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Forecasting of Traffic Jams at Disturbed Sections of High-ways

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Abstract

Disturbances of driving conditions on high-ways usually lead to evolution of traffic jams. Disturbances are often caused by traffic accidents, installed bottlenecks, adverse weather, etc, and result in a decreased road capacit. By using an estimate of a desired speed in the disturbed section the traffic information providers can forecast quantitatively the evolution of jams and inform the population about them in advance. The article presents a new mathematical method for this purpose. The corresponding intelligent unit first forecasts the traffic flow at a disturbed road section based upon records of traffic flow in the past. Forecast data are next mapped to characteristics of evolving jam by using the desired speed value and a new fundamental diagram of traffic flow. Performance of the method is demonstrated by forecasting the evolution of jam at the point of maximal traffic activity on a high-way in Slovenia.

Keywords: Forecasting; Flow dynamics; Traffic jam

Introduction

Modeling and forecasting of traffic activity pertains to basic tasks of traffic information provision [1-5]. For this purpose we have recently utilized a non-parametric statistical approach [6,7]. The model was created by using records of traffic flow rate in the past and is now applicable for prediction of traffic activity on the network of high-ways in Slovenia. The corresponding predictor was incorporated into an intelligent unit for forecasting of traffic flow rate and is used in the traffic information center at Ljubljana [8]. The goal of this article is to show how the applicability of this unit can be stretched to forecasting of traffic jams caused by various disturbances on high-ways [9]. For this purpose forecast data about traffic flow rate have to be transformed into jam characteristics. Here we consider forecasting of the number of jammed cars in front of disturbance as is for example a road section of decreased visibility due to fog, increased slipperiness, installed bottleneck, an accident, etc [9]. These disturbances can be most simply characterized by a decreased desired speed that is further used as a parameter in a corresponding analytical model describing the dynamics of traffic flow. To develop such a model we formulate a new fundamental diagram of traffic flow and use it in the formulation of partial differential equations describing the dynamics of traffic flow at a disturbed section [2,5,10,11]. These equations provide for prediction of jam evolution if we know the input flow [9]. For this purpose we describe in the next section the non-parametric statistical method of traffic flow forecasting, that is in the subsequent sections joint with analytical prediction of traffic jam evolution [6-8,12]. The applicability of the proposed method is then demonstrated by forecasting the evolution of traffic jam caused by a reduced desired speed at the point of maximal traffic activity on a high-way close to Ljubljana.

Our treatment contains two mathematical models: one for prediction of traffic flow at a critical section [6-8] and the other for a transformation of predicted flow into characteristics of jam. Professional literature contains many articles describing various approaches to modeling and resulting versions of both models [1-5,10,11]. They can be generally divided into micro- or macroscopic ones and deterministic (analytical) or statistical ones. By reviewing and testing their applicability we have found that in our case the most appropriate is the macroscopic treatment with the statistical description of the input flow to the disturbed section and the deterministic analytical description of the jam evolution.

Statistical Forecasting of Traffic Flow

The road traffic is a consequence of population activity that is generally of stochastic character [2-5,10]. Its proper description in a real situation is thus inevitably related with application of statistical methods [6,12]. However, the population activity is to certain extent synchronized by social agreements and environmental conditions that could be most simply described by calendar and hour. The synchronization renders possible simultaneous statistical description as well as quite accurate prediction of the mean properties of traffic activity on a complete roads network of a country [6-8]. Since our goal is to develop a general computational method that could be well applied for forecasting of local properties of traffic activity at various roads without any presumptions we here avoid analytical modeling of activity and follow just non-parametric statistical approach described in the following text [12].

The traffic activity at a certain road section is characterized by the flow rate $Q(t)$ in dependence of time t [1-5,10,11]. The corresponding time series $\{Q(t), Q(t\text{-}1),..\}$ is usually recorded by a counter, while weather observation and forecasting services provide time series of various environmental and other driving variables $\{V(t), V(t\text{-}1),..\}$. These variables also represent the hour and type of day [6-8]. The joint time series represents the traffic state vector $\mathbf{S}=\{Q(t),Q(t\text{-}1),..;V(t),V(t\text{-}1),..\}$. Its record forms the data-base pertaining to a particular observation point. Since there are generally many observation points on a road network, the complete traffic activity represents a dynamic field [2-6].

Traffic participants and information providers often want to know what would be the traffic load in the future. The answer could be obtained by the non-parametric method of chaotic time series modeling and forecasting [12]. For this purpose we treat the traffic flow as a non-autonomous chaotic process and describe its generation by

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the mapping relation [6-8]:

$$Q(t) = F\left(Q(t-1),..,Q(t-\tau);V(t-1),..,V(t-\tau)\right) \quad (1)$$

In order to extract the function F(…) from given records we consider the state vector $S=(Q(t),..,Q(t-\tau);V(t),..,V(t-\tau))$ as a stochastic variable that can be characterized statistically by N samples $\{S_n;\ n=1,..,N\}$ if the joint probability density function is expressed by the Parzen's kernel estimator [12]. Equation (1) indicates that the first component of the state vector: $P=Q(t)$ should be predicted from the remaining ones: $R=(Q(t\text{-}1),..,Q(t\text{-}\tau);\ V(t),..,V(t\text{-}\tau))$. Since we want to avoid any presumptions about the relationship between P and R we may not describe it parametrically by some regression function but have to specify it non-parametrically. As shown elsewhere, [12] an optimal non-parametric statistical predictor is the conditional average $P_{pr}(R)=E[P|R]$. It can be derived from the Parzen's kernel estimator and expressed in terms of N samples $\{S_{n=}(P_n, R_n)$, n=1,…, N$\}$ as [12]:

$$P_{pr}(R) = \frac{\sum_{n=1}^{N} P_n\, w(R-R_n,\sigma)}{\sum_{n=1}^{N} w(R-R_n,\sigma)} \quad (2)$$

The kernel $w(\dots)$ corresponds to some approximation of the delta function, as for example a Gaussian one, in which σ corresponds to a characteristic distance between sample points R_n. Predictor in Eq. (2) describes a general non-parametric regression that corresponds to a normalized radial-basis-function neural network [12]. Its structure is objectively specified just by the set of samples, while σ represents the inaccuracy of observation [12]. In order to use the proposed non-parametric estimator in modeling of traffic flow rate, we consider again Eq. (1) and interpret variables on its right side as the condition R and the variable on the left side as the value of the flow rate $P=Q(t)$ which we want to predict by Eq. (2). However, for this purpose we have to provide the condition R at a time t of interest.

Before the application of Eq. (2) we must specify the dimension of the state vector S by the value of parameter τ. Since it is generally not known in advance how many past values have to be utilized in modeling, we can proceed to a proper value of τ by observing the performance of the forecasting at increasing τ. For this purpose we describe the performance quantitatively by the correlation coefficient r between predicted and observed time series of the traffic flow rate [6-8].

In our case we utilize records of traffic flow rate collected in the past over one hour time intervals by automatic counters on roads network in Slovenia [6-8]. Although shorter time intervals could be of advantage, we use one hour intervals, since the corresponding data are commercially available on CD-s and provide for rather broad application of the method described in this article. As a representative example we here select a point of maximal traffic activity on a high-way close to Ljubljana. A record contains data about physical time of measurements and flow rate of various categories of vehicles. The time was transformed to a periodic hour-variable H that is uniformly increasing from 1 to 24 over each day. More demanding is a proper transformation of time to a proper day-variable. Phenomena depending on population activity essentially depend on the character of the day which we consider here as the driving variable of the traffic [6-8]. Based upon minimization of information cost function, expressed by the sum of information content and redundancy assigned to flow records of various days, we have found the following optimal code D: 1-Monday, 2-day after holiday, 3-normal working day, 5-Friday, 6-day before holiday, 7-Saturday, 9-Sunday, 10-holiday. Numerical analysis has shown that a more detailed specification of code values practically does not contribute to the quality of modeling. Among categories of vehicles we at present consider just the category of personal cars. Consideration of other categories does not represent any obstacle, but the time of calculations is increased that is not convenient for broad application of the method on mobile telephones. One year long record of the considered flow rate is shown in Figure 1. The record reveals rather regular seasonal variation of flow rate over the year. In the modeling the influence of seasonal variation can be accounted for by forming the model based upon shorter intervals. In our treatment we use a record spanning one month. Beside seasonal variation, the record exhibits rather regular variation of traffic flow in normal working days and rather irregular variations in holidays. To point out this property we next consider two characteristic examples corresponding to a normal week in April and the week that includes holidays at May 1st. For both cases the graphs of predicted Q_p (solid) and original Q_o (dotted) flow rate are shown together with variables $D(t)$ and $H(t)$ in Figure 2. When forecasting the flow the condition was comprised from the day-code D and the hour variable H alone. The agreement between predicted Q_p and original Q_o records of traffic flow rate shown in Figure 2 is quantitatively demonstrated by the correlation plots in Figure 3. To each hour of week there corresponds a point (Q_o, Q_p) in the graph. From the distribution of points the correlation coefficient r and the linear regression line (solid) were determined.

The dotted line represents an ideal agreement between original and predicted data. The value of correlation coefficient r and the agreement between regression and dotted line indicates the quality of forecasting. The values r=0.98 and r=0.88 correspond to the normal week and the week with included holidays, respectively. These values correspond to rather extreme deviations from the mean value of correlation coefficient over the year that for the selected point of observation amounts $\langle r\rangle$=0.94. This value indicates that the non-parametric statistical modeling and forecasting is on average quite successful.

Since the traffic develops on a network of roads it should be generally treated as a dynamic field $Q(t,r)$ [2,6]. The same modeling as described above can be generalized to simultaneous prediction of traffic on the complete network of observation points; just the numerical procedure requires more time. In this case the mean value of correlation coefficient over the year and all observation points is $\langle r\rangle$=0.965. Generally, the condition variables could include also the traffic flow at nearby points of observation and weather variables. Examination of such cases has shown that in our case the performance of modeling is not essentially changed [8].

Since the information about the traffic flow rate is of interest for participants in the traffic as well as for various services and agencies of the road authority, we have developed a graphic user interface (GUI) by which the predicted traffic flow field as well as a jam at a disturbed critical region of road can be demonstrated [8]. Its window is shown in Figure 4 and includes: three graphs and several buttons for controlling the GUI operation and selection of parameters for prediction. In the upper graph of the GUI the evolution of the predicted traffic flow field distribution is demonstrated by a movie. At a position of each counter on the road network the traffic activity is indicated by the radius of a color coded circle. The selected observation point is indicated by a horizontal and a vertical line. For the selected point of observation the dependence of the forecast traffic flow rate over the selected day is shown by the dotted line in the lower right graph. Its time series describes the flow of vehicles to the selected critical region where they are jammed. The flow that passes this region is shown by the solid line. The parameters of the critical region are set by the lower buttons.

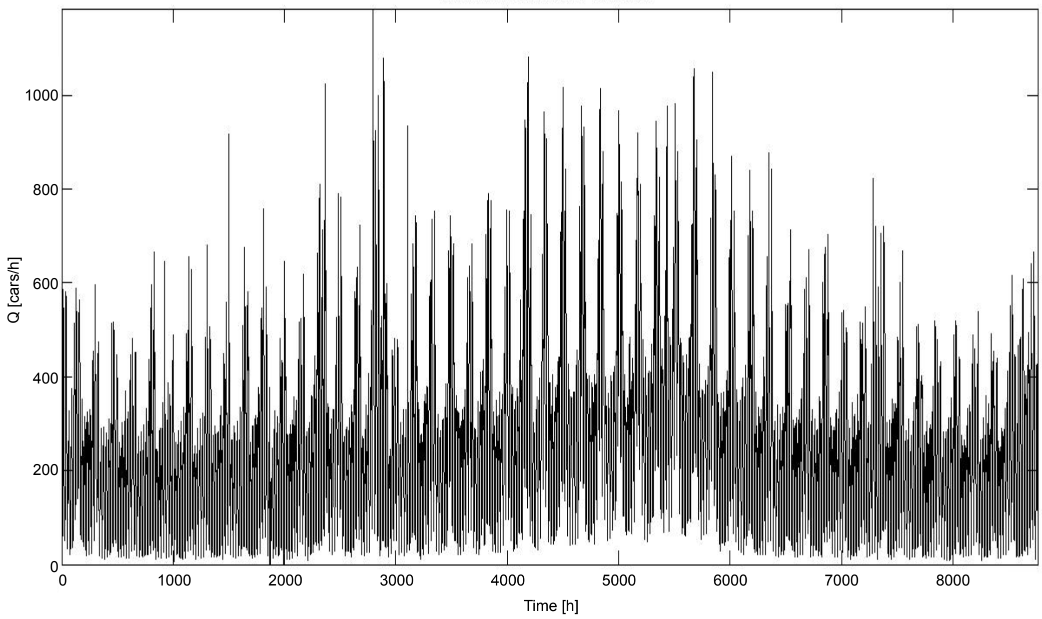

Figure 1: Record of the traffic flow rate Q(t).

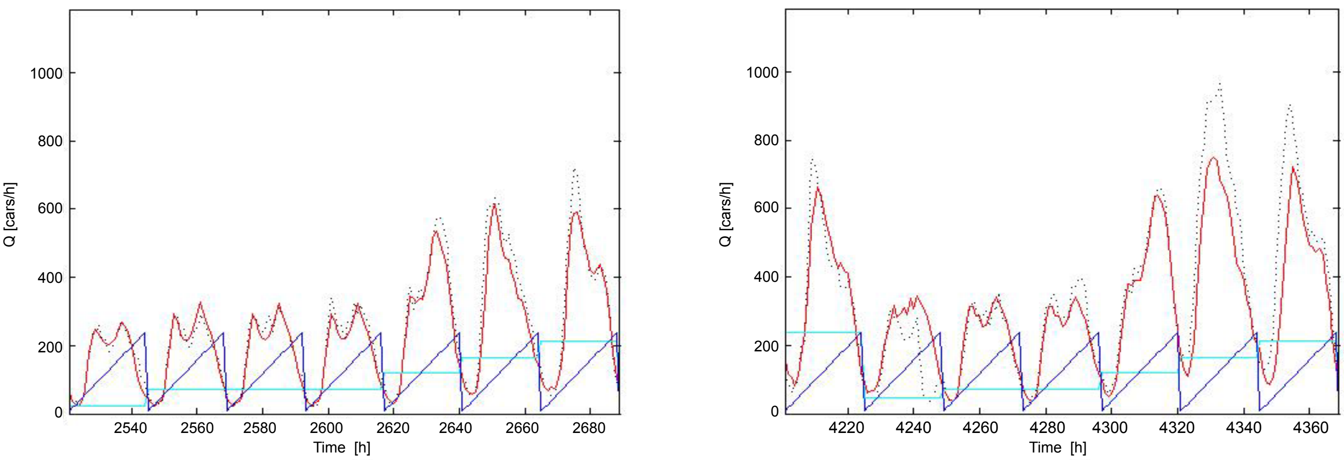

Figure 2: Graphs of characteristic variables in a normal week (left) and in a week that includes a holiday (right). The step-like and saw-like curves represent the day-code *D* and the hour *H*, respectively. Dotted line-original, solid line-predicted *Q*(*t*).

The properties of jam are demonstrated in the lower left diagram. The method for estimation of jam properties is described in the later section of the article.

The GUI was developed in the Matlab environment and compiled into an executable version for broad application on MS Windows by various users. In such a form it is now utilized in the traffic information center in Slovenia. It was recently upgraded by a module for forecasting of traffic jams. The record of predicted flow rate is in this case used as a source of information for prediction of traffic jam. For this purpose the GUI is complemented by the analytical model of traffic flow dynamics as described in the next section.

Analytical Description of Traffic Flow Rate

Dynamics of road traffic can be most thoroughly described by a set of rules that determine trajectories of particular cars [2-5]. However, such micro-dynamical description is usually too complex for on-line applications on mobile telephones or in traffic information centers where mean properties of traffic are mainly sought. Consequently, we turn to a macroscopic description based upon just two variables that describe the mean density ρ and velocity v of cars [2-5,10,11]. The corresponding mean flow rate $Q=\rho v$ is here considered as the basic variable for the description and analysis of the traffic state at the disturbed road section under consideration. In a simple case of a steady and homogeneous traffic state the variables ρ and v do not depend on position and time, but they are mutually related. The graph of the corresponding relation $v=v(\rho)$ represents the *first fundamental diagram of traffic* [2-5]. By the expression $Q(\rho)=\rho v(\rho)$ this diagram is transformed into the *second diagram* that represents the flow rate Q as a function of the density.

Professional literature contains various forms of fundamental

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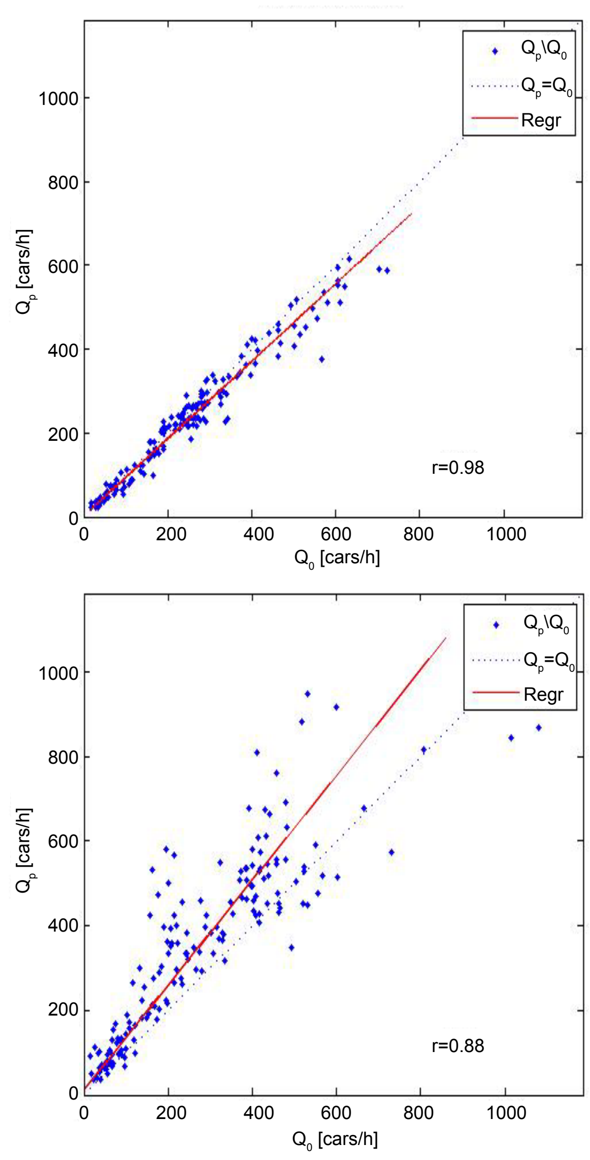

Figure 3: Correlation plot of predicted Q_p versus original Q_o flow rate corresponding to the normal week (left) and the week with a holiday (right).

diagram that correspond more or less to empirical data [2-5,10-11]. One could expect that the most acceptable form should result from a proper treatment of driving strategy and statistical treatment of the corresponding distribution that is related with physiological properties of drivers [5,10,13]. However, the problem is that it is very hard to describe these properties in a unique quantitative way and to relate them with the dynamics of real traffic flow. Consequently, the variety of published forms is stemming from intuitive propositions of their authors. In accordance with this situation we try to find a simple form of fundamental law that agrees well with empirical data and renders simple interpretation and expression of fundamental law by rational functions. To formulate it we consider quasi-static and homogeneous free flow of vehicles on a high-way with allowed maximal speed v_o. We characterize the traffic state by the density ρ determined by the distance between cars r as: $\rho=1/r$. The most fundamental property of the traffic stems from the experience of drivers which adjust their velocity to the spacing between cars and allowed or desired speed v_o. Measured data show [2,5] that at small spacing between cars (high density) this property can be approximately described by a linear relation $w=(r-\lambda)/\tau$ in which λ denotes the mean car length, τ the mean reaction time of drivers, and w a characteristic velocity determined by the transition of the clear spacing between cars $r-\lambda$ in the reaction time τ. In opposition to this, the velocity is approximately equal v_o at high spacing (low density). To account both characteristics simultaneously we assume that a driver on average tries to keep the velocity v of the car bellow the characteristic value w, and also bellow the desired value v_o. Consequently, we further considered the values w and v_o as components of a composed constraint. In order to describe it we represent particular constraints by the inverse values $1/v_o$ and $1/w$ and add them to get the following rule for the composed constraint: $1/v=1/v_o + 1/w$. This rule indicates that the mean value v is below v_o as well as below w. However, one could expect that still better expression of composed constraint could be obtained if a proper weight is assigned to particular terms in our rule. Such a weight should point out relative importance of one term with respect to another one; hence it is enough to assign a weight just to one term. We arbitrary assign a weight to the last term and assume that its importance grows with the increasing density of cars that corresponds to the decreasing value of w. The weight is then expressed relatively with respect to some characteristic parameter u which should be determined experimentally. Based upon this reasoning, the weight is expressed as u/w which yields the rule: $1/v=1/v_o + u/w^2$. Its more convenient form is given by the following expression for the velocity:

$$v=v_o / (1+ u\, v_o /w^2)=v(\rho) \qquad (3)$$

It is important that the characteristic value w depends on $\rho=1/r$ and consequently, the last equation describes the fundamental traffic law $v=v(\rho)$ and its first diagram.

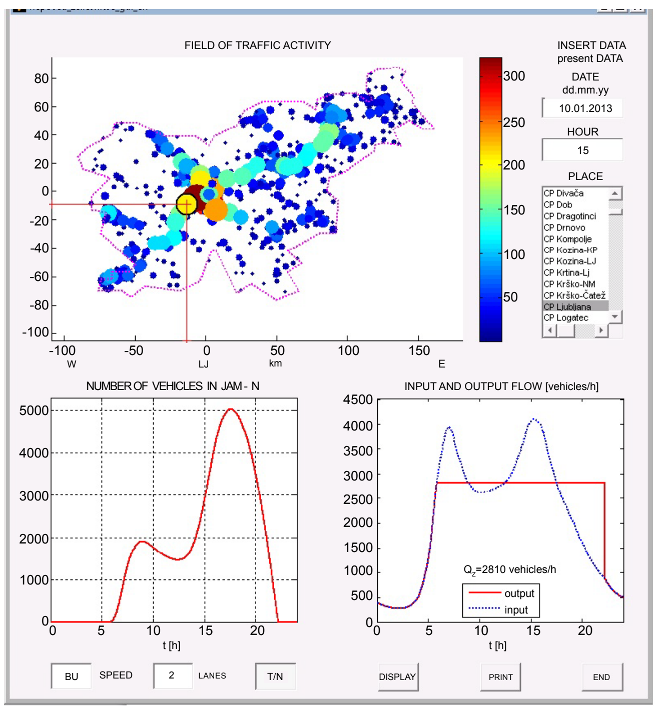

Figure 4: The window of intelligent GUI for traffic flow and jam forecasting in Slovenia [6-8]. Top left: forecast flow rate field $Q(x)$. The radius of the circle at a certain point indicates the flow rate at the time of forecasting. Bottom-right-dotted: forecast input flow $Q(t)$, bottom-right-solid: passed flow, bottom-left: forecast number N of cars in jam.

In order to complete our description the parameter u has to be specified. Since its unit must coincide with the unit of velocity, we arbitrary put $u=C\,\lambda/\tau$. Comparison of the rule Eq. (1) with the rules obtained from measured data has revealed that a good agreement is obtained if the value of constant is set to C=3.1. Simultaneously with this estimation, the following values: λ=4.5 m and τ=1.3 s have been estimated as proper ones. Figure 5 shows comparison of experimentally and theoretically determined fundamental diagram for the velocity $v(\rho)$ in the case with the desired value v_o=110 km/h. Similarly, Figure 6 shows the corresponding second diagram for the flow rate $Q(\rho)$. Experimental data are taken from the reference [2,10] and correspond to a high-way with desired speed 120 km/h that is decreased to the value v_o=110 km/h due to the presence of trucks. In addition to this, the diagrams corresponding to the value v_o=55 km/h are presented (--) in order to indicate the properties of the fundamental diagram corresponding to a half of the desired speed value.

An important characteristic of the second diagram is the maximal value of the flow rate Q_{max} that determines the *road capacity*. The corresponding dependence has been determined numerically from the fundamental law and is shown in Figure 7. The capacity is decreasing with the decreasing value of desired speed. In Slovenia allowed velocity on high-ways is $v_{o=}$130 km/h while most often observed allowed value on a disturbed section inside a bottleneck is $v_{o=}$60 km/h. For a single lane the capacities are Q_{max} ~ 2.2*10^{3}veh/h; Q_{max} ~ 1.4*10^{3}veh/h respectively. One could expect that a jam appears when the flow to a disturbed road section reaches its capacity. In relation to calculation of road capacity by the derived fundamental law it ought to be mentioned that the maximal value of v_o is determined by capabilities of drivers and cars even if allowed speed is not limited.

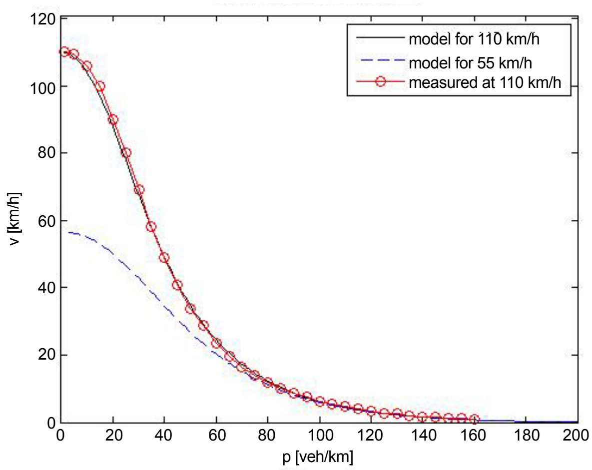

Figure 5: Dependence of velocity v on density of cars ρ. Experimental data are taken from the reference [2].

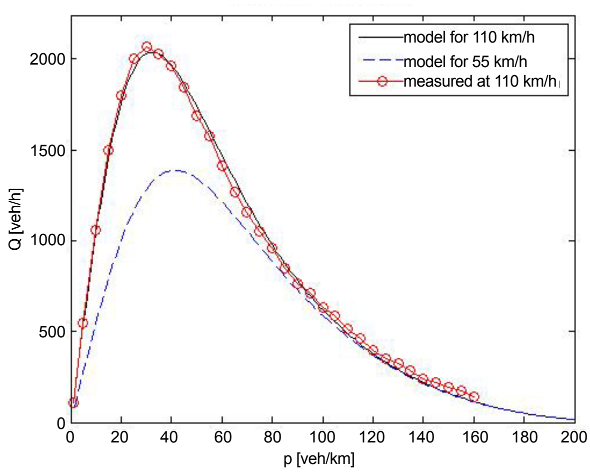

Figure 6: Dependence of traffic flow rate Q on density of cars ρ.

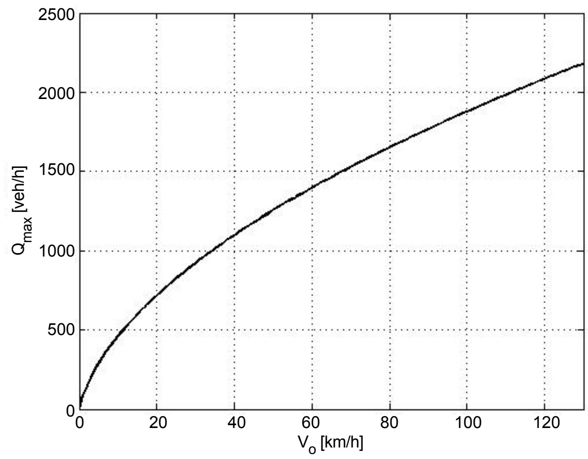

Figure 7: Dependence of road capacity Q_{max} on the speed limit v_o.

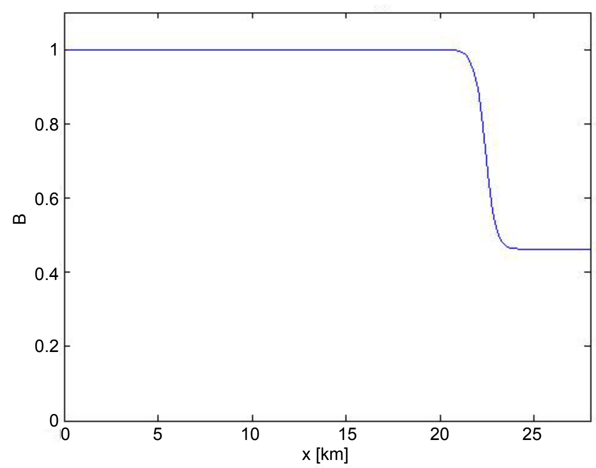

Figure 8: Reduction factor B of speed limit drop from 130 to 60 km/h.

Expression of the fundamental law by Eq. (3) is rather advantageous since it is simple and includes just rational functions that enable inversion which is not the case with many other models [5]. In addition, the interpretation of included parameters is straightforward and agreement with experimental data is rather good.

In our derivation of the law Eq. (3) we considered quasi-steady and homogeneous traffic state. However, this is not the case when treating evolution of traffic jams. Since the derived law Eq. (3) describes well the mean traffic properties in equilibrium, we further assume that the velocity at a certain position x and time t is adapted to the equilibrium value $v_e(\rho)$ determined by Eq. (3) during some characteristic adaptation time T [5,11]. We describe this adaptation by the most simple differential equation:

$$dv/dt = (v_e(\rho) - v) / T, \qquad (4)$$

and further consider the velocity and density as mutually dependent field variables $v=v(x,t)$ and $\rho=\rho(x,t)$. In accordance with this dv/dt in the differential Equation (4) is the convective derivative: $dv/dt=\partial v/\partial t + v\,\partial(v)/\partial x$. The fundamental dynamic law of the traffic field is then given by the continuity equation: [11]

$$\partial\rho/\partial t + \partial(\rho v)/\partial x = I(x,t) \qquad (5)$$

in which $I(x,t)$ denotes the traffic source term. If we start analysis at a certain point x_o where the traffic flow rate $Q(t)$ is forecast, then the source term can be described by the expression: $I(x,t)=Q(t)\ \delta(x-x_o)$ in which δ denotes the Dirac's delta function.

Drivers try to adapt their velocity predominantly to the leading car, but with a delay specified by the reaction time τ. Consequently, when describing the adaptation of velocity v at the position x and time t, the density in Eq. (4) has to be taken at some position Δx ahead of x and at the delayed time $t - \tau$. A typical value of Δx is several car lengths: $\Delta x \sim 3\lambda$. Similarly the relaxation time is several reaction times: $T \sim 3\tau$.

Expressions (3-5) represent a non-linear system of partial differential equations whose solution can be determined by standard numerical methods [5]. For this purpose initial and boundary conditions must be given. A typical example is described in the next section.

Development of Traffic Jam

In order to demonstrate the performance of the described method we consider the point of maximal traffic activity on a high-way near Ljubljana where the fog from a swamp often disturbs the traffic. Its position is shown by the vertical and horizontal lines in the top diagram of the forecasting unit shown in Figure 4. The dependence of flow on time is shown by the bottom right record. Two peaks in this record denote rush-hours.

Our next goal is to demonstrate what would happen during the selected day if the speed limit at the selected point is decreased as shown by the reduction factor in Figure 8. For this purpose we consider a road of 28 km length with the disturbed section from 22 km on. We assume that the desired speed is reduced from 130 km/h on the free road to 60 km/h by the disturbed section. To solve the problem, we select the cell size in the spatial direction equal to Δx=200 m, and the time step equal to Δt=1s. We next consider homogeneous initial and boundary conditions equal to 0, so that the traffic state is completely determined by the incoming flow rate $Q(t)$ shown by dotted line in the bottom right record of the forecasting module in Figure 4. For the calculations we consider the time interval that contains the selected day.

The calculated distributions of field variables are shown in Figure 9a and 9b using color coding for the amplitude of field variables. The flow enters the road section at x=0 and moves in the x direction. At the rush-hour its amplitude first grows with time t to the maximum and then falls again. In the disturbed region its maximal value is decreased and the peak is flattened. The velocity drop is observable in the graph of its distribution at the middle of Figure 9a and 9b as blue downward step. At low t the velocity is high at low x, but when cars pass the disturbed section their velocity is decreased due to drop of the desired speed. Simultaneously with decreasing velocity the density is increased as shown at the bottom of Figure 9a and 9b. With increasing time and flow at rush-hour the reduction of velocity in the disturbed region leads to evolution of jam in front of the disturbed section with an expressive peak in time. At the peak the jam exhibits wave-like structure indicating stepwise movement of cars [2-5]. When the rush-hour maximum is passed, the input flow again starts decreasing, which further leads to

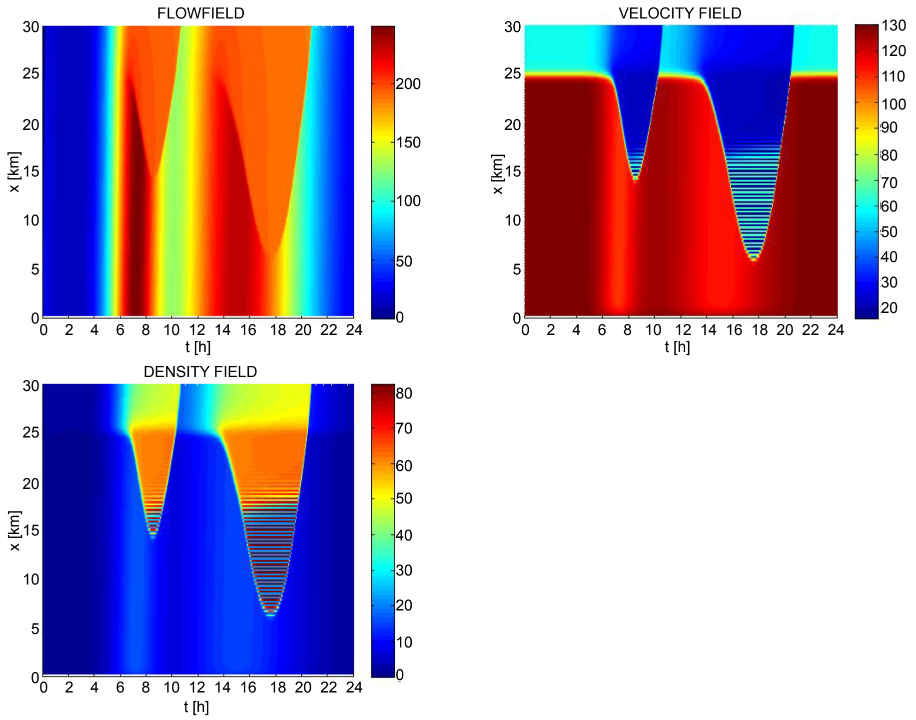

Figure 9a: Distributions of traffic field variables shown in ground plan: top-flow rate, middle-velocity, bottom-density.

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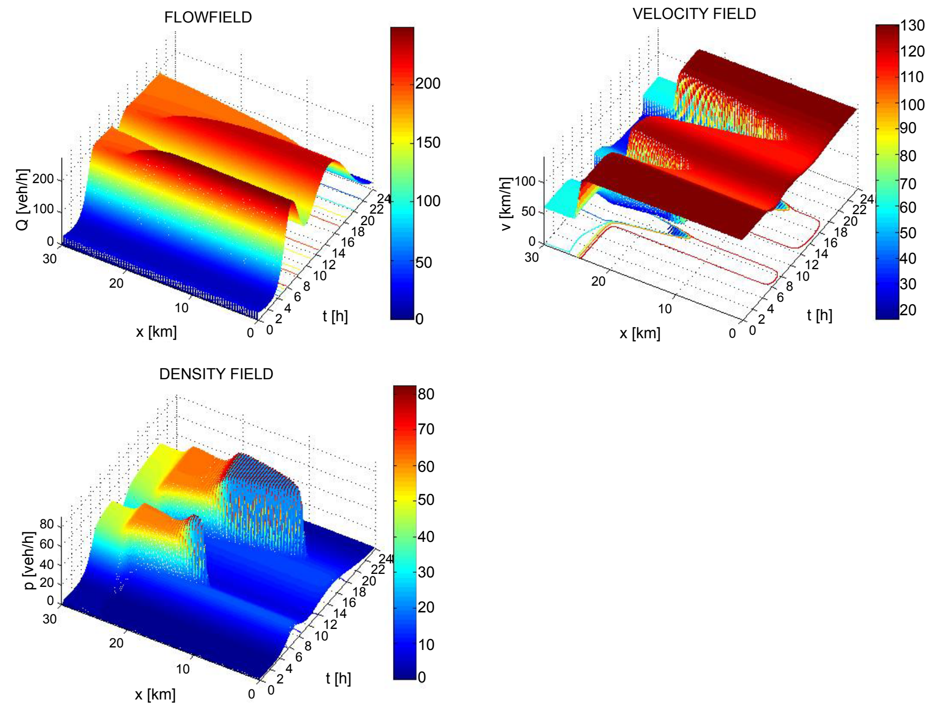

Figure 9b: Distributions of traffic field variables shown in side view: top-flow rate, middle-velocity, bottom-density.

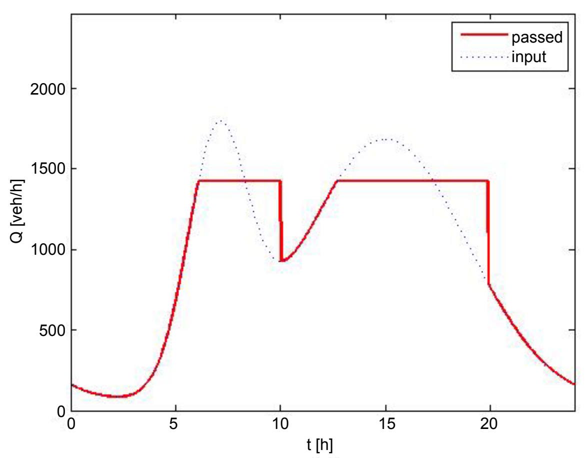

Figure 10: Dependence of passed (bold) and input flow (dotted) flow on time.

a decreased density, increased velocity and dilution of the jam by the flow. A similar evolution of jam as in the morning is observed also in the afternoon rush-hour time. From the graphs of field variables we can forecast the length of jam and its spreading velocity.

Estimation of Jam Length

Macroscopic modeling of traffic by partial differential equations yields rather general description of the traffic jam evolution at the bottleneck in terms of dynamic field variables. However, for practical purposes most often just the length of traffic jam is sought, and there appears a question how to avoid numerical treatment of partial differential equations. For this purpose we turn to an approximate treatment of the complete problem and consider the case when the input flow Q_i is increasing with time. As long as the input flow Q_i is below the capacity of the disturbed section Q_o we assume that all cars pass it fluently. But, when the input flow surpasses the capacity, a portion of the input flow: $\Delta Q = Q_i - Q_o$ is stopped in front of the disturbance. This difference then causes increasing number of cars in front of the disturbed section and an evolving jam. If we know the dependence of input flow on time, we can estimate the number of stopped cars Z by integrating $\Delta Q(t)$ with respect to time. We can then estimate the corresponding jam length L by multiplying the number of stopped cars by the distance between cars that corresponds to the decreased desired speed.

To demonstrate the approximate characterization we again consider the example from the previous section. Figure 10 shows the input and the output flow by dotted and solid lines, respectively. The latter is determined by the reduced capacity that determines the level of the horizontal section in the graph. The corresponding number of cars Z in the jam is shown in Figure 11.

Diagram on Figure 9 renders possible a rough estimation of the speed of jam propagation in backward direction that could be compared with the result shown on Figure 11. The reduced speed limit does not permit all incoming cars during the rush-hour time to pass the disturbed region when the input flow surpasses the reduced capacity 1422veh/h. The difference between input and output flow contributes to the formation of jam. If we assume approximately linear increasing and decreasing of flow from ~1400 to ~1800 and back to ~1400 veh/h in the time interval from 6-8 h, then we obtain that about ~200 veh/h is stopped in this interval which yields in 2 h about N~400 vehicles. If we assume quadratic dependence of flow on time during rush-hour we obtain the value N~540, which coincides well with the height of the first peak in Figure 11. If all cars were closely packed and not moving, the corresponding length of jam would be $L \sim N\lambda \sim 3$ km. But the cars

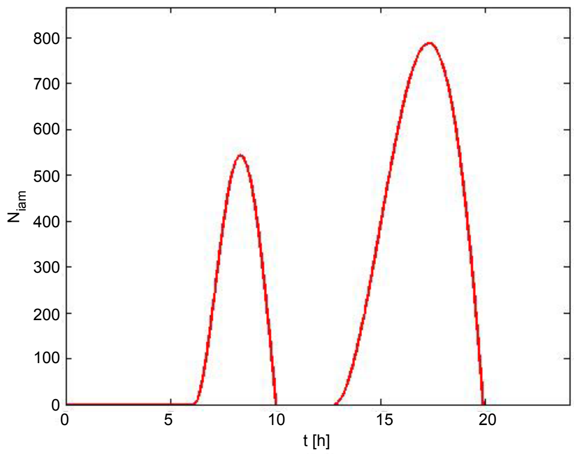

Figure 11: Estimated number of cars *N* in jam versus time *t*.

are moving in the jam approximately with the speed determined by its decreased desired speed, and consequently the approximate distance between them is $r=\lambda + \tau w \sim 20$ m that yields four times longer jam length $L{\sim}12$ km. This value coincides well with the length of the first peak shown in Figure 9. The time T of waiting in jam can be estimated as: $T=L / v(\rho)$.

Estimation of the jam length is less reliable than the corresponding number of cars, since the distance between cars is changing with their velocity that depends also on properties of the jam. However, the determination of the number of stopped cars is only approximate since the jam can also influence the dynamics of the flow in the bottleneck itself. More accurate determination of the jam length can thus be obtained just by a strict accounting of the flow dynamics, described by partial differential equations. Irrespectively of this deficiency, we can introduce the most important jam characteristic by the integral of stopped flow rate that is applicable for prediction of jam evolution. An advantage is that for this purpose we just need the predicted input flow in dependence on time and the reduced capacity.

Diagrams shown in Figures 10 and 11 indicate the properties of jam and have therefore been selected for demonstration by bottom graphs of GUI shown in Figure 4. The desired speed, the number of operating lanes, and the display of variable *N* or *T* can be set below the graphs in the GUI window. The desired speed must be determined by the user based upon the properties of the disturbance in the critical section. The proper value in a severe weather can be estimated from the friction coefficient and visibility distance that can be extracted from forecast weather data [14]. This further renders possible rather simple forecasting of the traffic jam evolution and estimation of the number *N* of jammed cars as well as the time *T* of waiting in the jam. The GUI is developed as a stand-alone application for MS Windows, while its adaptation to web pages and mobile telephones is still in preparation.

Conclusions

We have shown that in spite of rather complex, non-linear, and stochastic character of traffic, it is possible to forecast the traffic flow rate statistically and to model the equilibrium properties of the complete phenomenon by the fundamental diagram [5,11]. This diagram provides for definition of road capacity and rather simple estimation of properties of traffic jam evolving at the bottleneck. Inclusion of the relaxation equation and the continuity equation into description further stretches the applicability of our macroscopic description to non-equilibrium states [2-6,10,11]. These two equations describe the adaptation of velocity to its equilibrium value and the adaptation of the density to the velocity and with it related traffic flow rate. The flow rate is applicable also for description of the traffic source term in the continuity equation which further renders possible forecasting of traffic jam evolution caused by various disturbances. For this purpose the flow rate predicted by previously developed intelligent unit is readily applicable. The presented characteristic example of jam evolution reveals most characteristic features of this phenomenon. The method presented here has been developed recently, and consequently, it still needs a thorough experimental verification of performance in real situations before practical applications of the corresponding graphic user interface. The operation of GUI is adapted to traffic data from Slovenian roads, and consequently, comparison of the proposed method and its performance with similar methods of other authors could hardly be directly performed.

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