_e(\rho) = v_{\max}\left(1 - \frac{\rho}{\rho_{\max}}\right). \qquad (3)$$

concave with a unique maximum point $\rho = \sigma$. The elementary flow-density relationship used in the LWR model is given by:

The parameter $v_{\max}(> 0)$ denotes the maximum average velocity, which may be observed by vehicles on an almost empty road (e.g. the maximum speed limit on a road section).

2.2. Artificial Neural Networks model

Current research efforts in ITS arena are dominated by traffic flow rate forecasting methods. Recent research works, e.g. (Taylor and Meldrum, 1995), (van Lint et al, 2005), in the field of traffic flow- rate forecasting, have shown that the ANN approach over-perform some traditional prediction methods, such as statistical models which assume stationarity of the time series, due to their ability to map highly nonlinear input-output. Furthermore, when properly trained, ANN are relatively insensitive to missing data which is a valuable asset in traffic flow prediction since inductive loops are susceptible to transmission errors and mechanical failure.

The typical use of the ANN approach in the fields of traffic flow-rate forecasting is the estimation of traffic flow rate around intersections. For this aim, a multi-layer neural network consisting of three connected layers (the input layer, the hidden layer(s), and the output layer) is usually considered, see Fig. 1. The dimension of the experimental data as well as the geometry of the intersection under consideration determine the number of neurons, in the input and the output layers.

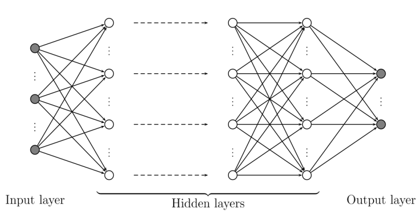

Fig. 1 Structure of an artificial neural network

3. TRAFFIC FLOW SIMULATION IN ROAD NETWORKS

To effectively capture traffic dynamics in a road network, a traffic flow model must be capable of considering the nonlinear traffic dynamics along road sections as well as the complex interactions between flow patterns around intersections. Since the ANN approach is not suitable for modeling traffic dynamics along road sections whereas continuum type models fail to capture the stochastic features of traffic patterns at intersections, the focus of this study is to develop an integrated framework for traffic flow simulation which will make use of the complementary features of the aforementioned models while alleviating their limitations. The key idea is to combine the two types of models in such a way that the ANN approach enables a dynamic routing procedure for traffic flow assignment at junctions while the correct propagation of irregularities along road sections and the conservation of the number of vehicles are ensured by the LWR model.

3.1.Coupling the LWR model with the ANN

The operational architecture of the proposed framework is structured as shown in Figure 2.

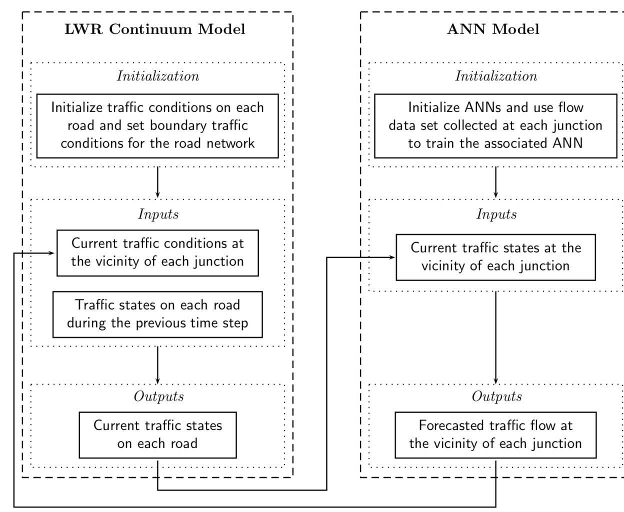

Fig. 2 Flow chart of the operational structure of the proposed integrated framework

3.2. Features of the proposed approach

The key features of the proposed integrated framework, compared to existing models in the literature, e.g. (Coclite et al., 2005), (Holden and Risebro, 1995), (Moutari and Rascle, 2007), (van Lint et al., 2005), (Lebacque and Khoshyaran, 2005), (Sun et al., 2006), (Taylor and Meldrum, 1995), (Dougherty, 1995), (Smith et al., 2002), include not only its predictive performance but also its ability to handle large, crowded road networks as well as its suitability for real-time applications. To be used in real-time, a model for traffic simulation in road networks must be able to run continuously and accommodate with missing data. Therefore, the model needs not only to be robust to the volatile and sometimes missing traffic flow data but also to be computationally powerful enough to produce output in real-time continuously, and the coupling of the LWR model with the ANN model complies with these real-time application requirements.

3.3. Case study

In this section, some numerical simulations have been carried out to illustrate the proposed framework on a case study. The studied area is a part of East Anglia (England, UK) road network – see the surrounded area in Fig.3 – which consists of the following highways: A12-A120, A120, A12 and A14. In this study, only a unidirectional traffic flow is considered on each highway due to the lack of available data to train the ANNs associated with the junctions; however, the proposed framework can effectively handle the case of bidirectional traffic. Therefore, as shown in Fig.3, the studied area consists of two consecutive junctions: Junction A12-A120/A120→A12 (a join junction) and Junction A12→A14-North/A14-South (a fork junction).

Traffic flow dynamics along road sections is described using the LWR model with the following parameters' values: $v_{\max}$ = 90km per hour and $\rho_{\max}$ = 140 vehicles per km. It is well known, in conservation laws theory, that solutions to equations of type (1)-(3) may develop discontinuities in finite time, see e.g. [5]. Therefore, numerical methods based on Riemann solvers are often used to approximate solutions to the LWR model. In this study, the Godunov scheme [8] will be used to approximate solutions to the model (1)-(3). Let's introduce some grid points in space ($x_j = j\Delta x$, where j is an integer) and in time ($t_n = n\Delta t$, where n is a positive integer) with $(\Delta x, \Delta t) \to (0, 0)$ and $\Delta t/\Delta x = constant$ such that:

$$\frac{\Delta t}{\Delta x} \max_{\rho} |f'(\rho)| \leq 1. \qquad (4)$$

Then the Godunov discretization of the LWR model (1)-(3) writes:

$$\rho_j^{n+1} = \rho_j^n + \frac{\Delta t}{\Delta x}\left[\Phi(\rho_{j-1}^n, \rho_j^n) - \Phi(\rho_j^n, \rho_{j+1}^n)\right], \qquad (5)$$

where $\rho_{kl} = \rho(x_k, t_l)$ and $\Phi(\cdot, \cdot)$ is the Godunov numerical flux function.

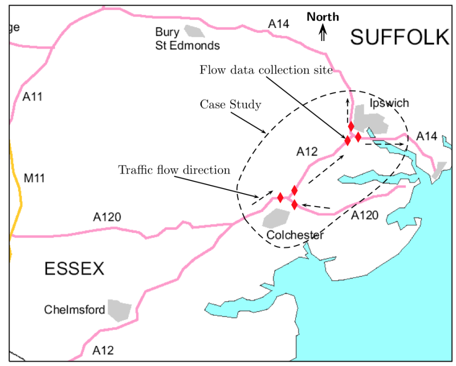

Fig. 3 Case study – East Anglia, England UK-: Only unidirectional traffic flow is considered on each road. The diamond on each highway around the junctions denotes the site where flow-rate data were collected

To estimate traffic flow rates at intersections, ANNs are constructed using flow-rate data collected by means of inductive loops installed on highways in the vicinity of intersections. For sake of simplicity, ANNs with one hidden layer are associated to intersections. To extract characteristics of the data set, the learning was achieved using a back-propagation algorithm with a sigmoid transfer function between the input and the hidden layer:

$$\begin{array}{rccl} f: & \mathbb{R} & \longrightarrow & [0,\gamma] \\ & x & \longmapsto & f(x) = \dfrac{\gamma}{1+e^{-x}}. \end{array} \qquad (6)$$

The ANN associated with the join junction consists of two nodes in the input layer and one node in the output layer, whereas the ANN associated with the fork junction has one node in the input layer and two nodes in the output layer. Inputs to ANNs are flow rates corresponding to traffic states at the vicinity of the junction on each incoming highway at each time step, while outputs of the ANNs correspond to the forecasted flow rate in the vicinity of the junction on each outgoing highway.

The locations of the sites, where flow-rate data were collected, are indicated with some diamonds in Fig. 3. From these sites, matching databases of three months of aggregate fifteen minutes traffic flow rates were assembled from May 1st to June 29th (2009), resulting in a database of 5760 observations. These flow-rate data sets are used to train the ANN associated with each junction. To highlight the accuracy of the ANN approach, inflow data on A12-A120 and A120 (Fig.4) are used to predict outflow on A12 at the join junction (Fig.4). The obtained results are shown in Fig.5.

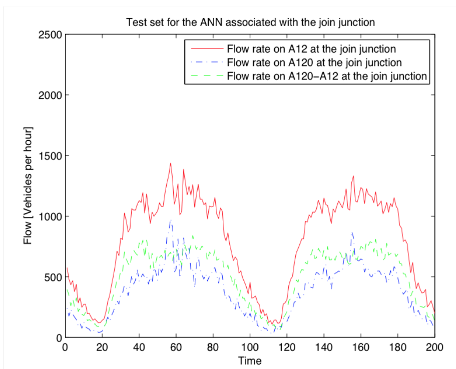

Fig. 4 Test sets: Inflows on A12-A120 and A120, and outflow on A12 at the join junction

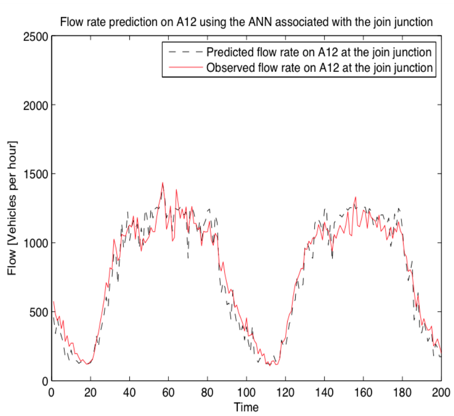

Fig. 5 Predicted outflow on A12 using the trained ANN and observed outflow on A12, at the join junction

Initially all the highways are assumed to be empty, and the numerical simulation of the proposed framework has been performed for 300 units of time (where a time unit is equivalent to 15 minutes). Using the inflows on A12-A120 and A120 (at about 30km upstream the join junction) shown in Fig.6, the results depicted in Fig.7, Fig.8 and Fig.9 have been obtained using the integrated framework. In Fig.7, the flowrates on each highway in the vicinity of the join junction are shown whereas Fig.8 shows the flow rates on each highway in the vicinity of the fork junction. The outflows on A14-North and A14-South (at about 20km downstream the fork junction) are depicted in Fig.9. Fig.10-14 show the traffic density on each highway throughout the simulation time: Fig.10 presents the contour plot of the traffic density along a section of 30km on A12-A120 upstream the join junction; Fig.11 shows the contour plot of the traffic density along a section of 30km on A120 upstream the join junction; Fig.12 shows the contour plot of the traffic density along A12 between the join and the fork junction (length of the section 40km);

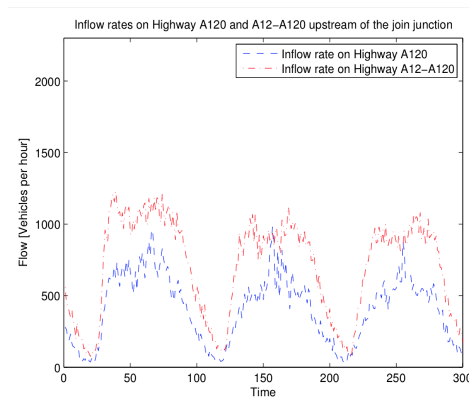

Fig. 6 Inflow rates on A12-A120 and A120 at about 30km upstream the join junction

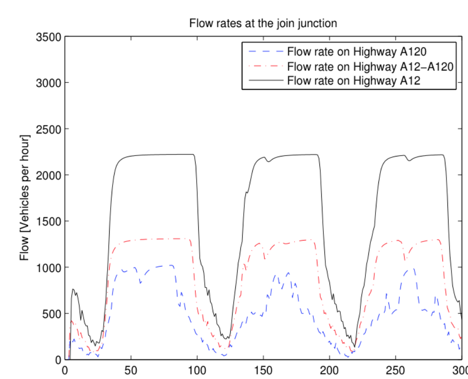

Fig. 7 Inflow rates on A12-A120 and A120 and the outflow rate on A12 around the join junction

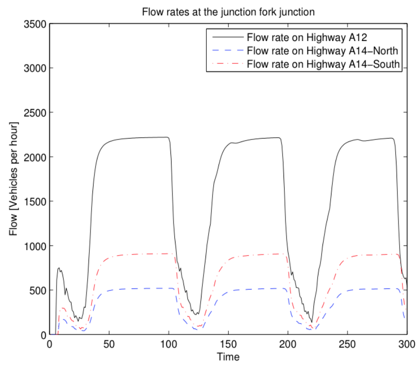

Fig. 8 Inflow rate on A12 and outflow rates on A14-North and A14-South around the fork junction

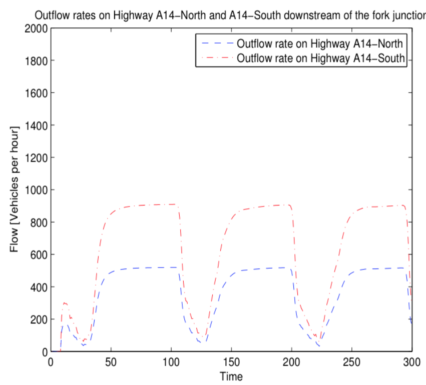

Fig. 9 Outflow rates on A14-North and A14-South at about 20km downstream the fork junction

3.4.Discussion of the Results

The numerical results obtained with the proposed framework, summarized in Fig.7-14, highlight some traffic patterns, which could not be observed when using either a continuum type model or an ANN model separately.

For instance, as shown by simulation results in Fig.10 and Fig.11, the spatial-temporal approach, which is commonly used, in short-term traffic flow forecasting models, e.g. [4], to define how traffic flows are related in the temporal and spatial dimension is only valid in certain traffic conditions. Indeed, a such approach is valid when the traffic is very light whereas for dense traffic the dynamics may evolve drastically along a road section (see Fig.10, Fig.11 and Fig.12) so that the spatial effect cannot be treated in a predetermined way.

On the one hand, although continuum type models enable to reproduce traffic dynamics along road section regardless of the traffic condition, their utilization to model intersections is based on the maximization of the total throughput at a junction which generally smooth out traffic flow patterns at intersections and does not allow to observe traffic dynamics around intersections such as those observed in Fig.12 on highway A-12 just before the fork junction. In particular, these patterns could be caused by the manoeuvres of drivers who are trying to change lane when approaching the fork junction: although the continuum model used in this study is a one lane model, the use of the ANN approach at the intersections enables to capture such traffic patterns.

On the other hand, the model exhibits the dynamics of some traffic patterns along road sections and enables a full view of these dynamics (see Fig.10-14), which could not be observed using only the ANN approach; furthermore, the model captures traffic patterns around intersections whereas these are generally smoothed out when using only a continuum type model.

Overall, the proposed framework can provide an effective short-term prediction of traffic flow downstream intersections as well as an overview of traffic conditions along road sections.

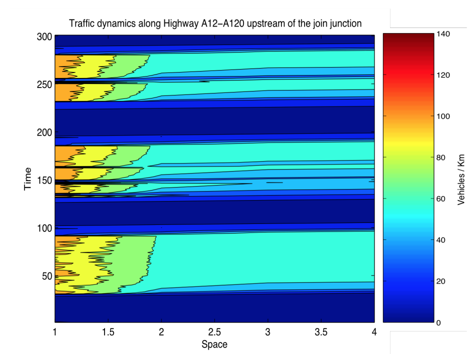

Fig. 10 Traffic density along a section of 30km on the highway A12-A120 upstream of the join junction

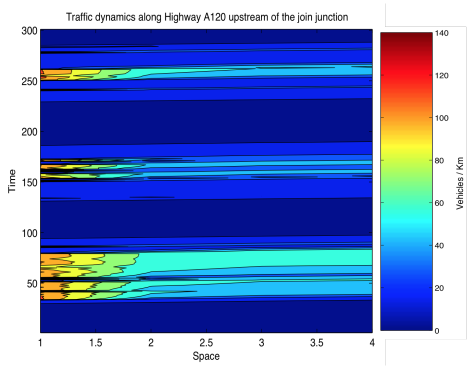

Fig. 11 Traffic density along a section of 30km on the highway A120 upstream of the join junction

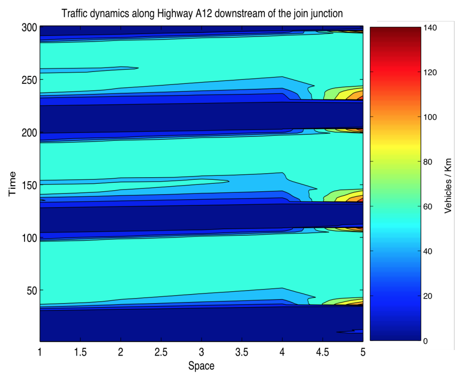

Fig. 12 Traffic density along a section of 40km on the highway A12 downstream of the join junction

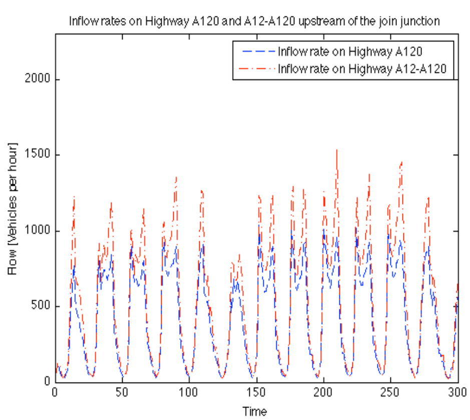

Fig. 13 Inflow rates on A12-A120 and A120 at about 30km upstream the join junction (hourly flow data)

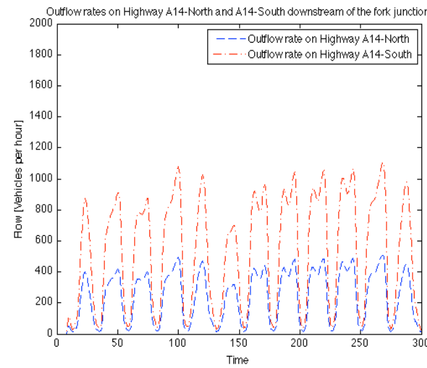

Fig. 14 Outflow rates on A14-North and A14-South at about 20km downstream the fork junction (hourly flow data)

Figures 13 and 14 present some long-run numerical simulations for the case-study area described in Fig.3, but now the time unit is 1 hour. An additional important feature of the proposed approach is its robustness. Indeed, even with hourly flow data, the model still captures traffic patterns observed previously in Figures 10 to 12, when using short-term flow data (i.e., 15 minutes flow data).

4. CONCLUSIONS

This study introduced an integrated framework for traffic simulation, which enables to effectively capture traffic flow dynamics in road networks. The proposed framework is based on a coupling of the LWR continuum model of traffic flow with the ANN approach: the core idea is to introduce dynamic routing procedure for traffic flow assignment at junctions through the ANN model while the LWR continuum model guarantees the conservation of the number of vehicles as well as the correct propagation of irregularities along road sections. The promising features of a such integrated framework, compared to the traditional models in the literature, includes its ability to reproduce traffic flow dynamics in road networks by considering the stochasticity of traffic flow patterns around intersections as well as its suitability for real-time applications. Computational results from numerical experiments confirm the ability of a such integrated framework to effectively capture traffic flow dynamics in road networks.

Future extensions of the proposed framework could include the use of alternative continuum models such as higher order models e.g. (Aw and Rascle, 2000), (Kerner, 2004) or multi-class models, e.g. (Herty et al., 2006), as well as the introduction of additional parameters, into the ANN model, such as weather conditions, incident data, ongoing and planned road works.

5. ACKNOWLEDGEMENT

The authors are grateful to the Highways Agency for providing the data used in this paper

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