A Quasi-Dynamic Traffic Assignment Model for Large Congested Urban Road Networks

Gaetano Fusco, Chiara Colombaroni, Andrea Gemma, Stefano Lo Sardo

Abstract – The paper deals with simulation of congested urban areas through dynamic traffic assignment models and presents a new quasi-dynamic traffic assignment model that improves realism and effectiveness of both usual static traffic assignment models and other quasi-dynamic models recently introduced in the literature. The new model has been applied to a real large-scale road network (the town of Rome) and has been validated through a comparison with a very large set of floating car data. Results of validation reveal that the quasi-dynamic traffic assignment model provided a rather satisfactory goodness of fit, which is comparable with that reported in literature as a result of application of a much more sophisticated simulation and calibration procedure, applied to a road network having similar characteristics of size and congestion degree.

Keywords – Road traffic simulation models, Dynamic Traffic Assignment, Quasi-Dynamic Traffic Assignment, Floating Car Data, Calibration methods.

I. Introduction

REDUCING traffic congestion of urban road networks is one of the toughest challenges in most Countries worldwide. To tackle this problem effectively, traffic plans and control techniques need to apply simulation models. The core problem of traffic network modeling consists of assigning a specified demand matrix of vehicle movements between points of entry and exit in a modeled road network. Traffic network models of increasing complexity and realism were developed in the last 50 years. Earliest models were based on simplistic assumptions on drivers' behavior and link performances [1]. Behavioral assumptions are: a) drivers have perfect information on topology and actual travel times of the road network; b) all drivers choose their most convenient route to reach their destination. Under these assumptions, for each O-D pair, the travel time on all used paths is equal, and (also) less than or equal to the travel time that would be experienced by a single vehicle on any unused path. This property is known as deterministic user equilibrium or DUE [2].

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Vehicle interactions are simplified by assuming that: a) vehicular traffic constitutes a homogeneous flow; b) origin-destination flow is constant during the time interval of simulation; c) travel time on a link is a continuously differentiable function of the flow. It has been demonstrated that, if link travel time functions are continuous for all values of link flows, a solution of the assignment problem exists. The solution is unique if the Jacobian of the travel time functions and that of its derivatives are positive definite [3].

In the following years, more general and more realistic models were introduced. Drivers have been assumed having different perceptions of route performances and complex choice mechanism. Drivers' choices were represented through probabilistic models among discrete alternatives [4]-[6]; existence and uniqueness conditions were derived for traffic network models with multiple classes of vehicles [7]; more realistic queuing models were introduced to reproduce capacity constraints and delays at bottlenecks [8]-[10], which on the other hand implied lacking uniqueness property.

The main drawback of many of these models lies in the assumption of time invariant demand, which implies steady-state traffic condition. It is clear that they cannot reproduce dynamics of traffic congestion on the road network.

To achieve a more realistic representation of traffic, different formulations of Dynamic Traffic Assignment (DTA) models were introduced [11]. While many of them generalize traditional static formulations, the most advanced and realistic models use a traffic simulator to replicate the complex traffic flow dynamics. Several sophisticated software tools for DTA have been developed; the most noticeable are mentioned here: DynaMIT [12], DYNASMART [13], Dynameq [14], AIMSUN [15]. Implementation of such complex models is a rather cumbersome task, which involves the construction of detailed graphs of thousands of links and requires a long process for calibrating hundreds or thousands of coefficients. In a recent paper, Ben-Akiva *et al*. [16] describe the cumbersome calibration efforts in implementing the mesoscopic dynamic traffic assignment models DynaMIT to a highly congested subnetwork of the city of Beijing, China.

In order to reduce both calibration and computational efforts required by simulation-based DTA models, several authors in the last years proposed a quasi-dynamic (or semi-dynamic) approach, which exploits some useful properties of simpler steady-state assignment models. Quasi-dynamic approach to modeling traffic resulting from time-varying demand is to divide the modeled period into time slices in each of which demand is steady and a corresponding steady-state assignment is modeled, and where demand exceeds capacity some links are overloaded [17].

The quasi-dynamic approach to traffic model is not new. It was firstly introduced by Van Vliet [18] and then abandoned for more complex dynamic simulation models. All quasi-dynamic models developed so far assume that most travelers reach their destination within the period in which they depart and represent residual flows propagation by modifying the O-D demand in the current and next periods [19]-[23]. Specifically, Ujii *et al.* add the remained flow in each period to the O-D flow of the next time period [19]. Nakayama *et al.* assign half of the remaining flow to the current period and the other half to the next period [20]. Chen *et al.* [21] apply a probabilistic logit model to reproduce drivers' route choice behavior and implement a cell transmission model [24] to load traffic to the network. They avoid so steady-state assumptions in each time period. However, they do not consider the queues at intersections and assume that links can accommodate all the vehicles assigned by the route choice model.

Our model does not require hypothesizing short trips to ensure steady-state conditions, but assumes that no great change in traffic conditions occurs from one time period to the next, so that the steady-state link performance functions can be applied to model congestion. Unlike other models in literature, it provides a realistic representation of flow progression onto the network as it moves forward each link flow according to the related speed at every time step.

The quasi-dynamic traffic assignment model reduces computation time and can be implemented in an online Intelligent Transportation System platform that provide predicting capabilities to traveler information and/or traffic management applications. In online application, the QDTA model works jointly with a dynamic Origin-Destination module [25], which takes as input real-time traffic flow measures collected by either fixed detectors (see: Klein, 2001 [26], for a review; among others, Bellucci *et al*. 2005 [27], for experimental tests; Dinescu and Giurgiulescu, 2010 [28], for an example of implementation requirements) or Floating Car Data (see El Faouzi *et al*., 2010 [29] for a review) and combines them with statistical information to estimate the current mobility demand. Modeling and predicting capabilities are crucial features for both Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS).

ATIS can exploit such forecasting features to provide users with reliable comprehensive information on the current and future state of the traffic network. Indeed, current commercial information systems provide users with information on the current state of the road links covered by real-time updated traffic measures and apply statistical methods to make any inference in space (uncovered road links) and time (future conditions). However, even very sophisticated statistical methods cannot provide reliable prediction of traffic conditions in case of sudden unpredictable changes of network performances due incidental phenomena like accidents or other anomalies (bad weather, road works, people demonstrations), for which a sufficient number of previous observations is not available. On the contrary, a modeling approach, after the incident is detected and its severity has been estimated, can simulate the physics of queue progression and dissipation and then provide users with more realistic forecasting information.

In the same general ITS platform, the QDTA model can support fleet management systems [30] as well as traffic signal control systems with short-term traffic predictions and perform simulations of signal plans for synchronized arteries generated online or off-line traffic signal programs (Robertson, 1969 [31]; Mauro, 1991 [33]; McDonald and Hounsell, 1991 [32]; Colombaroni *et al*.2009 [34], Jatmiko *et al*. 2011 [35]).

II. Quasi-dynamic assignment model

The quasi-dynamic approach carries out a traffic network simulation in different time intervals.

Starting from empty network, for each time interval the O-D flow (or demand flow) is loaded on the network.

In this approach for every time interval the relative components of O-D matrix are assigned supposing that in that time period steady state conditions are valid. Obviously, demand variation involves a variation of link flows that depend also on the progression in time of demand flows already on the network.

At each simulation time step, *i.e.* 15 minutes, the corresponding O-D demand fraction is assigned to the network links that can be reached in the upper bound of the time interval. In the next time interval the procedure is repeated for another fraction of O-D demand, while the flows on the links advance on the network up to reach the links achievable in the second time interval.

Fig.1 provides a very simple example of one O-D pair connected by one path composed by two links. In the upper figure, a solution of static equilibrium model is represented: the whole demand is assigned to the path and the corresponding links. The two figures below depict flow progression in two successive time periods according to QDTA approach. In the first period (ω=1) a first fraction of demand (one can envision a platoon of vehicles, although traffic is assimilated to a homogeneous flow) starts from the origin and travels up to the end of the link 1. In the second period (ω=2) that packet of flow reaches the link 2, while a second packet of flow, started during this second period, moves along the link 1. Because of the presence of flow started in the first period, the link 1 is no more in free flow conditions and the second packet travels at lower speed than the first one. In the figure the time instant every packet reaches each link is noted by parentheses, although in this simple example with only two links it is trivial exercise. Also elements of dynamic path-link incidence matrix is reported to illustrate the meaning of symbols that will be introduced in mathematical formulation, equation (3).

During the simulation process, travel times depending on assigned demand and O-D routes depending on the new travel times are computed at every time step.

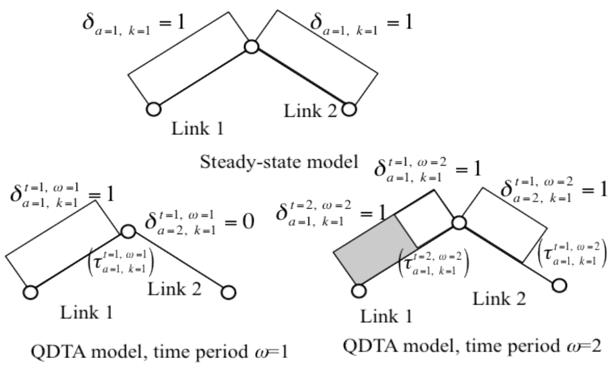

Fig. 1. Simple example of representation of flow progression in equilibrium model (above) and QDTA model (below).

Supposing that users don't modify the route choice during the travel, their paths are computed only for the new users that enter in the network.

As the network is represented by a series of steady-state conditions, the same typology of road cost functions of the static approach can be used, with only slight modifications, as it will be illustrated in Section V. This is a great advantage, because it allows the analysts exploiting link-cost functions largely used in the practical applications.

However, because of the time-dependent interaction of flows on the network, O-D flows starting at a generic time interval may be affected by flows starting at a successive time interval from a different origin that overlap their route and change so their travel time. Thus, there is no guarantee to find the user equilibrium solution and a heuristic solution procedure has to be applied for network loading.

III. Mathematical Formulation

Mathematical formulation of Quasi-Dynamic Traffic Assignment (QDTA) generalizes the steady-state deterministic user equilibrium assignment problem.

Unknowns of the problem are the flows h_{tk} on the generic route k departed in time interval t from origin i to destination j, both belonging to a given set of traffic zones Z. Flows h_{tk} are updated at every time interval t and are assumed to be independent of the solutions found in the successive time intervals. This assumption corresponds to a demand composed by usual travelers (e.g., commuters) that choose their routes according to their statistical knowledge of usual network congestion.

On each time interval t the flow conservation law holds for each O-D pair *(i,j)*, whose flow d is distributed on the set of K_{ij} feasible routes:

$$\sum_{k\in K_y^t} h_k^t = d_{ij}^t \quad \forall i,j\in Z$$
$$h_k^t \ge 0 \qquad \forall k\in K_{ij}^t \quad \forall i,j\in Z \tag{1}$$

Link flows x_a^ω at the generic time interval $\omega \ge t$ are determined by applying link-route incidence condition, which in the dynamic case is a function of the time interval ω in which the O-D flow d_{ij}^t that started at the time period t reaches link a:

$$x_a^\omega = \sum_{t=v}^{\omega} \sum_{k\in K_y^t} \delta_{ak}^{t\omega}\left(\tau_{ak}^t\right) h_k^t \tag{2}$$

For each link a, time interval ω is determined by computing travel time τ on the shortest path k for flows departed at time t.

$$\delta_{ak}^\omega = 1 \Leftarrow a\in k, k\in K_{ij}^t,\ i,j\in Z\ \left(\omega-1\right)\Delta t < \tau_{ak}^t \le \omega\Delta t$$
$$\delta_{ak}^\omega = 1 \Leftarrow otherwise \tag{3}$$

If steady-state conditions are assumed during every time period ω of length Δt, it is possible to apply the traditional link cost-flow functions

$$c_a^\omega = c\left(x_a^\omega\right) \quad \forall a\in A \tag{4}$$

and the related path cost-flow functions

$$c_k^\omega = \sum_{a\in k} c_k^\omega\left(x_k^\omega\right) \tag{5}$$

The route choice model is based on the assumption that a rational driver chooses the route that maximizes the utility related to his or her choice. Utility of each alternative is modeled as a function of the observed attributes of the alternative and the observed characteristics of the decision maker. To incorporate the effects of unobserved attributes and characteristics, the utility of a route k is expressed as a random variable consisting of a deterministic component V_k and an additive random term ε_k:

$$U_k = V_k + \varepsilon_k \tag{6}$$

If the random terms of each utility function are independently and identically distributed Gumbel variables with zero mean and parameter θ, the choice model is a multinomial logit function. In this case, the probability p_{tk} that a generic driver departing during time slice t chooses route k is:

$$p_k^t = \left(e^{V_k^t/\vartheta}\right) \Big/ \left(\sum_{h\in K(i,j)} e^{V_k^t/\vartheta}\right) \tag{7}$$

where the deterministic utility $V_k^{\omega t}$ at the decision time period t is defined as the linear combination with coefficients β_i of the attributes Y_{jk}^t of alternative k:

$$V_k^t = \sum_{i=1}^{n} \beta_i Y_{ik}^t \tag{8}$$

In congested urban networks it is usual to assume the attributes coincide with travel costs (that is, with travel times and tolls, if any), which, of course, are time-dependent.

However, we assume that drivers choose their route at their departure on the basis of their statistical knowledge of the network and do not modify their choice during their trip. The model allows considering different classes of users having different levels of knowledge of usual road traffic conditions, that is, different coefficients θ.

According to these assumptions, the expected flow h_k on route k is:

$$h_k^t = d_{ij}^t p_k^t \quad k \in K(i,j) \tag{9}$$

where d_{ij}^t is the flow started in the time period t from origin i to destination j and p_k is the probability of choosing the route k.

It is easy to verify that, since p_k^t is a probability, route flows comply the conservation conditions (1). It is also worth noting that p_k^t is time-dependent, as link and route costs vary with the time.

IV. Solution procedure

The solution procedure consists of:

- compute, in every time interval, the optimal O-D routes;
- calculate the fraction of O-D demand on each route;
- move, in every time interval, the flow assigned on each route of the distance travelled, depending on the traffic speed.

Step 0: Computation of initial solution (empty network)

Let $c_a = c_a(0)$, $\forall$ a $\in$ A;

Let current time period ω = 1.

Step 1: Shortest paths computation

Let $t=\omega$ and $\forall$ origin $i \in$ R with d_{ij}>0 and each destination $j \in$ R, compute K shortest paths trees, their relative costs { C^1_{ij1}, C^1_{ij2} ,..., C^1_{ijK} } and time instants $\tau_{a,k}^{\omega,t}$ in which OD flow d_{ij} started at period $t=\omega$ reaches each link belonging to route K.

Step 2: Computation of path flows departed at time interval $t=\omega$

In this step the route choice model (7) is applied using the route costs computed at step 1. O-D demand departed at time interval t is assigned to the different routes by applying equation (9).

Step 3: Traffic flow simulation on the network at generic time interval ω

It consists of simulation of flows progression on the network by applying equations (2) and (3); the results of this step are link flows in every time interval.

Step 4: Updating of link travel times at generic time interval ω

Link costs corresponding to link flows computed at step 3 are calculated through (4).

Step 5: Stopping criterion

If $\omega=T$, the algorithm stops; otherwise, let $t=\omega+1$ and come back to step 1.

The procedure for computation and storage of shortest paths is worth of a more detailed description, because it is rather different to traditional K-shortest path algorithms. In our time-dependent context, paths may change dynamically and their list has to be updated. So, the number of paths may increase linearly with the simulation time and make explicit formulation intractable. On the other hand, there is no reason to take memory of early K optimal paths after all the users who chose them reached their destination. Thus, the algorithm uses two lists of paths: L_B, for the currently best routes, which are still in use, and L_O, for obsolete routes. The two lists are managed in such a way that their intersection is null.

At each time interval ω, step 1 of QDTA algorithm applies a Dijkstra algorithm to compute the shortest paths between all O-D pairs according to travel times estimated at previous time interval. Optimal paths that were not yet included in the list L_B, are added to it. Optimal paths that were included in the list L_O are moved from L_O to L_B. Then, the list L_B is resorted according to the latest computed travel times and all paths in position $k>K$ are moved from L_B to L_O. They are stored in memory until users on them have reached their destination; then, they are deleted.

On Step 2, only paths in list L_B are considered to model route choice of users starting in the current time period w. QDTA model assumes that users do not modify their choice during their trip and will remain on the path chosen at departure time period t<ω. So, on Step 3, paths of both L_B and L_O lists are used in the simulation of movement of packets that are already on the network.

It will be exemplified in the next section how the procedure reduces the use of memory and allows simulating even large networks on standard workstations.

V. Application and validation of Quasi Dynamic Traffic Assignment Model on the road network of Rome

A. *Network description and path computation*

QDTA model has been applied to a large-scale road network, namely, the network of Rome, Italy. This is modeled by a road graph composed by about 15,000 directed links and 6,000 nodes. O-D flows are represented by a matrix of 855×855 items. Total demand in the morning peak hour is about 350,000 trip/hour. As only O-D trips in the rush hour were known from statistical surveys, this static demand was processed to derive a time-dependent demand every 15 minutes interval from traffic counts detected over the 24 hours.

By considering a number of 6 alternative paths for each OD pair, a traditional K-shortest path algorithm would have to compute n(n-1)K= 4,381,020 paths on each time period of simulation. If length of time interval is Δt=300s, more than 410 millions of paths would have to be managed in a 24-hour simulation. As in our case study a path contains on average 54.7 links, such a set of paths would require listing 23 billion of links.

Considering that in our application the maximum travel time lasts no more than 120 minutes, only paths computed in the last 8 intervals could be taken in memory, that is about 35 millions of paths and about 2 billions of links.

It is to be noticed that in such a traditional K-shortest path algorithm the memory would not be allocated in an efficient way; in fact, the constant number K may be oversized for some O-D pair and undersized for others.

However, the procedure introduced in this paper updates the set of optimal paths dynamically by adding, at each time interval, the current shortest paths and by deleting obsolete unused paths. Thus, the total number of paths connecting one O-D pair may be even larger than K, if in more than K consecutive periods several congestion; on the other hand, lower than K number of paths may be considered for O-D pairs connected by uncongested paths in a weakly connected network.

In the case study, this procedure allows us reducing, statistically, by 25% the number of used path; in fact, the number of paths per O-D pair ranges between 1 and 10, with an average value of 4.5. Thus, at each iteration we deal with 3.2 millions of paths and 1.6 billion of links.

B. *Model calibration*

Calibration of the model has been performed thanks to the availability of a large database of floating cars data. In study area the equipped fleet counts 80,000 vehicles, which travelled 9 millions trips and provided 104 millions of records, containing their positions and speeds collected during one month of observations. About 16,000 trips have been monitored during the morning peak hour in an average working day.

An accurate calibration of the model would require a very cumbersome process, consisting of estimating both the coefficients of cost-flow functions of each link (4) that minimize the error with respect to observed values and the coefficients of route choice model composed by equations (7) and (8). Such a simple adjustment is motivated by the fact that in the case study, the road network is modeled by a graph featured by more than 4,500 different performance functions. However, floating car data provide direct measures of link speed and only a sample of traffic flow, so that only rough estimations of flow are possible for many links. Moreover, by connecting successive detected positions makes it possible to build paths followed by tracked vehicles. Since successive positions of each vehicle are recorded every 2 km, path building becomes a very cumbersome task.

The great advantage of quasi-dynamic approach is that, since steady-state traffic conditions hold in each time interval, traditional cost-flow performance functions used in deterministic equilibrium models can be applied. As in many towns in the world traffic agencies usually calibrate equilibrium models for their applications in planning studies, the same functions can be exploited for use in the quasi-dynamic model.

In our case study, usual BPR functions were used

$$c = c_0\left[1 + \alpha(q/s)^{\beta}\right] \tag{10}$$

where, for each link:
c: travel time
c_0: free flow travel time
x: traffic flow
s: link capacity
α and β: calibration coefficients.

It is worth noticing, however, that in the quasi-dynamic model cost-flow performance functions are applied in a quite different way with respect to equilibrium model, which does not represent progression of traffic flow on the network. In fact, equilibrium model represents congestion through increase of travel time, neglects holding back of traffic in congested conditions and assigns the whole demand on the network as it could reach its destination within the time period of analysis.

However, the quasi-dynamic model simulates the progression of traffic on the network, so that, in congested conditions, a fraction of traffic flow is hold back and the traffic demand is not entirely assigned until its destination during the time period of analysis, usually 1 hour, and will be on network even in the next time interval. In other words, the time interval of 1 hour is not sufficient to serve the whole demand. It follows that the travel time predicted by steady-state performance functions (if they are well calibrated) is correct, but the flow on the link is overestimated because the equilibrium model assigns the demand instead of the actual link flow.

In order to correct the bias affecting the equilibrium model, performance functions calibrated for be used in equilibrium model have been reshaped by increasing travel time at the capacity as to account for the time interval needed to serve the demand at capacity.

A very quick adjustment procedure was applied, consisting of modifying all performance functions were modified by the same adjustment factors. An example is depicted in Fig. 2, where initial performance function $c_{eq}(x)$ and adjusted function $c'(x)$ are shown.

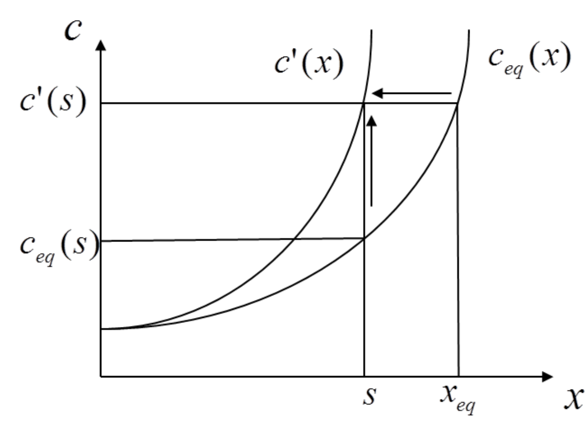

Fig. 2. Adjustment of performance function of equilibrium model in order to be used in QDTA model.

C. *Model validation*

The same floating car data have been used for validation and to test the goodness of fit of the model after the calibration phase. A further comparison has been executed applying Deterministic User Equilibrium model (DUE) to the same network, which is assumed as benchmark. The results of this comparison are summarized in the table below, where mean speed and mean travel time are shown.

The analysis of results show that QDTA model, in spite of the very quick adjustment in calibration phase, provides a quite satisfactory approximation of mean speed and mean travel time revealed by floating cars.

The difference in terms of mean speed between QDTA and FCD is about 5,2%, while the difference in terms of mean travel time is about 4,3%. The mean speed computed by applying DUE model is higher than that calculated by QDTA (16,5%), while the mean travel time is lower than that calculated by QDTA model (-18,4%). Similar results are obtained comparing the DUE model with FCD (speed is higher as 13,6% and travel time lower as -11,9%).

Table I. Difference between observed (FCD) and simulated road network performances by QDTA and static DUE models

	Mean Speed (Km/h)	Mean Time (min)
Floating Car Data	27,1	53,3
Quasi-Dynamic Traffic Assignment	25,7	55,7
QDTA vs FCD	-5,2%	4,3%
Static DUE Traffic Assignment	30,8	47
DUE vs FCD	13,6%	-11,9%
QDTA vs DUE	16,5%	-18,4%

In a second step of validation, the time period of analysis has been extended to a whole day and focused and focused on several main road arteries.

In Fig. 3 and Fig. 4 the fit-to-link flows and fit-to-link speeds on a sample of 12 relevant links of the network during the whole day are depicted to evaluate the model calibration. In both figures, observed data are reported on x-axis and simulated data on y-axis. The 45° line indicates a perfect match between the simulated and observed values. Although the very simple calibration process, error statistics (Root Mean Square Error (RMSE) and Root Mean Square Normalized Error (RMSNE) reported in the figures) are close to those obtained in one of the most advanced applications of a dynamic simulation traffic assignment model reported in literature [16], where a root mean square normalized error on link travel time as 0.436 has been obtained after having applied a very advanced calibration procedure to a sub-network in Beijing that has comparable size and characteristics of that experienced here.

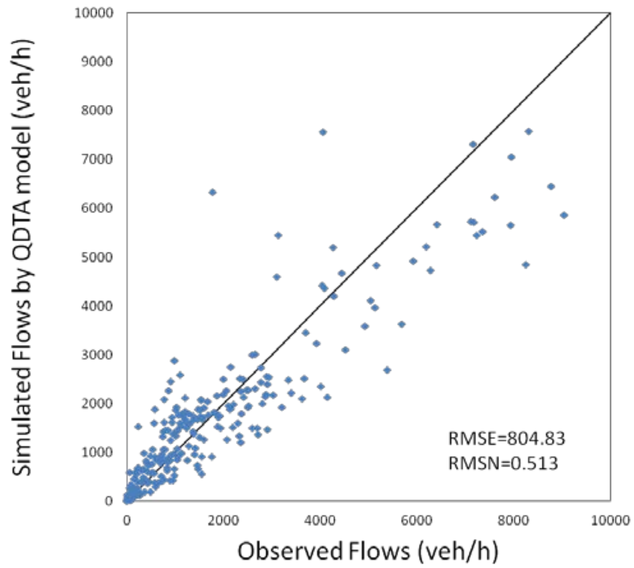

Fig. 3. Comparison between observed and simulated flows on a sample of main road links.

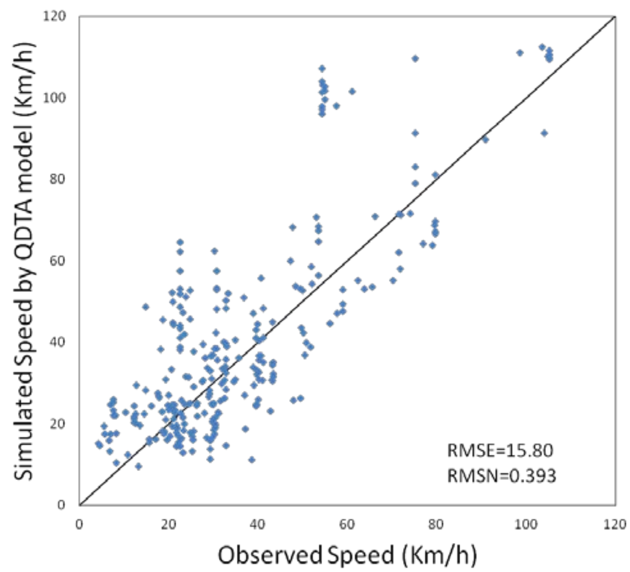

Fig. 4. Comparison between observed and simulated speed (Km/h) on a sample of main road links.

A more detailed validation has been carried out on specific links comparing speeds computed by QDTA with speeds relieved by FCD, for each hour of day.

It's possible to note that in some hours of the day speeds computed by QDTA and revealed speeds have very similar values and the same the trend (*e.g.*: Viale Marconi in time interval 05:00 a.m.-10:00 a.m.; Viale Emo in time interval 04:00 a.m.-09:00 a.m.). Observing these results it is evident that a better calibration has been achieved for the peak period in the morning, even if a rather good trend of speeds can be appreciated also in the peak hour of the evening (Fig. 5). On this regard, it is worth mentioning that a statistical estimate of traffic demand was available for the peak hour of the morning, while a very simple method has been applied to estimate travel demand in the remaining hours of day. Such differences should be reduced in a further calibration phase.

D. Model output

The pictures in Fig.6 illustrate the output supplied by the QDTA model in the simulation of two successive time intervals of the road the network of Rome. Widths of road links are proportional to traffic flow, while different colors represent different values of speed, ranging from higher values (in green), intermediate (in yellow and orange) and lower values (in red). It is possible to appreciate a slight increase of congestion on several main radial arteries connecting to the city centre.

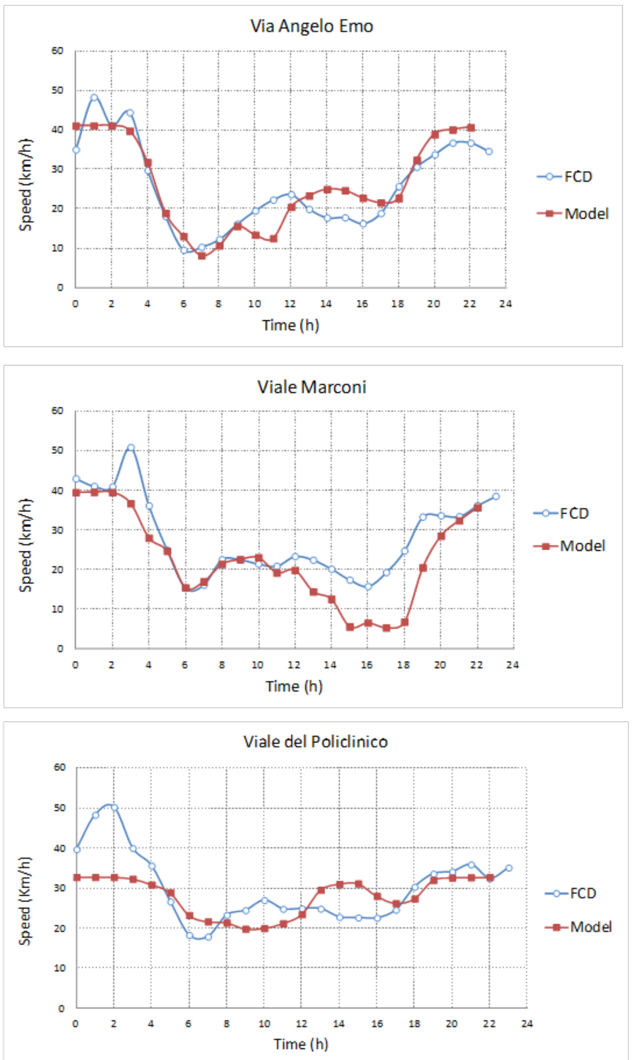

Fig. 5. Observed and simulated time variation of trend of speed (Km/h) on a sample of main road links.

Fig.7a and 7b depict a detail of the network that focuses on the Eastern area of the town. A red oval highlights spill back of traffic congestion on the expressway A14: as traffic flow directed to the city centre grows, speed decreases and a queue propagates back from a bottleneck caused by an entering ramp.

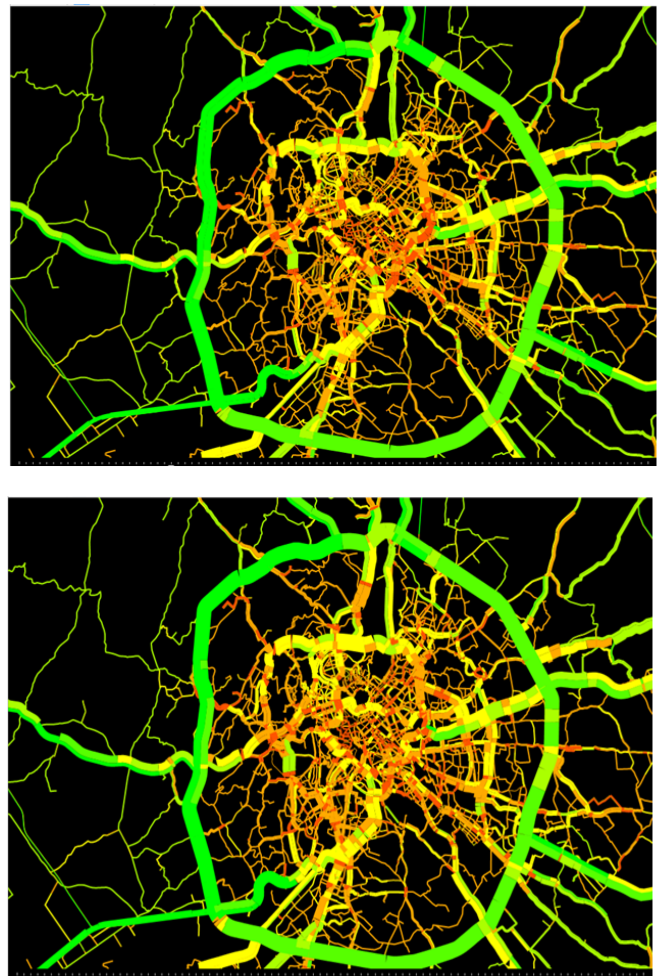

Fig. 6. Flows and speed on the road network of Rome in two different time intervals, in the time intervals 7:30 -7:45 a.m. (above) and 7:45-8:00 a.m. (below).

VI. Conclusions

In the paper a Quasi-Dynamic Traffic Assignment (QDTA) model has been presented that deals with time-dependent traffic demand and simulates time evolution of traffic congestion on an urban traffic network.

Results of the model application to the road network of Rome, Italy, show that the quasi-dynamic traffic assignment model is a good compromise between sophisticated simulation-based dynamic traffic assignment models and traditional static user equilibrium traffic assignment models.

In fact, the aggregated representation of traffic dynamics provided by QDTA allows simulating several hours of traffic on a large road network in few minutes by using a standard personal computer. Use of traditional link-cost functions facilitates the calibration process, which is however very cumbersome in simulation-based dynamic traffic assignment models. On the other hand, the dynamic network loading procedure introduced in this model has shown a capability of reproducing traffic phenomenon which is fairly comparable to that obtained by much more complex simulation-based dynamic traffic models.

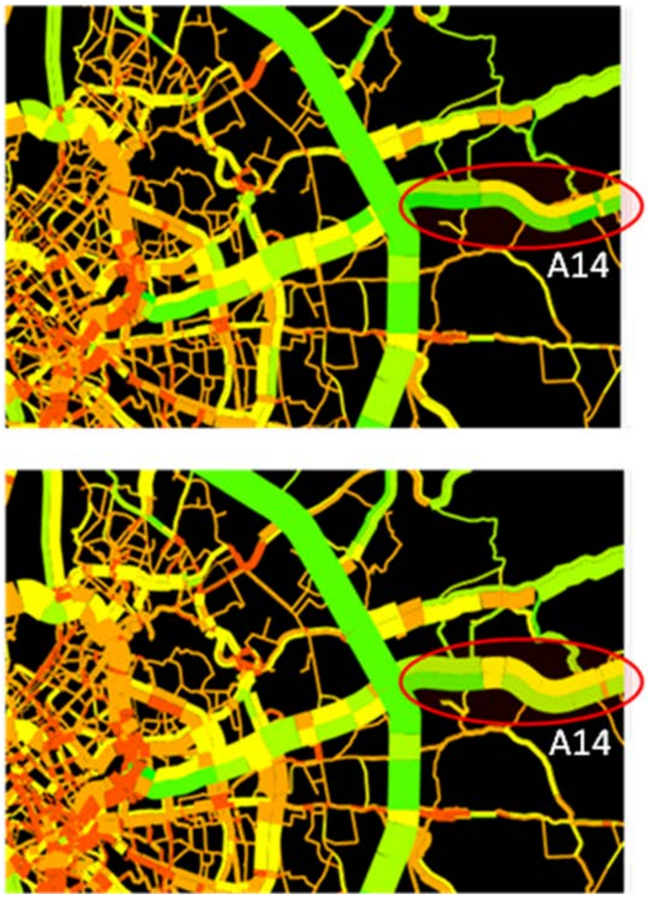

Fig. 7a. Flows and speed on a detail of the road network of Rome in two different time intervals, in the time intervals 7:30 -7:45 a.m. (above) and 8:00-8:15 a.m. (below)

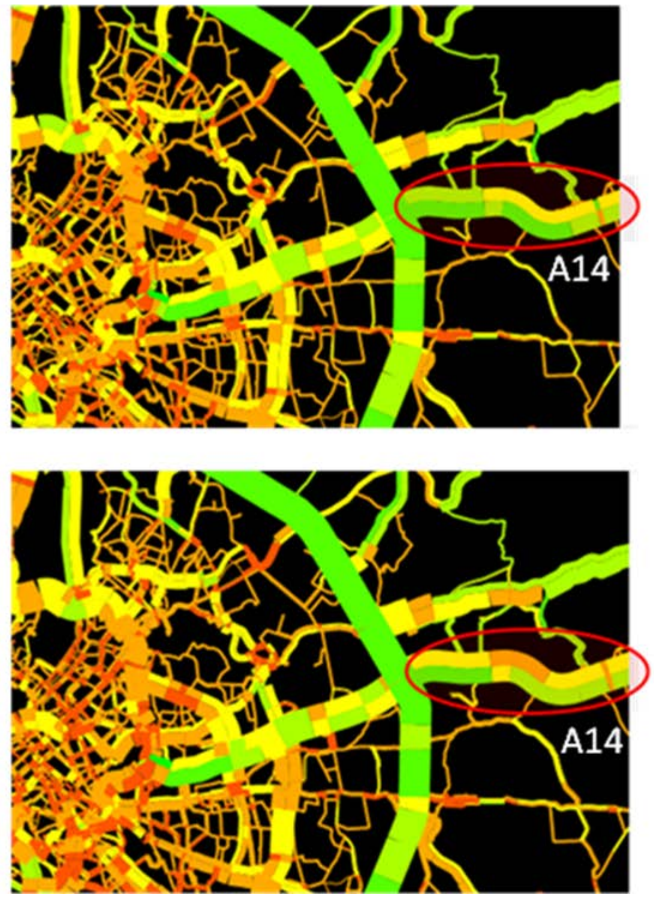

Fig. 7b. Flows and speed on a detail of the road network of Rome in two different time intervals, in the time intervals 7:45-8:00 a.m. (above) and 8:15-8:30 a.m. (below).

Further research will concern exploitation of floating car data to improve reliability of K-shortest path algorithm and the implementation of a general optimization technique for global calibration of the quasi-dynamic traffic assignment model.

In fact, the aggregated representation of traffic dynamics provided by QDTA allows simulating several hours of traffic on a large road network in few minutes by using a standard personal computer.

Use of traditional link-cost functions facilitates the calibration process, which is however very cumbersome in simulation-based dynamic traffic assignment models.

On the other hand, the dynamic network loading procedure introduced in this model has shown a capability of reproducing traffic phenomenon which is fairly comparable to that obtained by much more complex simulation-based dynamic traffic models.

Further research will concern exploitation of floating car data to improve reliability of K-shortest path algorithm and the implementation of a general optimization technique for global calibration of the quasi-dynamic traffic assignment model.

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