STOCHASTIC MODELING OF LANE DISTRIBUTION FOR CONGESTED HIGHWAYS

[Extended Abstract]

Sofia Samoili[1], Nikolaos Geroliminis[2], André-Gilles Dumont[1]

[1] Laboratory of Traffic Facilities, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne, Station 18, Lausanne, CH-1015

[2] Urban Transport Systems Laboratory, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne, Station 18, Lausanne, CH-1015

Problem Statement

Recurrent congestion and increase of extended daily peak periods are universals trends in highways. Congestion mitigation is polarized between invasive approaches, such as infrastructure interventions, and traffic management through implementation of Intelligent Transportation Systems (ITS), which promote ameliorated network performance with sustainable economic, spatiotemporal requirements. The amelioration of current traffic management strategies, such as the traffic supply and demand management, control policies and managed lanes, stands as the most aspiring between the two approaches, as conduces to the restrain or prevention of network's performance aggravation. However, traffic intra-class variability, adaptability of drivers' behaviour to existent ITS policies, in conjunction with networks' complexity in highways, fortify congestion and challenge the strategies' efficiency. Abrupt fluctuations ensued by transitional traffic regimes advocate the congestion phenomenon that could be anticipated and mitigated by a timely activation of designated control policies. To provide reliable monitoring and controlling, stochastic modeling of impending traffic dynamics compounds one of the focal points of this study, so as to unveil synergistic properties of parameters to be integrated in these systems.

In this scope, a multi-level algorithm is introduced that models and forecasts lane traffic distribution in succeeding traffic regimes through lane-scale parameterization of static and dynamic expression, and examines the existence of an inter-dependence of lane vehicle distribution patterns and congestion formation. An optimization approach concludes the stochastic scheme, aiming to ameliorate the performance of an existing reactive managed lanes system (MLS) and to reconfigure it to proactive, namely a hard shoulder running (HSR), by minimizing time delays through minimization of density per lane. The graphical methodological framework to succeed this challenging goal is presented in Figure 1.

In the first level, a clustering approach captures patterns of lane stream dynamics, which corresponds to an unbiased definition of peak periods and prevailing traffic regimes. Data mining leads to the conjecture that inter-lane traffic propagation denotes the onset of another regime. Therefore, the hypothesis regarding the underlying spatial inter-dependence between traffic lane distribution and traffic states occurrence is assessed in the subsequent level, through lane-scale spatiotemporal parameterization. The stochastic method that is introduced, forecasts lane traffic distribution in succeeding traffic regimes, through a novel introduced parameter, lane density distribution ratio (LDDR). Ultimately, at the lower level, the developed dynamic multivariate models are implemented to an indicative single managed lane (ML) per direction system in a Swiss highway, or else Hard Shoulder Running (HSR), equipped with variable speed limit (VSL). Due to fixed activation thresholds and to observed underutilization of the ML, over favouritism of the general purpose (GP) lanes, the systems' operations are undermined. Hence, the designated control policy is subject to optimisation, through the minimisation of delays and thus densities per lane, in order to achieve timely activation.

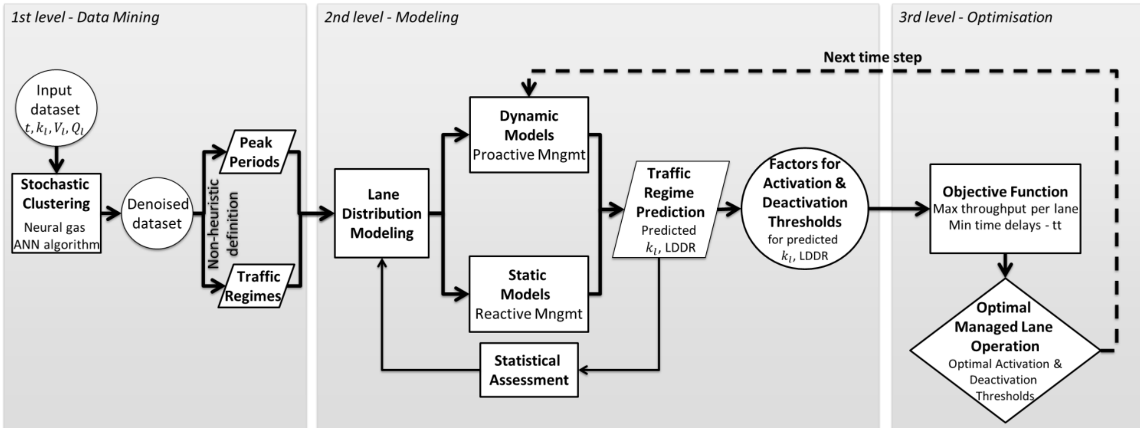

Figure 1. Stochastic algorithm framework for modeling and dynamic operation of managed lanes systems.

Level 1: Data Mining for Traffic Patterns Identification

The aim of the first level is to render a) the temporal patterns of time span, during which maximum capacity is attained per sections of a network, hereinafter referred to as the peak period, and b) the spatial patterns of the three prevailing traffic regimes that capture stream dynamics in three homogeneous groups (free flow, saturated, congested). Additionally, any detected outliers are removed, generating a denoised and concise input dataset, which promotes accuracy prediction at the subsequent level of modeling. An exploratory data mining is performed by employing a neural network (NN) algorithm, namely the "neural-gas" algorithm, in independent stochastic clustering procedures. The algorithm is a fuzzy extension of the k-means that outperforms standard clustering techniques, according to a dissimilarity measure, that might tend to converge to local minima for non-smooth data, as in the case of rapidly fluctuating traffic flow. Moreover, it requires an order of magnitude fewer weights to achieve the same order prediction error.

The studied data vectors are: (a) a two-dimensional vector of time and densities per direction, $v_{tk_{dir}}$, for the distinction between peak from off-peak periods, and (b) a θ-dimensional vector of normalized densities and speeds per lane, $v_{k_{n_l}v_{n_l}}$, and a θ-dimensional vector of normalized densities per lane and lane density distribution ratios (LDDR) per lane, $v_{k_{n_l}r_{k_l}}$, for the identification of traffic regimes, where $\theta = \zeta \cdot \lambda$ is the number of lane-scale parameters ζ that are considered for clustering and λ the number of lanes in the section. Hence, $(2\lambda) + 1$ separate clustering procedures are invoked for each of the three vectors, $v_{k_{n_l}v_{n_l}}$, $v_{k_{n_l}r_{k_l}}$, $v_{tk_{dir}}$. For every reference to v hereinafter, each of these vectors is implied, depending on the case.

Three separate clustering procedures are invoked for each of the three vectors. Each of the resulted clusters comprises indications about stream patterns that contribute to the targeted delineation of traffic dynamics. The morning and evening peak periods serve to reduce the research area and target the optimal thresholds of a traffic responsive activation. The relationships of density per lane and LDDRs, which capture transitions between regimes and highlight the thresholds for a timely activation of an ITS, provide an insight into traffic behaviour and traffic distribution dynamics in lanes. In these transitions between free flow and congested regimes, represented by the saturated regimes, lay the range of thresholds to be inquired for a traffic responsive system operation, related to the system's activation or deactivation.

Furthermore, the clustering analysis on the relationships between density per direction and LDDRs revealed uneven vehicles' distribution. The right lane is preferred even at impending saturation, while left lane remains underutilised up to the onset of congestion conditions. These lane density patterns that are intermittently occurring during respective traffic conditions, induce the conjecture that congestion moves from right to left in the onset of peak periods and contrary in the offset. Hence, traffic inter-lane propagation delineates a potential transition to another state. This justifies the initial hypothesis of inter-dependence between patternised lane vehicle allocation and traffic regimes.

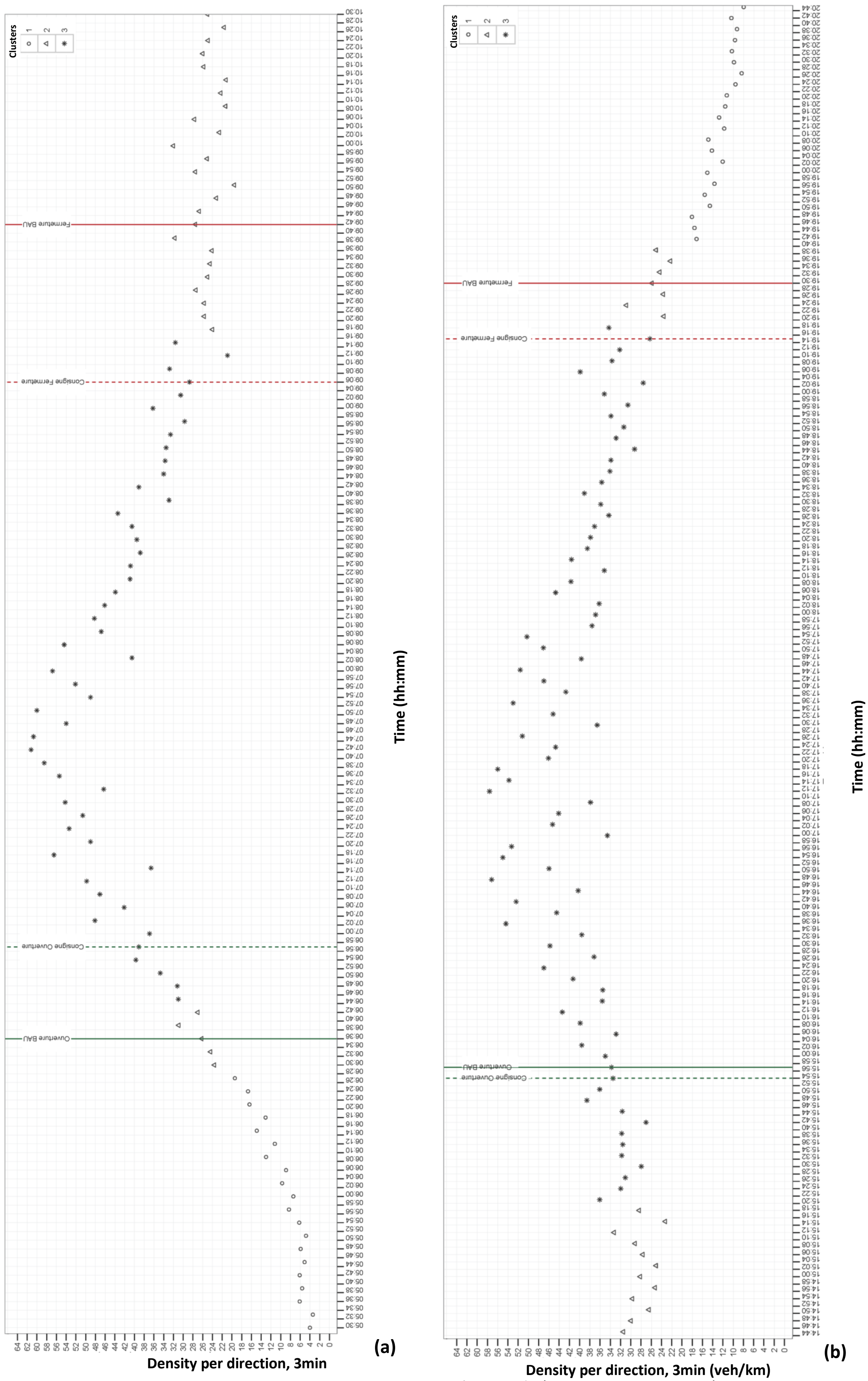

Figure 2. Clusters of (a) morning,(b) evening peak periods (L-60590, 18.03.2014)

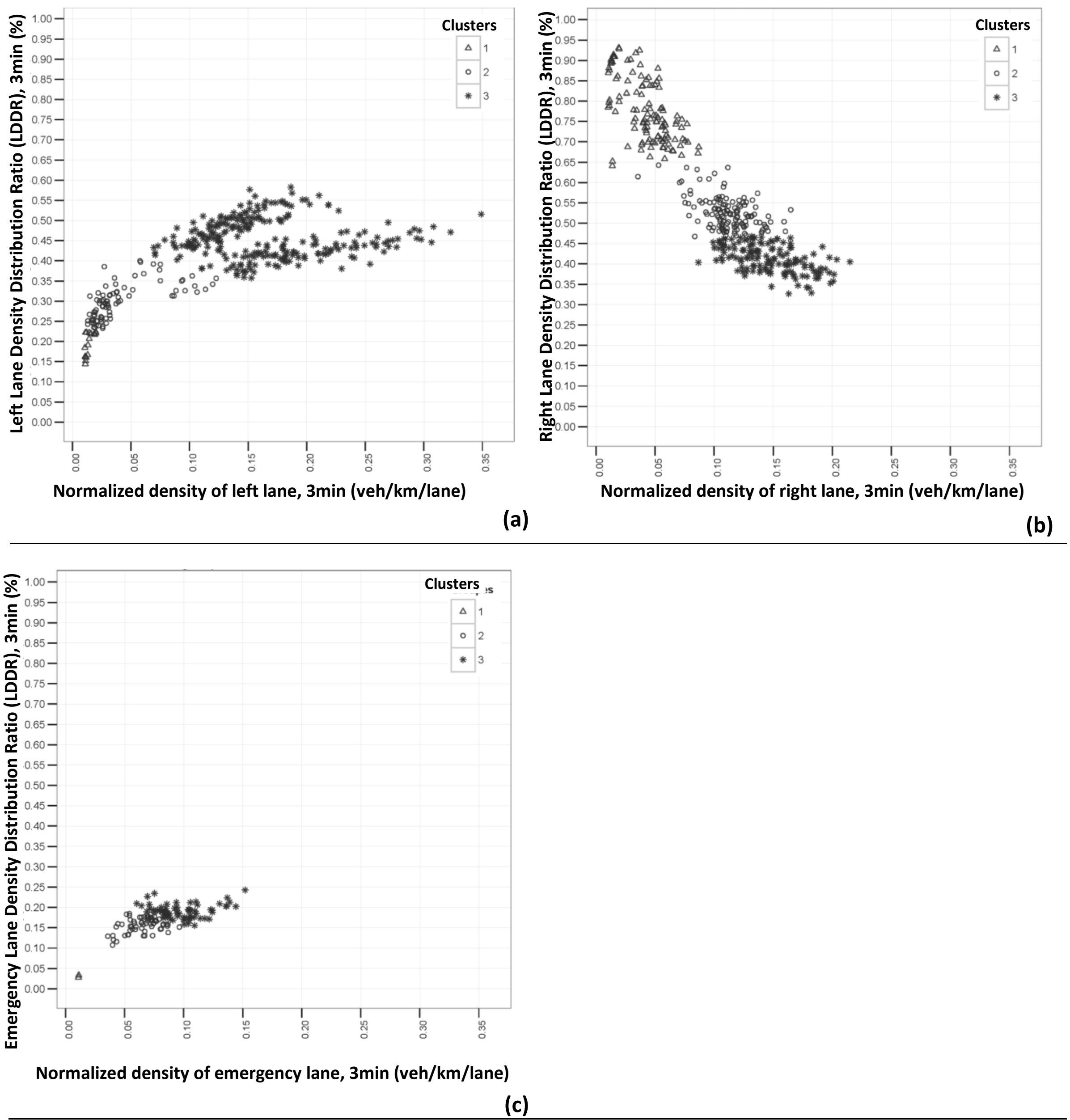

Figure 3. Clusters of traffic regimes per lane (a) left, (b) right, (c) emergency lane (L-60590, 18.03.2014).

Level 2: Lane Distribution Modeling and Forecasting for Managed Lanes Management

In the this level, the aim is to predict and hence alleviate part of the causes of the mechanisms that cause extended congested phenomena, through impending spatiotemporal distributions that could be integrated to existing control algorithms of ITS schemes, moderating thereby delays and costs. The hypothesis regarding the underlying spatial inter-dependence between traffic allocation per lane and traffic states emergence is assessed, through separate models with lane-scale variables for each of the resulted homogeneous clusters.

The data mining of the preceding level revealed that in a site that traffic propagates from an initially preferred outer lane to the remaining outer lane, in this case study from right to left, in ascending passage at the offset of saturated conditions and at the onset of peak periods, a transition to congested regimes is implied. Based on these findings, the sequence between congested and uncongested conditions, as those are ensued by the traffic behavioural patterns of each cluster, can be anticipated through lane-related parameterisation of the stream. Thence, following the verified assumption that at the onset of congested conditions the left lanes receive the inflow, left lane LDDR is introduced as determinant response variable for congested conditions, since any increase of their values could suggest transition from free flow or saturated regimes, and density of the right lane for the uncongested.

Pursuing a simple approach that would ensure feasibility of implementation into real-time control policies, dynamic multivariate general regression models are deployed, of type $\mathrm{Y(t+1)-Y(t)} = \sum[\alpha + \beta_i X_i(t)]$ with α, β constant coefficients $\in \mathbb{R}\backslash\{0\}$. Separate dynamic prediction models are developed for each of the resulted homogeneous clusters, enhancing thus their statistical power and contributing to the acquired significant accuracy for both congested and uncongested regimes. Their dynamic character lays on the fact that they are providing predictions for an interval, t+1, one time step subsequent to the current time t. The prediction horizon is set on t=3-minutes, which is considered as adequate to detect transitions, without overleaping or accentuating rapid fluctuations. The forecasting parameters are subject to unity-based normalization, in order to be scale invariant for comparability reasons. Although multicollinearity within independent variables is negligible, since they are normalised and on account of the bounded response variables, it is inquired based on the significance of the estimated regression coefficients.

To statistically assess the proposed models, an exploratory analysis is effectuated at the aforementioned reactive ML system highway site. To provide the system's timely operation, forthcoming stream dynamics are monitored in two sections, upstream and in the system, ensuring sufficient time interval for its activation before the propagation of any upstream triggering conditions to downstream. From the study period are excluded holidays and days with accidents (March, May of 2013 and 2014).

The dynamic model for congested conditions (Equation (1)) is intended to describe stream dynamics during this regime, through a left lane related variable for the reasons described to the corresponding static model. The model predicts the response variable of left lane LDDR upstream one time step subsequent $r_{k_L}^{up}(t+1)$ to the current, $r_{k_L}^{up}(t)$, with an accuracy of 5% (Table 1), when as explanatory variables are set the current step's t: normalized density of the left lane downstream, $k_{n_L}^{dwn}(t)$, right lane LFDR downstream, $r_{Q_R}^{dwn}(t)$, derivative of the normalized left lane speed upstream, $\frac{dV_{n_L}}{dt}^{up}$, and discrete normalized number of lanes that are used as general purpose lanes downstream, $nb_{lanes}^{dwn}(t)$ ($nb_{lanes}^{dwn}(t)$ =0 for 2 lanes, $nb_{lanes}^{dwn}(t)$ =1 for 3 lanes).

Multivariate dynamic regression model for congested conditions:

$$Y_{r_{k_L}^{up}}(t+1) - Y_{r_{k_L}^{up}}(t) = \beta_{k_{n_L}^{dwn}(t)} \cdot X_{k_{n_L}^{dwn}}(t) + \beta_{r_{Q_R}^{dwn}(t)} \cdot X_{r_{Q_R}^{dwn}}(t) + \beta_{\frac{dV_{n_L}}{dt}^{up}} \cdot X_{\frac{dV_{n_L}}{dt}^{up}} + \beta_{nb_{lanes}^{dwn}(t)} \cdot X_{nb_{lanes}^{dwn}}(t) \quad 1)$$

Based on N=4293 observations, the LLDDR upstream one time step following to the current is inversely related to the right lane LFDR (RLFDR) downstream and the derivative of the normalized left lane speed upstream, which suggests that a decrease to the latter indicates a subsequent 3-min transition towards denser conditions, thus the decrease of the left lane LDDR upstream is justified as the congestion propagates up to the section in question. The model successfully provided adequate fitting to the data with an adjusted R^2 of 81% (Table 1).

Table 1. Summary statistics of dynamic multivariate models for congested and uncongested conditions, as resulted by clustering.

Congested		**Uncongested**	
Variables*	$\boldsymbol{\beta}$	**Variables***	$\boldsymbol{\beta}$
$Y_{r_{k_L}^{up}}(t+1) - Y_{r_{k_L}^{up}}(t) \sim$	(N=4293)	$Y_{k_{n_R}^{up}}(t+1) - Y_{k_{n_R}^{up}}(t) \sim$	(N=3765)
Intercept	0.43	Intercept	0.06
$\beta_{k_{n_L}^{dwn}(t)}$	0.15	$\beta_{k_{n_R}^{dwn}(t)}$	0.03
$\beta_{r_{Q_R}^{dwn}(t)}$	- 0.45	$\beta_{r_{Q_R}^{dwn}(t)}$	0.17
$\beta_{\frac{dV_{n_L}}{dt}^{up}}$	- 2.67	$\beta_{\frac{dQ_{n_R}}{dt}^{up}}$	17.85
$\beta_{nb_{lanes}^{dwn}(t)}$	0.01	$\beta_{nb_{lanes}^{dwn}(t)}$	0.01
Res. S.E.	0.05	**Res. S.E.**	0.02
$\mathbf{R^2}$ **adj.**	0.81	$\mathbf{R^2}$ **adj.**	0.67

* All variables are statistically significant at the 99.9% confidence level, based on t-test.

Idem, the developed dynamic model for uncongested conditions (Equation (2)), predicted with significant accuracy (2%), the normalized right lane density upstream one time step subsequent, $k_{n_R}^{up}(t+1)$, to the current, $k_{n_R}^{up}(t)$. The explanatory variables comprise the current step's t: right lane normalized density downstream, $k_{n_R}^{dwn}(t)$, right lane LFDR downstream, $r_{Q_R}^{dwn}(t)$, derivative of the normalized right lane flow upstream, $\frac{dQ_{n_R}}{dt}^{up}$, and discrete normalized number of lanes that are used as general purpose lanes downstream (0 for 2 lanes, 1 for 3 lanes), $nb_{lanes}^{dwn}(t)$.

Multivariate dynamic regression model for uncongested conditions:

$$Y_{k_R^{up}}(t+1) - Y_{k_{n_R}^{up}}(t) = \beta_{k_{n_R}^{dwn}(t)} \cdot X_{k_{n_R}^{dwn}}(t) + \beta_{r_{Q_R}^{dwn}(t)} \cdot X_{r_{Q_R}^{dwn}}(t) + \beta_{\frac{dQ_{n_R}}{dt}^{up}} \cdot X_{\frac{dQ_{n_R}}{dt}^{up}} + \beta_{nb_{lanes}^{dwn}(t)} \cdot X_{nb_{lanes}^{dwn}}(t) \quad (2)$$

The normalized right lane density upstream one time step subsequent to the current is positively affected by all the explanatory variables, which suggests that an increase to any of the variables results to an increase to the right lane density and implies less attractiveness to the left lane, hence a subsequent 3-min transition towards less dense conditions is induced.

Optimisation of Control Algorithm for Managed Lanes

In order to improve the performance of a reactive HSR system, an optimization of its activation/deactivation thresholds is currently on-going. The approach is considered as novel, as relevant frameworks are not acknowledged in literature in this scope, apart from the application-driven empirical adjustments where decisions for timely operation are solely empirically-driven. In addition, an Application Programming Interface (API) is under development in a simulation environment, as part of an evaluation of the system's performance upon implementation of the suggested optimal set of thresholds before the prospective field test, with the employment of certain scenarios of control, demand and additional policies variations that could challenge its efficiency and engage accordingly any adjustments.

Keywords

Lane distribution forecasting; Lane Density Distribution Ratio (LDDR); Fuzzy data mining; Neural-gas ANN clustering modeling; Proactive control activation; Managed lanes; Hard Shoulder Running