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RESEARCH ARTICLE

Vehicular Traffic Flow Reconstruction Analysis to Mitigate Scenarios With Large City Changes

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ABSTRACT Drastic changes into city road traffic may impact in large portions of the city, then hypothetical scenarios have to be analyzed to identify the best solutions to maintain high quality of city services. In this paper, a solution for unexpected or planned events is proposed and validated with the major focus on traffic flow fields. In order to mitigate the effects on wide area, assessments are needed to evaluate the city changes impact on traffic flow in short time. The proposed solution takes into account static, historical, real-time/dynamic, and forecasting information, with long terms and range of Traffic Flow Reconstructions (multiple simulations, predictions and data transformations) integrated with a specific assessment model to provide support for decision makers. Such a solution dynamically reshapes the road network with many connected critical areas and it automatically computes multiple traffic reconstructions in consecutive time slots, while considering the evolution of traffic flow data according to the related traffic re-distribution at junctions, solving their indeterminacy. Each scenario can be grounded for different road graph solutions, and each solution is evaluated by means of specific indicators taking into account traffic flow criticisms, and topological road graph features. The solution herein presented has been developed into the Snap4City framework for Sii-Mobility national mobility and transport action of the Italian Ministry of Innovation and Research.

INDEX TERMS Traffic analysis, traffic flow reconstruction, traffic distribution, traffic scenarios, large scale traffic flow analysis.

I. INTRODUCTION

Smart city solutions have to cope with high complex situations of city scenarios addressing unexpected and/or planned events. On this topic, the major focus is often dedicated on vehicular traffic flow which has a strong impact in the framework of urban behaviors. In fact, most simulations in city context deal with mobility and transport, including traffic flow, parking, pollutant production, people flow, accidents, etc. [1]. Closing a part of a city is an extreme occurrence, while less critical situations such as changing road direction, closing a single road, may be more frequent and less complex to be managed and analyzed. Whenever such closures/changes are planned, there is time to identify the best solutions to maintain high quality of services [2]. On the contrary, when critical changes are determined by events (e.g., a broken pipe, a relevant accident), the rearrangement of services inside/around the area must be performed as fast as possible to recover functionalities and to reduce any risk/damage/discomfort to city users by means of a cascading approach and according to resilience strategies [3], [4].

In case of unplanned events, the number of possible cases may be very high, since they vary in terms of locations and entities, and impact on city services. Ideally, experts could foresee the occurrence of certain events, while many other cases are impossible to be foreseen and they are somehow unexpected, as to precise date and time, relevance, location, context, reactions from city users, and cascade effects on multiple services and areas, which substantially makes the simple prediction offered by single traffic flow sensors unuseful in terms of decision making on changes. They are the so-called unexpected unknowns [5], for which both models

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and contexts are doomed to change at any event occurrence, thus making long-terms prediction almost infeasible.

The actual goal to cope with unexpected unknowns on traffic road network is based on the possibility in short time to understand how the traffic would autonomously react as to the changes in place. Which directions would be taken by vehicles arriving in the critical area and finding out that roads and the area itself have been radically changed? It is not only a matter of dynamic routing (routing with real time changes in the road network structure), but it means also to estimate traffic flow changes in real time, since the context has been changed, which is much more complex. Traffic flow analysis requires having an input context which describes the substantially changed scenario and conditions. This kind of problem could be addressed by performing specific simulations with a certain margin of error, having high complexity in large scale contexts. The simple outcome prediction computing could not be possible, since such detailed scenarios may be typically unknown.

In literature, traffic flow estimation is performed by using Traffic Flow Reconstruction, TFR, solutions which are processes to produce a value of traffic density (flow) - e.g., number of vehicles per meter (or vehicles per minute) - for each road or road segment (or a large number of road segments for example of 20mt each) by starting from a limited number of traffic sensors measuring traffic density (flow in terms of vehicles per meter) [6] on strategic positions (e.g., 100 in a city of 300.000 inhabitants) or in other devices (e.g., mobile apps navigators). In most cases, TFR solutions are based on both LWR model (Lighthill-Whitham-Richards) [7], [8] and error analysis in traffic flow estimation. The solution of the LWR model [9], [10], can be based on modeling traffic density in terms of Partial Differential Equation (PDE), and it is not trivial for large networks [6], [7], [11], [12], [13], [14]. In alternative, TFR can be performed by using agent-based solutions which are typically more difficult to scale, since they need a specific process for each agent/vehicle. In literature, many studies concerning concepts on traffic analysis focused on routing [15], [16], signal control systems [17], [18], and autonomous driving [19].

The related literature also provides a set of traffic or city simulators which could be used for TFR in small area. DEUS [20] is a Discrete-Event Universal Simulator used to simulate a Vehicular Ad-Hoc Network. VANET [21] has been used with SUMO (Simulation of Urban Mobility, http://sumo.dlr.de) which can create microsimulations of traffic crossroad distribution. MATSim (Multi-Agent Transport Simulation, https://www.matsim.org/) is an agent-based simulator which can cope with a limited number of agents/vehicles [22]. Most of these simulators are unsuitable for large scale analysis of changes to understand how they impact in the whole city. Large scale simulators are often based on origin destination and population characteristics. Transport System Models (TSMs) try to predict the impact of city changes (projects or plans) to assess their technical suitability and to support intermediate and final decision-makers through the process of project/plan evaluation. They focus on basic concepts and methods of discrete choice analysis, and describe the applications of the methodology to travel demand modelling. Demand forecasting deals with the travellers' behaviour and the one of goods in urban, interurban, and international transport contexts. Discrete choice models use the principle of utility and benefit maximization, and operational models often consist on the characterization of parameterized utility functions via statistical inference. More precisely, an operational model consists of parameterized utility functions in terms of observable independent variables and unknown parameters, and their values are estimated from a sample of observed choices made by decision makers, when confronted with a choice situation, thus adopting the concept of random utility [23]. Discrete choice models are usually applied to forecast trips by starting from origins and destinations (O-D) data and considering different transport modalities [24]. The approach for the identification of a useful travel path by minimising the cost has been proposed by [25]. These models assume the knowledge of O-D data which are not often accessible, and in some cases, cities are trying to avoid collecting vehicles plates due to privacy regulations. On the other hand, anonymization approaches are expensive to be applied on legacy solutions.

InterSCSimulator [26] is an agent-based simulator which may scale up to large roads and cases at the expense of memory and computational time, for instance 51 GByte of memory for 50.000 nodes, 22 minutes of computation. Also, a commercial solution such as OPTIMA proposed by PTV has a limited capability in forecasting traffic behavior within 60 minutes (https://www.ptvgroup.com/en/solutions/products/), which means the motivations for traveling could be parametrized but not assessed from actual data.

Other simulators have been reviewed and compared in [27], identifying the limitations when it comes to traffic flow evolution with Bayesian-based models, and in addressing large scale cases, and small events not large cases.

The available solutions in the current state of the art for traffic analysis typically perform simulations only of single elements of the road graph, in cases of general road blocking conditions [28], road bottlenecks and congestion, as well as disaster management [29], [30]. The analysis of the computed KPI (Key Performance Indicator) for city traffic would be used to compare solutions. Generally, traffic flow study can also exploit network analysis according with the topological features of each scenario, since the related road network is modelled as a directed graph. And thus, a new graph implies a different redistribution of traffic. For example, [6] shows that the highest value for betweenness [31] is in proximity of one of the typical areas where traffic congestion often occurs. In [32] it is proven that the nodes characterized by higher values of betweenness potentially represent critical regions (intersections) of the network. On the other hand, nodes having high eccentricity [31] are in the decentralized zones of the urban graph admitting more distance from the other side of the network. In [33], some integrated performance indicators in urban road infrastructure are also developed for an evaluation of the network functionality and the impact of transport system interventions such as average degree of saturation. Traditional indicators used to measure traffic congestion include travel delays with respect to average travel time at signalized intersections to estimate the saturation flow rate [34]. In many studies, urban traffic state is explored in different ways. For example, in [35] travel speed and travel time are directly obtained through the loop detector, GPS, video, etc. In [36] both traffic volume and occupancy are integrated to form a new value for network-wide traffic state observation and analysis via pseudo-color maps. In [37], a comprehensive traffic state estimator derived from traffic flow variables (flows, mean speeds, and densities) is presented. The architectural aspects of a future scenario traffic analysis tool should be also addressed [38]. It must take into account multiple simulations, and probably most of them are going to exploit TFR in the modified context to assess/simulate the impact of traffic changes on public transport, parking, people flow, commercial areas, etc. Some developers of custom scenario analysis complain about the lack of formalism to make the setup of the solutions easier and compute several simulations based on the same scenario [39].

Traffic conditional routing in vehicular networks has been addressed in literature, as a measure for mitigating as well as preventing traffic congestions. Several strategies have been proposed, such as Dynamic Shortest Path (DSP), Random k Shortest Paths (RkSP) [40] and Entropy Balanced k Shortest Paths (EBkSP) [30]. Some works also have addressed the traffic routing problem due to natural disasters, such as in [41], where a traffic rerouting system is presented exploiting Bayesan Networks Analysis to provide possible reroute paths to avoid flooded areas.

The TFR analysis in future and evolved scenarios should not be confused with sensitivity analysis which aims at evaluating how sensitive is the behavior of the system/subsystem with respect to small changes of one or more parameters (for example the size of a road). Moreover, there is an important difference with respect to traffic flow predictions. Predictions are produced by extrapolating short/long-term trends from historical time series in sensor locations [42]. Therefore, the single traffic flow sensor prediction cannot provide hints on the impact of changes in the context (road network). Approaches for traffic flow predictions may be based on AI, machine learning, provided that in a stable context, data are accessible for any training of the model.

Thus, according to the state of the art, the computation of TFR in large scale and providing responses in real-time for long-term scenarios, for example months in advance, is a challenge, as well as the computation of large-scale indicators of traffic flow conditions.

A. SCOPE AND STRUCTURE OF THE PAPER

When a small city area is closed, then the simulation of traffic data could be performed on the basis of historical data of traffic flow, traffic predictions, origin destination matrices, typical time trends of traffic flow on sensors, and/or by taking into account the typical paths done by city users in the city. Changes in the road network structure (as well as on the number of operating sensors) imply the redistribution of traffic on modified crossroads and the propagation of effects to a large part of the road network up to the whole city; therefore the model should lead to compute the TFR in the whole city area, and the TFR computation for each new scenario into large road networks definitively has to be considered a data intensive process, which has to be replicated for each time slot, for several days [39], [43]. In fact, a scenario may imply road network modifications for a given period of time (e.g., closing roads and areas, changing road directions and use for a week) and it may predict the traffic evolution in those planned or suddenly unexpected changed conditions over time. Thus, small scale simulations or predictions (covering few roads or single sensors) fail in providing solutions, since cascade effects are provoking consequences in many other areas, and small-scale solutions do not take them into account. One of the main issues, is the presence of traffic cascade effect, long terms predictions of single sensors seem to be un-useful for decisions in larger scale contexts, where critical conditions can propagate in other part of the city. For example, a block in a part of the city may undermine many other parts of the city, though apparently unconnected to that area, and yet reached by the propagation of the queues. Generally, the whole number of vehicles entering and exiting the city over time would be conserved [6], which is a condition of solving LWR problem, while the balance is not generally preserved in smaller city area, thus forcing state of the art simulators to build a large number of hypotheses.

On such grounds, the solution proposed in this paper aimed to solve the above presented problems and provide a data driven instrument for decision makers in order to select which are the most viable city changes to cope with the unexpected unknowns impacting on traffic and to carry out changes to reshape traffic viability in short time - i.e., change city viability. The aim of our work is to *understand how the vehicular traffic would react* with respect to a hypothetical scenario in order to mitigate such outcomes and their large-scale changes in the whole city. The main paper contributions are on a real time TFR analysis involving:

(i) definition and formalization of the scenarios as a set of descriptive parameters on space and time according to vehicular traffic behavior, including formalization of scenarios; a formal definition of a scenario has to include: (a) single or multiply connected areas, representing spatial blocking constraints which interdict specific kinds of traffic (private, public transportation, cycling, pedestrian, etc.), (b) a starting and ending date and time;

(ii) definition and implementation of large parametrized TFR computation and simulation in real time against scenarios to produce an outcome for each time slot of the scenario (addressing the related changes into the road graphs, as well as on the number of operating sensors, and automatically estimating traffic redistribution on modified crossroads), together with TFR validation against complex scenarios thus requiring high precision.

(iii) a set of assessment metrics depending on road structure and traffic values, which the outcomes could be assessed according to. The identification of the most suitable solutions has to be performed on the basis of objective KPIs which allow to assess traffic conditions and would wrap up/finalize the process to minimize the dysfunction, thus reducing/limiting any crowding conditions as much as possible.

With the intention of providing responses in real-time for complex scenarios we have extended the TFR solution of [6] by (a) dynamically reshaping of the road graph network on the basis of scenarios with multiply connected critical areas, (b) computing multiple TFR in consecutive time slots taking into account the road graph evolution, junction redistribution and traffic flow data. The vehicular route choice at junctions (on a macrosystem urban traffic model) is determined by means of Stochastic Relaxation Approach on the basis of traffic flow data in a given number of sensor points, at each time instant, to reduce any possible system error. The solution can address static, historical, real-time/dynamic, and forecasting information, in a functional model, where TFR processes (simulations, predictions, data transformations) are integrated with the business logic of visualization and user interaction made available to decision makers.

The solution has been developed in the framework of Sii-Mobility, which is a national project on sustainable mobility and transport. The architecture of the traffic reconstruction analysis tool has been based on Snap4City framework (https://www.snap4city.org), where the business logic is defined by using Node-RED and Snap4City MicroService Libraries [44]. Such a solution is currently exploited in several cities which have adopted the Snap4City framework.

The paper is structured as follows. In Section 2, both general architecture and data flow are presented together with some details regarding scenarios, prediction and changes on the road network graph. Section 3 brings up the approach for TFR computing. In Section 4, some metrics, fit for assessing changes from topological point of view, are presented according to the new road graph identification or scenario. Besides, more complex metrics based on the reconstructed traffic flow values are considered to mitigate any scenario-provoked changes. Section 5 provides the analysis tool's validation, when multiply-connected areas are blocked. In Section 6, an analysis with multiply connected scenario is provided, while performance is discussed in Section 7 and conclusion are drawn in Section 8.

II. GENERAL ARCHITECTURE AND DATA FLOWS

In order to cope with the above complexity, a flexible analysis architecture has been defined and implemented as reported in Fig. 1. It exploits Historical and Real Time Data from

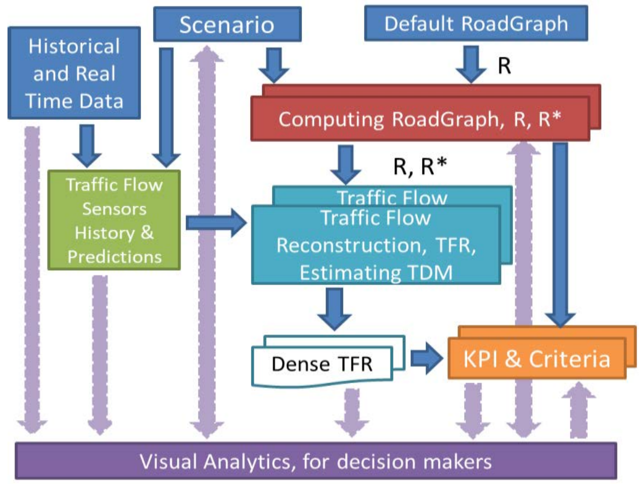

FIGURE 1. Functional Architecture of the traffic flow analysis in future scenarios.

traffic flow sensors to compute predictions and to enable any computing of dense TFR in the whole city, both within regular and evolved/changed scenarios. As described above, the most effective solutions for large scale TFR are the ones based on solving differential equations. Thus, in agreement with TFR approach of [6] and while considering the reference scenario, a number of steps are needed to compute traffic flow in each time slot and day of the scenario. According to [6], dense TFR at time t can be computed by: (i) taking into account an annotated Road Graph, R, (a network of road segments and cross roads with turns, max velocity, number of lanes, any other constraints, etc.); (ii) measuring or estimating the traffic flow distribution at each cross road for each time slot of the day and week, named Traffic Distribution Matrices, TDM; (iii) being aware of traffic flow conditions in terms of flow data in any previous time instants.

On the other hand, the above-described problem of computing TFR in some radically changed city conditions is much more complex, since an evolved Scenario (inception of changes for some disaster, or changes planned to assess their impact) could change the Road Graph and this would impact on TDM and TFR for the whole city, lasting up to hours and days, according to cascade effects and duration of changes. For example, if we consider analyzing a future scenario where some city areas are forbidden to vehicular traffic for 3 days, 6 months from today, we would be interested to assess what it will happen on traffic. Thus, for example, the following problems should be addressed by: (i) registering the scenario blocking some city areas on that specific time lapse, 3 days, 6 months from today; (ii) changes on Road Graph which could be decided, so as to mitigate the effects of that scenario (e.g., changing road directions, closing other roads); (iii) predicting any possible traffic flow sensor values 6 months ahead and thus also at the border of the involved scenario areas, or forcing to zero traffic flow the sensors in the blocked areas; (iv) computing TDM and dense TFR during the selected span of 3 days in the whole city to understand what is going to happen on traffic flow according to those changes due to the scenario and according to the modified Road Graph; (v) computing KPI to assess the impact of changes within the city in terms of objective indicators, so as to choose the best scenarios to reduce city user dysfunction, traffic conditions, costs, security preservation, service quality, safeguarding a routing for emergency vehicles, etc.

Therefore, for each Scenario a number of Road Graph solutions could be proposed and KPI & Criteria can help decision makers to select the best Road Graph in order to mitigate the scenario. Actual and proposed changes and results have to be accessible for decision makers, thus turning out into a Visual Analytics tool, which in our case has been developed according to the exploitation of Snap4City environment [45], [46]. Decision makers can interact on Visual Analytic by changing the Scenario, mitigation aspects on Road Graph, and by selecting possible decision support KPI and criteria.

In this paper, only aspects regarding TFR and related KPIs are discussed, since most of the other predictions/simulations strongly rely on the distribution of traffic flow density, as to the scenarios under study. In fact, once the dense TFR in one or more possible Road Graph has been estimated, it can be exploited to assess its impact on: (a) public transportation services, which could lead to moving bus stops out of the blocked area and changing lines/rides, timelines, etc. [47]; (b) parking lots availability, since some of the parking areas could be included within the blocked city area scenario or could be less easily accessible [48]; (c) pollutant changes on the basis of traffic flow, thus provoking more emissions of NO2 [49] and on CO2 [50], according to the related dense estimation [51]. In the following subsections, the most relevant aspects and steps of the above data flow architecture are described, while the computing of dense TFR with its corresponding TDM and KPI is described in Section 3.

A. SCENARIO MODELING AND MANAGEMENT

According to Fig.1, each scenario is denoted as SC_{ID}, and it is identified by a unique ID, a description, involved areas, a set of time intervals and additional constraints, such as any category of users or vehicles which must be restricted/enabled. A Scenario is formalized as tuple $SC_{ID} = \{ID, D, \boldsymbol{A}, \boldsymbol{T}, \boldsymbol{C}, R\}$, where:

- ID is the unique Identifier of the scenario;
- D is a textual description of the scenario;
- $\boldsymbol{A}$ is a simple or multiply connected blocked Area, that is a set composed by one or multiple blocked areas: $\boldsymbol{A} = \{A_1, A_2, \ldots, A_N\}$, where N is the number of blocked Areas;
- $\boldsymbol{T}$ represents a set of time slots or intervals: $\boldsymbol{T} = \{T_S, T_E\}$, where T_S and T_E represent, respectively, the starting and ending dates and times of the period when the blocking constraints are active;
- $\boldsymbol{C}$ is a set of blocking constraints representing which transportation mean has been blocked/limited, for instance: $\boldsymbol{C} = \{C_{ped}, C_{priv}, C_{pub}, C_{spec}, C_{cyc}, \ldots\}$, where C_{ped} represents a pedestrian constraint, C_{priv} a private vehicle constraint, C_{pub} a Public transport constraint, C_{spec} a special vehicle constraint, C_{cyc} bike cycling path constraint, etc. Changes in any specific constraints of a road segment (e.g., velocity, direction) can be defined as a set of constraints;
- R is the reference road graph network.

Scenarios can be produced for: planned or unplanned events, with the aim of solving/limiting problems, as well as managing either events or changes. As to an area which has to be closed to perform some recovery maintenance works, multiple Scenarios ($SC_i = \{i, D_i, \boldsymbol{A}_i, \boldsymbol{T}_i, \boldsymbol{C}_i, R\}$, where $i = 1, \ldots, N$ represents different scenario IDs) could be defined on the basis of changes occurring during the intervention. Thus, different changes on the road graph, for example in the viability, direction of roads, etc. can be applied. The impact of the application of a certain scenario $SC_{i,\widehat{\boldsymbol{T}}} = \{i, D_i, \boldsymbol{A}_i, \widehat{\boldsymbol{T}}, \boldsymbol{C}_i, R^*\}$, where R^* is the modified Road Graph starting from R, should be compared with others $SC_{j,\widehat{\boldsymbol{T}}} = \{j, D_j, \boldsymbol{A}_j, \widehat{\boldsymbol{T}}, \boldsymbol{C}_j, R^*\}$, as well as against the original scenario in the same time slots $\widehat{\boldsymbol{T}}$ without any restrictions, which is called the UnChanged Scenario, $SC\_UC_{i,\widehat{\boldsymbol{T}}} = \{i, D_i, \emptyset, \widehat{\boldsymbol{T}}, \emptyset, R\}$.

Blocking areas of the scenario are drawn via the user interface (see Fig.2) by means of geometric shapes (rectangles, circles and polygons) on the map; some the above-described metadata have to be provided and among them some mandatory values are identifier, blocking areas, starting and ending times and constraints. Saved scenarios can be shared with other operators and loaded and used to automatically change the Road Graph. The modified Road Graph can be further modified by operators to mitigate any possible cascade effect (e.g., any viability adjustment based on specific needs). Thus, the finally modified Road Graph, R*, can be used: (i) for computing the dense TFR, and (ii) by the routing engine to provide dynamic alternative routings for different types of traffic means: private cars, public transportation busses, bikes and pedestrians. The routing engine exploits the open source GraphHopper library [52], which has been extended to manage simple or multiply connected constraints as formalized in the Scenario.

B. COMPUTING PREDICTIONS

The short and/or long terms predictions of traffic flow data at sensors for time slots $\widehat{\boldsymbol{T}}$ can be computed on the basis of historical data plus some contextual elements. For example, short terms predictions in the range of minutes and hours of traffic flow may be carried out/performed on the basis of historical [53], [54]; while midterms predictions within a day may be computed as well, by taking into account weather conditions and forecasts [55], [56], [57], [58]. Then, as to very long-term predictions, most predictive algorithms cannot produce satisfactory results with errors smaller than 15%. In those occurrences, the computation of typical time

FIGURE 2. **Example of a Scenario with 3 areas and dynamic computation of routing avoiding blocked areas. Please note that start and end points can be moved from web page to see the new routing in real time. Also, intermediate points can be arranged. https://www.snap4city.org/dashboardSmartCity/view/index.php?iddasboard=MjE5MA==.**

trends concerning that period's traffic flow can be done, if considering the historical data of the same day of the week, of the month and of the year. For example, a typical time trend can be computed as the median or average of data related to October 2018, while the actual values are those of the same day of the week of October 2019. According to this approach, the computed averaged MAPE (Mean Absolute Percentage Error), between observed (obs) and predicted (pred) data over the whole set of city sensors in that period, is 11.2% where

$$MAPE = \frac{\sum_{i=1}^{n} |\frac{obs_i - pred_i}{obs_i}|}{n} * 100.$$

C. COMPUTING AND CHANGING ROAD GRAPH

The Road Graph describes all details of the road network graph, including for each road network arc/segment: size, bounded velocity, number of lanes, directions, and also crossroads with their patters, right turns, etc. The application of a Scenario $SC_{i,\widehat{T}}$ leads to imposing changes, which in turn may provoke other changes to the road network. For example, if a city area has to be blocked, roads leading or departing to/from that area may need to be adapted as well.

Thus, the review of the Road Graph network on the basis of a scenario brings forth a modified Road Graph, denoted by R^*, by following a number of steps and actions which can be automatically executed on a semantic model of the Road Graph excluding some elements from the viability paths:

- road graph arcs/segments included or partially included within the no-go areas of the Scenario (segmentation of the arcs is performed on every 20m, thus allowing the discretization to be very fine)
- junctions (crossroads) having the related nodes within the no-go areas, also modify all the intersections, wherever a given arc is no longer considered in the new setting and thus modifying in an appropriate way the distribution of the incoming and outgoing traffic according to the remaining arcs' features,
- sensors which are inside the blocked areas.

In our case, a new Road Graph implies to perform a number of semantic queries in SPARQL to generate a new knowledge base model of the city according to the Km4City ontology, the latter being instantiated in a separated Docker to be exploited for TDM and TFR computing purposes. Moreover, on the same modified graph, several changes may be needed in order to re-establish the viability within the areas and that operation may need to be performed by operators. Some changes can be straight forward (namely, they can be suggested by the system), while others could be somehow performed on the basis of experience. Actually, a number of Road Graph: R^* could be produced by different experts and/or according to different hypothesis in order to mitigate the same Scenario, see Fig.1.

III. COMPUTING CONSTRAINED DENSE TRAFFIC FLOW RECONSTRUCTION

Actually, a number of different Road Graphs mitigating the scenario can be proposed or generated, with slight changes into the Road Graph structure. In this section, the dense TFRs computation according to a changed Road Graph is discussed. The step consists in computing the updated TDM according to the modified Road Graph and scenario, which also defines the set of time slots which the TDM has to be computed for. The assessment of TDM allows to compute TFR, thus solving PDE for the scenario time slots. Finally, the assessment of a set of relevant metrics allows to evaluate and identify which are the best solutions among those proposed, as described in Section 4.

The computing of dense TFR is performed by solving a nonlinear model based on the conservation of vehicles described by the following scalar hyperbolic conservation law, in a single road, $\frac{\partial \rho(t,x)}{\partial t} + \frac{\partial f(\rho(t,x))}{\partial x} = 0$, where: $\rho(t,x)$ is the traffic density of vehicles, which admits values from 0 to ρ_{max}, where $\rho_{max} > 0$ is the maximal traffic density; $f(\rho(t,x))$ function is the vehicular flux which is defined by means of the product $\rho(t,x)\,v(t,x)$, where $v(t,x)$ is the vehicle speed; and boundary conditions $\rho(t,a) = \rho_a(t)$, $\rho(t,b) = \rho_b(t)$, initial values $\rho(0,x) = \rho_0(x)$, with $x \in (a,b)$. As to first order approximation, we assume that $v(t,x)$ is a decreasing function, depending on the density, then the corresponding flux is a concave function. Thus, we consider the local speed of the vehicles as $v(\rho) = v_{max}(1 - \frac{\rho}{\rho_{max}})$ and then $f(\rho) = v_{max}\left(1 - \frac{\rho}{\rho_{max}}\right)\rho$, where v_{max} is the limit speed on a given road segment (these assumptions are known in the literature as the Greenshield's Model.) The solution is obtained by an iterative process, at finite differences on the basis of traffic flow data in sensors points or, as in this case, by exploiting the predicted sensor values for each time slot of the future scenario [6].

Changes on road graph implies changes on TDM which describes the distribution of traffic at crossroad junctions, not only those directly involved, but also those which can be far away from the Scenario areas. The TDM is a distribution matrix describing the percentage of vehicles getting out each outcoming road with respect to those getting in each incoming road. Thus, it is defined as $TDM = \{w_{ji}\}_{j=n+1,\ldots,n+m,i=1,\ldots,n}$ so that $0 < w_{ji} < 1$ and $\sum_{j=n+1}^{n+m} w_{ji} = 1$, for $i = 1,\ldots,n$ and $j = n+1,\ldots,n+m$, where w_{ji} coefficients (called weights) are the percentages of vehicles arriving from the i-th incoming road and taking the j-th outcoming road (assuming that, on each junction, the incoming flux coincides with the outcoming flux). The values of weights w_{ji} may depend on the time of the day, on the road size, cross light settings, etc., and thus, it is unknown a priori. When one (or more) roads are closed, then the traffic has to be redistributed in other directions. In particular, the network would take a reassessment of the traffic distribution in the junctions such that $\sum_{j=n'+1}^{n'+m'} v_{ji} = 1$, for $i = 1,\ldots,n'$ and $j = n'+1,\ldots,n'+m'$ where $n' \leq n$, $m' \leq m$ and $v_{ji} = w_{ji}\frac{\sum_{j=n+1}^{n+m} x_{ji}}{\sum_{j=n'+1}^{n'+m'} x_{ji}}$ where x_{ji} are the values giving the lower mean error for each time slot of the scenario, as to weight assignment.

Weights can be measured or estimated, while in cases of Scenarios they cannot be measured, therefore they have to be estimated on the basis of the traffic arriving to crossroads and thus taking into account any road graph changes. $TDM(t)$ values over time are unknown, since traffic flow cannot be measured in each inflow/outflow road of all crossroads, in each time slot t. A first approximation of the $TDM(t)$ could be the typical values for $TDM\ (t)$in a given day, for each day of the week. These trends are an approximation, since the $TDM(t)$ is conceptually changing at each time slot. Thus, the first approximation can be produced by means of a computation of typical trends at junctions over time, in the period. The solution is obtained by a Stochastic Relaxation Approach on the basis of traffic flow data in a limited number of sensors points at each time instant. At each timestamp, the solution produces a value of traffic flow density in each road segment of the network, typically of 20mt, as unit. The dense TFR accuracy mainly depends on the stochastic relaxation approach for estimating the TDMs. The computing of TFR is progressively performed on a parallel architecture, since the estimation of traffic flow density for the city (e.g., in Florence there are more than 30.000 road segments or units) at time instant t would depend on traffic flow at time *t-1* in the whole network, and on the new measures/predictions coming from sensors.

TFR is computed in the road network, and it is assessed by computing the Root Mean Square Error, RMSE of the reconstructed values with respect to the predicted ones in specific sensor locations. TFR accuracy is performed by computing the solution excluding data from each different sensor (all of them) by means of a Leave-One-Out Crossing-Validation (LOOCV) approach, to estimate the deviation from dense TFR with respect to the sensor predicted density, for each time t in T. Then, in a road network having m traffic sensors, LOOCV approach consists in the application of the model to the set of observed data at time t by excluding the k-th observation/prediction, for each $k = 1,\ldots,m$. Then, model is applied to the remaining set of $m-1$ sensors' observations and the reconstructed density in the road segment (unit) where the k-th sensor is located can be estimated and compared with the observed/predicted value via RMSE or MAE. For each round, the stochastic relaxation may produce a new minimum of the RMSE that is taken as a reference status together with the produced $TDM(t)$, for next iterations. Such an approach turned out to produce dense TFR with a RMSE smaller than 20% in the internal parts of the city [6].

IV. ASSESSING GLOBAL TRAFFIC FLOW CONDITIONS

According to Fig.1, KPIs are conceived / meant to assess globally city traffic conditions, therefore the impact of changes has to be calculated on the basis of the computed dense TFR, taking into account the different Road Graphs of each scenario, $SC_{i,\widehat{\boldsymbol{T}}}$. Each estimation of KPI has to be compared against values for the same time slots $\widehat{\boldsymbol{T}}$, and it is obtained in different conditions against the original scenario (that is, without changes on Road Graph) called UnChanged Scenario, $SC\_UC_{i,\widehat{\boldsymbol{T}}}$. In addition, it is also possible to compute KPI average values and related differences which may provide support to make some decisions among multiple scenarios and solutions. On the other hand, changes in the topological structure of the road network can provide useful information, as well.

A. TOPOLOGICAL ASSESSMENT OF THE ROAD NETWORK

Each modified road graph determines a different traffic network. The properties of betweenness, centrality and eccentricity metrics can be computed on the basis of the topological structure of the city traffic network, without taking into account the actual flow. On the other hand, [6] and [32] showed that the highest value for betweenness is located in proximity of areas where traffic congestions often occur. The vertex betweenness (also known as betweenness centrality) of a node v of the road graph network R is the number of shortest paths which pass through v in R, formally we have

$$b_R(v) = \sum_{i \neq j, i \neq v, j \neq v} g_{ivj}/g_{ij}$$

where g_{ij} is the total number of the shortest paths from node i to node j in R, and g_{ivj} is the number of those paths passing-through v in R. The vertex betweenness represents the degree to which nodes stand between each other and it measures the extent to which a vertex lies on paths between other vertices. Nodes having high betweenness may have considerable influence within a road network by virtue of their control over traffic data passing between others. Such nodes are also the ones whose removal from the network will most disrupt communications between other vertices, because they lie on the largest number of paths inside the network. The correctness of a given information which goes through the nodes of a network depends also on other issues related to node properties. An example is given by the (eigenvector) centrality [31] of a vertex v in R, labelled with $c_R(v)$, which is a measure of the influence of the vertex v in the road graph network R. In general, vertices with high (eigenvector) centralities are those which are connected to many other vertices which are, in turn, connected to many others (and so on). Another topological metric is given by the eccentricity [31] of a vertex v in R, labelled with $e_R(v)$, which is defined as the shortest path distance that a given vertex v has from the farthest node in the road graph network R. Nodes having high eccentricity are located in the urban graph's decentralized zones, admitting more distance from the other side of the network. Then, such metrics can be considered as structural features of the road network describing a given scenario, and they can help us to understand how the related and restricted road network changes in terms of connectivity.

Formally, the connectivity KPI (denoted by $\boldsymbol{KPI}_C$) according to a certain scenario $SC_{i,\widehat{\boldsymbol{T}}} = \left\{i, D_i, \boldsymbol{A}_i, \widehat{\boldsymbol{T}}, \boldsymbol{C}_i, R^*\right\}$ can be defined as

$$\boldsymbol{KPI}_C(SC_{i,\widehat{\boldsymbol{T}}}) = \{B_{R^*}, C_{R^*}, E_{R^*}$$

where:

- $B_{R^*} = (\max\{b_{R^*}(v) : v \in R^*\}, b)$ with b representing the corresponding node assuming the maximum value,
- $C_{R^*}(\max\{c_{R^*}(v) : v \in R^*\}, c)$ with c representing the corresponding node assuming the maximum value,
- $E_{R^*} = (\max\{e_{R^*}(v) : v \in R^*\}, e)$ with e representing the corresponding node assuming the maximum value.

Therefore, computing $\boldsymbol{KPI}_C(SC_{i,\widehat{\boldsymbol{T}}})$ and $\boldsymbol{KPI}_C(SC\_UC_{i,\widehat{\boldsymbol{T}}})$ may produce different values, and distinct representative nodes can be observed in the map in order to understand changes in terms of road graph network connectivity. The computing of the above-described road graph metrics can be performed on the original road graph R, and immediately after obtaining the graph R^*. This means that $\Delta\overline{KPIc}(.)$ and some considerations can be carried out, before moving to the complete simulation, also observing (statical) changes on the map and the absolute values of those KPIs. In order to evaluate dynamical changes on traffic flow evolution according to the considered Scenario, via multiple traffic reconstructions in consecutive time slots, additional KPIs in terms of traffic state to assess the related critical conditions, are presented in the following.

B. ASSESSMENT CRITICAL TRAFFIC FLOW CONDITIONS

According to the definition of the Scenario, it provokes changes on Road Graph and TFR, on several time slots. City traffic is a dynamic system represented by the TFR(t) which essentially is a sequence of TFR. Specific KPIs are needed to compare traffic viability taking into account all time slots of the scenario. At each time stamp, common metrics, used in the area of vehicular traffic flow theory, have to be considered, namely traffic density and traffic flow values, which respectively stand for the number of vehicles in terms of road occupancy and the number of vehicles crossing the supervised location during a given period of time (which is usually equal to one hour).

More precisely, traffic density of a road graph network R at a given time slot t, denoted by $D_R(t)$, is defined as the array $D_R(t) = \{\rho_R(i, t) : i = 1, \ldots, S$ where S is the total number of the road segments in R having length of about 20 meters. In a similar way, the corresponding traffic flow is defined as $F_R(t) = \{f_R(i, t) : i = 1, \ldots, S$. Fixing the i-th road segment in R (with $i = 1, \ldots, S$) such that $\rho = \rho_R(i, t)$ in $D_R(t)$ and $f = f_R(i, t)$ in $F_R(t)$, thus if $\rho = 0$ then $f = 0$.

Otherwise, when ρ grows, also f grows up to the maximum $f_{\max}$, for which the vehicular density assumes its critical value $\rho_c = \rho_{\max}/2$. In the case where $\rho > \rho c$, other increases of traffic density lead to a congested scenario of traffic flow up to its maximum value ρ max, where the cars' speed is 0 and then $f = 0$. The critical density associated to the i-th road segment in R depends on its road capability according, for example, to its number of lanes. So that, some thresholds on the road segments of R can be defined in terms of traffic density. Critical values of the traffic density (according to the number of lanes) can be observed when some congestion situations are occurring and a set of thresholds $\{\rho_c(i) : i = 1, \ldots, S\}$ in terms of traffic density can be defined describing the state of traffic of the i-th segment road in R, for each $i = 1, \ldots, S$. "FREE", "FLUID", "HEAVY" or "VERY HEAVY" traffic states can be determined by assigning numerical intervals on the value $\rho = \rho_R(i, t)$ according to the corresponding threshold $\rho_c = \rho_c(i)$, for each $i = 1, \ldots, S$, considering for example $0 < \rho < \rho_c/2$, $\rho_c/2 \leq \rho < \rho_c$, $\rho c \leq \rho < 3/2\rho_c$ and $3/2\rho_c \leq \rho < 2\rho_c$, respectively, as a regular partition of the fundamental diagram, describing the traffic flow and density relationship, as depicted in Fig. 3.

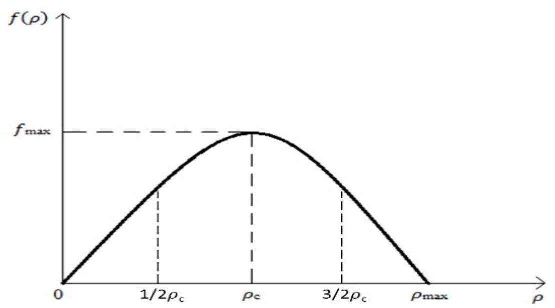

FIGURE 3. Simple classification of the fundamental diagram in order to define "FREE", "FLUID", "HEAVY" or "VERY HEAVY" traffic states in the context of decision support results.

Actually, a more accurate classification could be carried out in such a context, but the presented one is easily used as an immediate comparative tool within decision support field. In particular, the percentages of road segments admitting the above traffic states, with respect to the total number of road segments in R, can be considered in order to determine KPIs via temporal features of a given scenario, making it easier to understand comparative results.

Moreover, in [33] some integrated performance indicators in urban road infrastructure are also developed to evaluate both network functionality and impact of transport system interventions. To determine a value of traffic congestion in the network, the most informative metric seems to be the so-called average degree of saturation. More precisely, the average degree of saturation of a road graph network R at a given time slot t, denoted by $S_R(t)$, is defined as $S_R(t) = \frac{\sum_{i=1}^{S} \frac{\rho_R(i,t)l(i)}{\rho_c(i)}}{\sum_{i=1}^{S} l(i)}$, where $l(i)$is the length of the i-the road segment in R. Please note that, in the considered road graphs, $l(i)$ is almost constant equal to 20m. Thus $S_R(t) \cong \sum_{i=1}^{S} \frac{\rho_R(i,t)}{\rho_c(i)}$. Please note that $\rho_c(i)$ is not constant since it depends on the structure of the road in terms of lanes. Formally, the traffic flow KPI (denoted by $\boldsymbol{KPI}_F$) according to a certain scenario $SC_{i,\widehat{T}} = \{i, D_i, \boldsymbol{A}_i, \widehat{\boldsymbol{T}}, \boldsymbol{C}_i, R^*\}$, where $S_{R^*}(t) \cong \sum_{i=1}^{S*} \frac{\rho_{R*}(i,t)}{\rho_c(i)}$, can be defined as

$$\boldsymbol{KPI}_F(SC_{i,\widehat{T}}) = \{\boldsymbol{FR}_{R^*}, \boldsymbol{FL}_{R^*}, \boldsymbol{HE}_{R^*}, \boldsymbol{VH}_{R^*}, \boldsymbol{S}_{R^*}$$

where

- $\boldsymbol{FR}_{R^*} = \{\frac{|FR_{R^*}(t)|}{S^*}100 : t \in \widehat{\boldsymbol{T}}$ is the FREE traffic state percentage for each time t in $\widehat{\boldsymbol{T}}$ and $|FR_{R^*}(t)| = |\left\{i \in [1, S^*] : \rho_{R^*}(i,t) < \frac{\rho_c(i)}{2}\right\}|$ is the number of road segments in R^* admitting FREE traffic state at time t in $\widehat{\boldsymbol{T}}$, where S^* is the total number of road segments in R^*.
- $\boldsymbol{FL}_{R^*} = \{\frac{|FL_{R^*}(t)|}{S^*}100 : t \in \widehat{\boldsymbol{T}}$ is the FLUID traffic state percentage for each time t in $\widehat{\boldsymbol{T}}$ and $|FL_{R^*}(t)| = |\left\{i \in [1, S^*] : \frac{\rho_c(i)}{2} \leq \rho_{R^*}(i,t) < \rho_c(i)\right\}|$ is the number of road segments in R^* admitting FLUID traffic state at time t in $\widehat{\boldsymbol{T}}$.
- $\boldsymbol{HE}_{R^*} = \{\frac{|HE_{R^*}(t)|}{S^*}100 : t \in \widehat{\boldsymbol{T}}$ is the HEAVY traffic state percentage for each time t in $\widehat{\boldsymbol{T}}$ and $|HE_{R^*}(t)| = |\left\{i \in [1, S^*] : \rho_c(i) \leq \rho_{R^*}(i,t) < \frac{3\rho_c(i)}{2}\right\}|$ is the number of road segments in R^* admitting HEAVY traffic state at time t in $\widehat{\boldsymbol{T}}$.
- $\boldsymbol{VE}_{R^*} = \{\frac{|VH_{R^*}(t)|}{S^*}100 : t \in \widehat{\boldsymbol{T}}$ is the VERY HEAVY traffic state percentage for each time t in $\widehat{\boldsymbol{T}}$ and $|VH_{R^*}(t)| = |\left\{i \in [1, S^*] : \frac{3\rho_c(i)}{2} \leq \rho_{R^*}(i,t) < 2\rho_c(i)\right\}|$ is the number of road segments in R^* admitting VERY HEAVY traffic state at time t in $\widehat{\boldsymbol{T}}$.
- $\boldsymbol{S}_{R^*} = \{S_{R^*}(t) : t \in \widehat{\boldsymbol{T}}$ is the collection of the average degree saturation values for each t in $\widehat{\boldsymbol{T}}$.

Finally, the scenario KPI (denoted by$\boldsymbol{KPI}$) according to a certain scenario $SC_{i,\widehat{T}} = \{i, D_i, \boldsymbol{A}_i, \widehat{\boldsymbol{T}}, \boldsymbol{C}_i, R^*\}$ can be defined as the union of the related traffic flow KPI and the related connectivity $\boldsymbol{KPI}_C$ (see Section 4.1), so that

$$\boldsymbol{KPI}(SC_{i,\widehat{T}}) = \boldsymbol{KPI}_F(SC_{i,\widehat{T}}) \cup \boldsymbol{KPI}_C(SC_{i,\widehat{T}}).$$

KPIs produce different values for each time slot in the future simulation/scenario analysis. Thus, comparison among the effects of different choices and scenarios has to be performed on the basis of MIN, MAX, average, median or the values obtained in each time slot. When computing: $\boldsymbol{KPI}(SC_{i,\widehat{T}})$, $\boldsymbol{KPI}(SC\_UC_{i,\widehat{T}})$, for the averages $\overline{KPI}(SC_{i,\widehat{T}})$, $\overline{KPI}(SC\_UC_{i,\widehat{T}})$, and the derived differences of KPIs in different scenarios we may have: $\Delta\overline{KPI}$.

V. VALIDATION IN A SIMPLE CASE

In order to validate models and solution, a real case in Florence city has been considered. It has consisted in performing the future scenario analysis in terms of traffic flow in the case of changes in viability, due to the creation of large restructuring area for a new tram line in Florence. The blocked area of the main scenario is reported in Fig. 4 and it describes the shape of road-works begun in December 2019 around ''Piazza della Libertà'' square. Such a modification in the road network removed a number of road segments within the square to allow the construction of tramway rails line #3 in Florence.

The selected area of the scenario presents a high level of traffic flow, and it is one of the key junctions in Florence city. This fact is also shown by means of the location of the road graph node having the highest betweenness as depicted in Fig. 4 (the case of the blocking area has not yet been considered) and such a node is very closed to the selected area.

The presence of blocking area in the road network slightly modifies the related suitable directed graph and, for instance, the highest value of betweenness changes node location, thus determining the junctions where traffic congestion often occurs. In particular, in the case of a blocking area scenario, the junction assuming the highest value is the green node depicted in Fig. 4. By setting $SC_{i,\widehat{T}}$ as the

FIGURE 4. **Scenario represents the real blocking area caused by the roadworks begun in December 2019 around "Piazza della Libertà" square due to future rail location in Florence. Red dot represents the location of the road graph network, having highest betweenness before the starting date of such works in the city, green dot stands for the position when graph road changes have been applied.**

described scenario named "ScenarioANov2019", we have $\boldsymbol{KPI}_C(SC_{i,\widehat{\boldsymbol{T}}}) = \{(469640.5, n_{253179120}), (1, n_{3262140609}), (88, n_{298511990})\}$ and $\boldsymbol{KPI}_C(SC\_UC_{i,\widehat{\boldsymbol{T}}}) = \{(464605.71, n_{246843224}), (1, n_{3262140609}), (88, n_{298511990})\}$ where the nodes' indexes correspond to the OSM (Open Street Map) indexing. In this case, the highest value of betweenness in $SC_{i,\widehat{\boldsymbol{T}}}$ admits an increment of about 1% with respect to the one in $SC\_UC_{i,\widehat{\boldsymbol{T}}}$ and a North-West shift appears in the corresponding node position. Note that, the highest values of eccentricity and centrality are assumed by the same nodes in both cases of the road network, since their modification only happens when significant changes in the related suitable directed graph are operated, and this is not the case since a small blocking area is under review (see following example for a case with more relevance changes). Since December 2019, the presence of roadworks in the area has contributed to some inconveniences in vehicular traffic, thus causing an increase in vehicular density during daylight hours. Provided that the number of road segments is reduced in the area, then drivers cannot but have forced choices for their travel directions by converging on the same option. So that, a congested situation has been observed in relevant and primary roads surrounding the square. In order to validate the described approach and simulation tools, we have carried out the TFR simulation, while imposing the needed modifications in the road graph network. The aim has been two folds: (i) to study the effect of changes (see Section 5.1), and (ii) to predict traffic behavior some months in advance (see Section 5.2), also verifying that predicted values have been precise enough with respect to the produced effects on traffic flow due to works on the roads.

A. ASSESSING THE EFFECTS OF CHANGES

By setting $\widehat{\boldsymbol{T}} = \{2019\text{-}11\text{-}20\text{T}07{:}00,\ 2019\text{-}11\text{-}20\text{T}20{:}00\}$, the results of the simulation of $SC_{i,\widehat{\boldsymbol{T}}}$ (representing the described scenario named "ScenarioANov2019") are related to a working day period when the traffic is usually heavy with respect to the weekend days. The simulation has been based

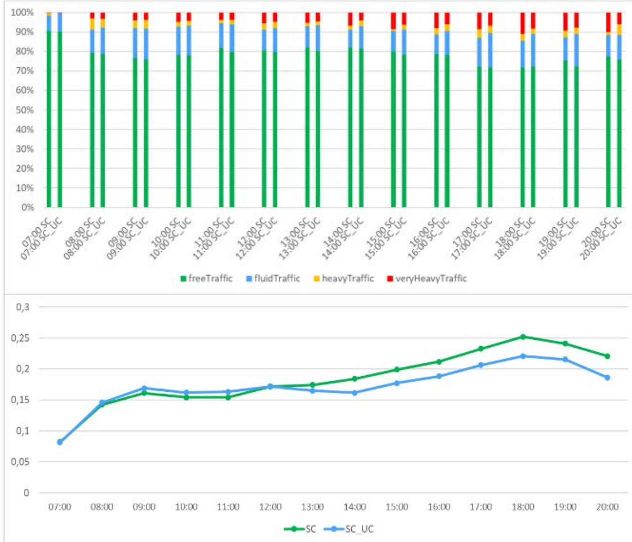

FIGURE 5. **Graphical comparison between $\boldsymbol{KPI}_F(SC_{i,\widehat{T}})$ and $\boldsymbol{KPI}_F(SC\_UC_{i,\widehat{T}})$. In the upper part, traffic states are compared for each time slot hour by hour, in term of distribution of free, fluid, heavy and very heavy traffic segments. In the lower part, the related average saturation degrees over time values are depicted. The green line is related to $SC_{i,\widehat{T}}$ and it represents a more congested situation with respect to the blue line related to $SC\_UC_{i,\widehat{T}}$.**

on the above-described traffic predictions on sensors (placed at Florence city borders that are marginally influenced by what changes in the city core where the scenario is set). Such simulation has been computed during the six weeks spanning from 2019-10-14 to 2019-11-24. When computing the analysis regarding traffic flow related to $SC_{i,\widehat{\boldsymbol{T}}}$ and $SC\_UC_{i,\widehat{\boldsymbol{T}}}$, we can observe different vehicular traffic situations. The analysis including TFR by simulation of $SC_{i,\widehat{\boldsymbol{T}}}$ did produce a more congested situation with respect to $SC\_UC_{i,\widehat{\boldsymbol{T}}}$ and its related computation of both $\boldsymbol{KPI}_F(SC_{i,\widehat{\boldsymbol{T}}})$ and $\boldsymbol{KPI}_F(SC\_UC_{i,\widehat{\boldsymbol{T}}})$ are graphically compared in Fig. 5, where the suitable road graph network is restricted to the area under review, that is, a circle area having its center at the center of "Piazza della Libertà" and radius 1 km, so that, it is a small part of the city (about 10% of the whole city).

The bar-series provides a comparative distribution, hour by hour, of free, fluid, heavy and very heavy traffic roads in terms of vehicular density during rush hours of the day. As to the second part of Fig. 5, it is evident that the new configuration will produce a certain increment of traffic saturation in the area during the last hours of the day (from 13:00 to 20:00), which are the most critical. The mean increment of the saturation is equal to 5.1%, while the maximum saturation increment has been equal to 12.4% at time 18:00 (for the city part under analysis).

B. VALIDATING THE EFFECT OF CHANGES WITH RESPECT TO ACTUALLY MEASURED EFFECTS OF CHANGES

As a validation approach, the computation of the analysis for $SC_{i,\widehat{\boldsymbol{T}}}$, modeling the effect of the roadworks for tramlines, has been compared with respect to actual measured traffic flow,

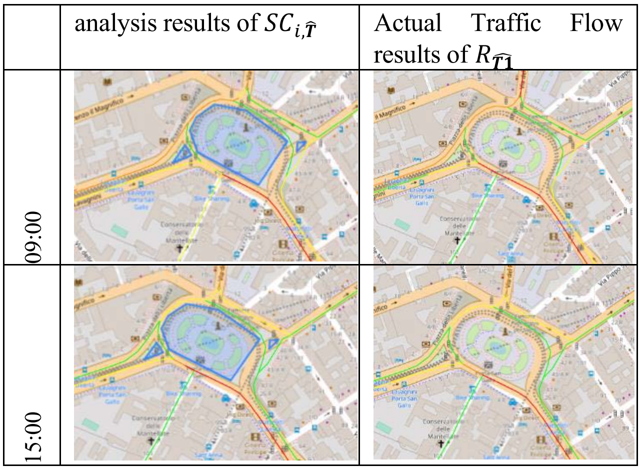

FIGURE 6. Graphical comparison between the simulation $SC_{i,\widehat{T}}$ with respect to $R_{\widehat{T1}}$ where two selected frames are considered, at time 09:00 and 15:00, respectively.

FIGURE 7. Comparison between $KPI_F(SC_{i,\widehat{T}})$ and $KPI_F(R_{\widehat{T1}})$. In the upper part, traffic state is compared for each time slot of the day. In lower part, its related average saturation is reported with its degree values. The green line is related to $SC_{i,\widehat{T}}$ and it depicts a similar behavior with respect to the blue line related to $R_{\widehat{T1}}$.

when related works have been actually performed. By setting $\widehat{T1}$ ={2020-02-05T07:00, 2020-02-05T20:00}, $R_{\widehat{T1}}$ denotes the real traffic situation modelled when roadworks took actually place. Both simulations related to $SC_{i,\widehat{T}}$ and $R_{\widehat{T1}}$ admit a similar vehicular traffic behavior. Fig. 6 shows a graphical comparison of traffic for $SC_{i,\widehat{T}}$ and $R_{\widehat{T1}}$ respectively, where the interested area is under review.

Moreover, the related computation of $\boldsymbol{KPI}_F(SC_{i,\widehat{T}})$ and $\boldsymbol{KPI}_F(R_{\widehat{T1}})$ can be graphically compared in Fig.7, where the suitable road graph network is restricted to the area under review, that is, a circle area having its center at the center of ''Piazza della Libertà'' and radius 1 km.

In order to estimate any possible error between the results obtained with the analysis on $SC_{i,\widehat{T}}$ and those coming from actual TFR on $R_{\widehat{T1}}$, traffic densities in the corresponding road segments have been compared. To this end, mean absolute error (MAE) is considered. Since $R_{\widehat{T1}}$ and $SC_{i,\widehat{T}}$ admit the same road graph network, named R^*, then $MAE(t) = \frac{\sum_{i=1}^{S*} |\rho_{R*}(i,t) - \rho'_{R*}(i,t)|}{S*}$, where $\rho_{R*}(i,t)$ and $\rho'_{R*}(i,t)$ are the traffic densities in the i-th road segment of R^*(with $i = 1, \ldots, S^*$) according to $R_{\widehat{T1}}$ and $SC_{i,\widehat{T}}$ respectively, at the corresponding time slot t. To estimate any error in the area of interest, an analysis has been conducted in the area of ''Piazza della Libertà'' around 1 km, which is equal to 1/10 of the whole city, for a total of about 3000 road segments. Then, $MAE(t)$ is estimated in such a circular area, together with its related percentage error (with respect to the average traffic density) $MAE_p(t) = \frac{MAE(t)}{d(t)}100$, where $d(t)$ is the average traffic density in the considered circular area at time t. For t running from 07:00 to 20:00 we have MAE = (0.0591, 0.0966, 0.0833, 0.0791, 0.0768, 0.0531, 0.0617, 0.0694, 0.0617, 0.0852, 0.1080, 0.1111, 0.1225, 0.1055) in terms of vehicle/20m, and the related error percentage is MAE_p = (22.16, 20.89, 16.83, 17.67, 18.30, 12.09, 13.93, 15.09, 11.97, 16.06, 18.41, 17.29, 19.43, 18.67). Values of $MAE_p(t)$ seem to be in accordance with the comparison between $\boldsymbol{KPI}_F(SC_{i,\widehat{T}})$ and $\boldsymbol{KPI}_F(R_{\widehat{T1}})$ as shown in Fig. 7.

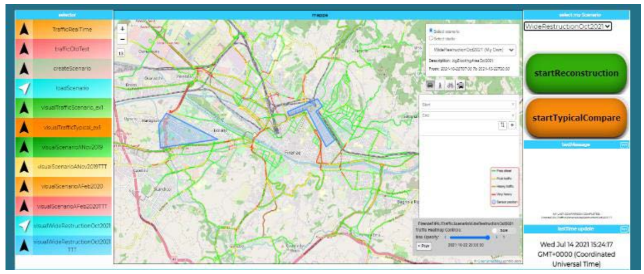

FIGURE 8. An example of the tool with complex scenario presenting multiply-connected blocking areas in the city.

VI. MULTIPLY CONNECTED SCENARIOS

This proposed model and tools allow to perform an analysis based on large scenarios of changes in the original road network, by defining large blocking areas by means of multiply connected blocking constraints. In this manner, the road network structure can be strongly modified, and complex scenarios can be analyzed. An example of scenario having large multiply connected areas, named ''WideRestructionOct2021'', is shown in Fig. 8, where two polygons covering a considerable part of the city road network graph are defined according to the description in Section 2.3. This complex scenario has been defined with the aim of stressing the solution's computational complexity and assessing its performance.

By setting $SC_{j,\widehat{T'}}$ as the described scenario named ''WideRestructionOct2021'' and considering $\widehat{T'}$ ={2021-10-22T07:00, 2021-10-22T20:00}, then the scenario represents a situation of the network graph occurring in a determined period in the future, from 2021-10-22T07:00 to 2021-10-22T20:00, where two multiply-connected areas (depicted in blue in Fig.8) are forbidden to vehicular traffic. In particular, this scenario admits 32299 units of road network segmentation, having length of 20m, and 1463 junctions, thus reducing the original road network of 1529 units and 77 junctions. Which means a 4.7% reduction on traffic road segments and a 5% reduction in terms of junctions.

In this given analysis, the reconstruction model allows to calculate any traffic state at each hour of the selected period, in the case from 2021-10-22T07:00 to 2021-10-22T20:00. In particular, any traffic state at a given hour influences the subsequent traffic state of the scenario's following hours, in terms of traffic flow propagation. By running the simulation on this model, the user can understand how the system would evolve over time as a direct consequence of conditions. Moreover, the resulting calculation of the reconstruction model can be graphically visualized by means of the corresponding 14 traffic flow maps (one for each hour, from 07:00 to 20:00) that can be sequentially selected via a control panel and widgets, with its related animation that can be presented as well. When TRF is computed with scenarios featuring, then it is possible to compare any produced results in terms of KPI reference (see Section 4), in order to evaluate the impact in terms of changes of traffic patterns with respect to previous or different conditions.

A. ASSESSMENT OF TRAFFIC FLOW

$\boldsymbol{KPI}(SC_{j,\widehat{T'}})$ and $\boldsymbol{KPI}(SC\_UC_{j,\widehat{T'}})$ represent the collection of both connectivity and traffic flow KPIs related to $SC_{j,\widehat{T'}}$ and $SC_{UC_{j,\widehat{T'}}}$ and they are considered and compared hereafter. In the case, we have $\boldsymbol{KPI}_C(SC_{j,\widehat{T'}}) = \{(323488.76, n_{2471190}), (1, n_{4924703865}), (94, n_{298511990})\}$ and $\boldsymbol{KPI}_C(SC\_UC_{j,\widehat{T'}}) = \{(464605.71, n_{246843224}), (1, n_{3262140609}), (88, n_{298511990})\}$ where the nodes' indexes correspond to the OSM indexing. In particular, the presence of high dimension blocking areas in the road network strongly modifies the related suitable directed graph, while junctions assuming the highest values of betweenness and centrality are the nodes as depicted in Fig. 9. The road graph network modification according to the scenario "WideRestructionOct2021" causes a new orientation of the traffic viability by means of a redefined graph balancing with respect to the unchanged graph.

Moreover, a related computation of KPI traffic flow can be also performed. In particular, $\boldsymbol{KPI}_F(SC_{j,\widehat{T'}})$ and $\boldsymbol{KPI}_F(SC\_UC_{j,\widehat{T'}})$ can be graphically compared in Fig. 10, where each traffic state presents a similar behavior. Please note that areas having typical congestion situations are included in the blocking components and the nodes assuming the highest values of betweenness and centrality in $\boldsymbol{KPI}_C(SC\_UC_{j,\widehat{T'}})$ are included in the blocking components (see Fig. 9). Moreover, note that $S_R(t)$ and $S_{R*}(t)$ are computed on different road graphs, while the number of vehicles involved should be the same.

When large city areas are blocked, they may include traffic flow sensors which may strongly influence the simulation of TFR. If sensors are not included in the blocked area, or if they are in the center of the city, a diffusive approach of the computational model can compensate any lacks. On the contrary, when sensors included into the blocked areas are at city borders, then their exclusion may reduce the number of simulated vehicles entering/exiting into/from the city. Thus, in order to preserve some balance on boundary conditions of this traffic flow mathematical model, flows measured by specific virtual sensors are added, or the total number of vehicles involved in the simulation has to compensate the missing sensors. This compensation is performed by scaling the density by hour in the computation of saturation by a corrective factor, according to the actual volume of predicted vehicles. The resulting saturation degree by hour is reported in Fig. 10. The average change in saturation of the changed solution with respect to original unchanged is equal to 2.9 % computed for the whole city.

FIGURE 9. Connectivity KPI comparison. Nodes assuming highest betweenness and centrality are depicted in orange and green, respectively. Filled dots are related to $KPI_C(SC\_UC_{j,\widehat{T'}})$, whileempty ones to $KPI_C(SC_{j,\widehat{T'}})$.

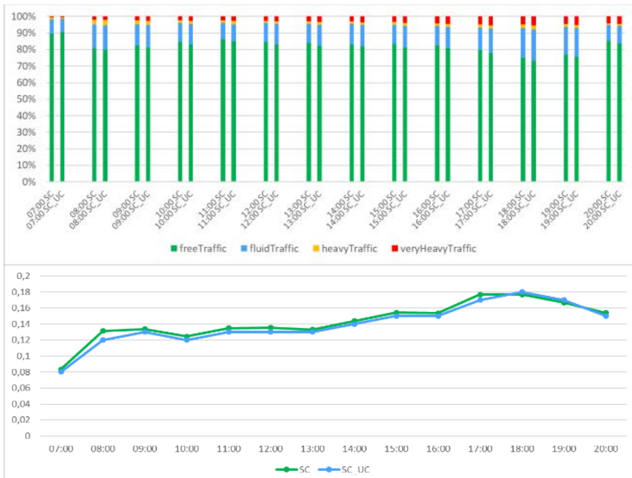

FIGURE 10. Graphical comparison between $KPI_F(SC_{j,\widehat{T'}})$ and $KPI_F(SC\_UC_{j,\widehat{T}})$. In the upper part of the image, traffic states are compared for each time slot. In the lower part, the saturation degree values are depicted for the whole city due to the breadth of the involved area. Green line is related to $SC_{j,\widehat{T}}$ and it shows a slight increment with respect to the blue line related to $SC\_UC_{j,\widehat{T'}}$.

VII. PERFORMANCE ASSESSMENT

As to performance assessment, major costs are due to the TFR computing, also when they are exploited as simulation. As above described, complexity is due not only to TFR, but also to the road graph computation and to the TDM computation. On the other hand, this current model overcomes past limitation of the solutions proposed in literature, which are based on agents' simulation models (as above described). Most of them have relevant limitations both on the road network graph dimensions and number of changes they can afford. On the other hand, in most real cases of future scenario analysis, the considered graph may be very large and multiply connected as highlighted above, thus leading to change large number of road segments from the original graph. When large network graph simulations have to be addressed, high computational costs and considerable memory usage are required, as presented in [26]. On the other hand, the analysis framework approach presented in this paper is based on a fluid dynamics model of vehicular traffic via LWR PDE model and equation, which has kept the same computational cost presented in [6] also when large blocking area scenarios are defined. In [6], the TFR precision has been proven with respect to the state of the art and with respect to topological aspects, together with the fact that the error can be higher in cross points. When it comes to estimating the computational cost of our model, the scenario "WideRestructionOct2021" has been considered. Experimental tests are conducted on the Snap4city platform, leaning on DISIT Lab Cluster of 26 hosts based on multi CPU and multi core XEON on cloud with 10Gbps multiple connections (main cluster with 330GHz), 4 TB Ram, 15.000 GPU, 250 TFlops Tensor, 300 TB of online storage in RAID, a part in SSD and a part in 15Krps, 10Krps. Traffic reconstruction is computed by using a machine having an Intel Xeon E5-2630 v4 CPU with 10 physical cores at 2.2 GHz (20 hyper-thread cores), 25MB cache, 128 GB Ram and the execution time has been obtained as a mean value of results taken on 10 distinct executions of the scenario. It admits an average time execution for the complete performance of the selected scenario equal to 16 minutes and 52 seconds and each reconstructed scenario of one hour takes about 62.43 seconds for its computation. This largely overcomes the state-of-the-art solutions in quality, being based on [6], and on computational performance and capabilities as described in this paper.

VIII. CONCLUSION

In this paper, we develop a solution for assessing traffic evolution when unexpected and planned events occur. The proposed solution has been validated with a major focus on traffic flow field since it has greater impact in every city service. The aim of this current work is to understand in short time how traffic would react with respect to the occurred changes, so as to mitigate any possible outcome of changed scenarios and their large-scale changes in the whole city. The present case of study is meant to address more complex situations if compared with cases where the analysis is done simply to assess the impact of changing road direction or closing a single road; such simpler occurrences are managed and analyzed by the already existing tools in literature. In our context, a given scenario is primarily determined by means of the related road network modifications in large scale environments, multiple unconnected areas, for a given period of time, for example few months in advance. To cope with such large-scale complexity, some topological and structural changes in the suitable graph are considered, as well as the redistribution of traffic on modified crossroads leading to different traffic propagation effects with respect to current traffic behavior. The solution provides a data driven instrument for decision makers, in order to select which are the most viable changes providing lower impact on traffic, thus allowing to reshape traffic viability in short time or perform planning in advance. Due to traffic cascade effect in larger scale contexts, specific simulations regarding Traffic Flow Reconstruction (TFR) in the whole urban network are needed in order to evaluate the propagation of traffic congestion in the city area, also within zones apparently unconnected with the given Scenario. To provide responses in real-time for complex scenarios we have (a) computed TFR by dynamically reshaping the road graph network according to scenarios with multiply connected critical areas, (b) computed multiple TFR in consecutive time slots taking into account the evolution of road graph, junction redistribution and traffic flow data. The presented solution takes into account static, historical, real-time/dynamic, and forecasting information, in a functional model, where TFR processes (multiple simulations, predictions, data transformations) are integrated with the business logic of visualization and user interaction made available to decision makers. The solution has been validated by different road graph solutions and each solution on specific KPI and Criteria which help decision makers to select the road graph changes creating less problems as to traffic flow in the whole city over all the addressed time slots. In particular, KPIs are meant to assess globally any city traffic conditions; therefore, the impact of changes has to be calculated on the basis of the computed dense TFR, taking into account various Road Graphs for each scenario, and all time slots.

Each modified road graph determines some differences in terms of connectivity features, according to the related suitable network. The topological properties of betweenness, centrality and eccentricity metrics are computed in order to evaluate in a quantitative manner any structural graph modification for each scenario. Moreover, each scenario also determines dynamically changes on traffic evolution according to TFR, on several time slots, so that additional KPIs in terms of traffic density, traffic flow and saturation degrees are also considered to compare global traffic conditions and viability in all time slots of the scenario. Both model and solution have been validated against real cases of restructuring Florence city for major maintenance activities.

The architecture of the presented analysis tool has been based on Snap4City framework, where the business logic is defined by using Node-RED and Snap4City MicroService

Libraries which allow to interact with Visual Analytic tool for changing Scenario and selecting both decision support KPIs and criteria to mitigate traffic aspects. This current solution has been developed in the framework of Sii-Mobility national sustainable mobility and transport project.

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