Modeling the Effects of Weather and Traffic on the Risk of Secondary Incidents

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ABSTRACT

The purpose of this paper is to develop neural network models with enhanced explanatory power in order to extract useful information on the variables that affect secondary accident likelihood. Traffic and weather conditions at the occurrence of a primary incident are explicitly considered. Two influence measures to extract variable significance are introduced: mutual information and partial derivatives. The proposed approach is also compared to other classical statistical approaches of the Logit family. Results suggest that changes in speed and volume, number of blocked lanes, and percentage of trucks significantly influence the probability of having a secondary incident, whereas changes in rainfall intensity are less influential to secondary incident likelihood. Finally, the managerial implications of the proposed modeling approach are evaluated and discussed.

Keywords: Secondary incidents, traffic flow, rainfall, neural networks, Logit, mutual information, partial derivatives.

INTRODUCTION

Severe freeway incidents cause excessive delays and are frequently associated with secondary incidents. Secondary incidents are generally defined as incidents that occur within a predefined spatiotemporal region of a primary incident and reduce roadway capacity (Moore et al., 2004; Zhang and Khattak, 2010). Secondary incidents have increasingly been recognized as a major source of freeway incidents as their occurrence causes significant additional traffic delay. Compared with primary incidents, secondary are more severe and are more demanding regarding traffic management resource allocation implications (Karlaftis et al., 1999); as a consequence, their identification will help increase safety and maintain operational levels on freeways.

The literature on secondary incident management has revolved around two major issues: first is the detection of secondary incidents. Research has used predefined spatiotemporal boundaries to delimit the influence area of a primary incident and, consequently, the spatio-temporal area of increased secondary incident likelihood (Raub, 1997; Moore et al., 2004). Recently, the concept of dynamic thresholds for secondary incident occurrence has been introduced by some researchers; methods range from visually observing the progression of the queue formulated upstream of a primary incident (Sun and Chilukuri, 2010), to queue based analytical estimations (Zhang and Khattak, 2010), cumulative arrival and departure plots (Zhan et al. 2009), and or other analytical estimation of the produced congestion from loop detector data (Orfanou et al., 2011).

The second issue refers to modeling secondary incident likelihood and identifying determinants related to the different incident, traffic and geometric characteristics. Karlaftis et al. (1999) examined the primary incident characteristics that influence secondary incident occurrence likelihood. Clearance time, season, type of vehicle involved, and lateral location of the primary incident were the most influential factors. Hirunyanitiwattana and Mattingly (2006) examined differences in the characteristics of primary and secondary incidents with respect to time of day, roadway classification, primary collision factors, severity level and type of incident; they found that secondary incidents are more likely to occur in urban freeways with more than 4-lanes and during peak periods, and are associated with exceedances of posted speed limits.

Recently, Zhan et al. (2008) identified the number of involved vehicles and number of lanes and primary incident duration as the most significant factors influencing secondary incidents; one year later Zhan et al. (2009) suggested that the primary incident type, primary incident lane blockage duration, and time of day are the most significant factors of secondary accident likelihood. Khatak et al. (2009) focused on further studying the interdependency between the primary accident duration and the secondary accident likelihood via a two stage least squares model where the duration was the endogenous variable and detection type, incident type, lane closure, vehicle involved, response vehicles, AADT, left shoulder/ramp, and time of day the independent variables. Vlahogianni et al. (2010) proposed a Bayesian framework for combining incident and queue information on freeways to reveal the characteristics of primary incidents that affect secondary incident likelihood. Results indicated that traffic conditions at the time of the incident as well as the time to respond to, and clearing of, the incident scene, are the most significant determinants in defining the upstream influence area of an incident. Finally, Zhang and Khattak (2010) developed an ordered Logit model to address the interrelations between secondary incident probability occurrence and primary incident characteristics; the duration of a primary incident, the number of vehicles involved, and the segment length - but not curvature - were found to be influential. A thorough and critical review of previous research can be found in Khattak et al. (2011).

Most previous studies have used aggregated traffic related information in the form of AADT or the type of day and time period of incident occurrence to account for prevailing conditions. Further, the effect of weather conditions has not been explicitly considered, although they may significantly affect the predictability of travel speed and its influence on traffic incidents cannot be disregarded (Tsirigotis et al., 2011). Regarding the methods employed, there has been extensive use of classical statistical models such as the Logit, largely disregarding many flexible computational intelligence models that are both systematically implemented in various transportation problems and which may allow for important insights into the secondary incident mechanism (Karlaftis and Vlahogianni, 2011).

In this paper past research on secondary incident risk modeling is extended by developing transparent neural network models combined with different influence measures to enhance their explanatory power. To detect secondary incidents, a dynamic threshold methodology that considers real-time traffic information from loop detectors is used. Factors such as prevailing traffic conditions (speed and volume), and weather conditions are explicitly considered and evaluated. The proposed modeling approach is compared to popular statistical models. The managerial implications of the proposed modeling approach are evaluated and discussed.

NEURAL NETWORKS FOR CLASSIFICATION PROBLEMS

Neural Networks (NNs) are considered in transportation as efficient predictive models widely applied in function approximation and classification problems (Karlaftis and Vlahogianni, 2011). NNs provide for a flexible and adaptable representational framework for developing familiar statistical models (Cheng and Titterington, 1994). In general, most popular structures of NN classifiers based on Multi-Layer Perceptrons (MLPs) bear several similarities with the popular Logit models (Sarle, 1994; Tu, 1996); a logistic regression model with no interaction terms (main effects logistic regression) for example, is identical to a single layer Perceptron. In parameter estimation, logistic regression converges when the likelihood function is maximized, whereas in a neural network the algorithm usually converges when a least-squares error function between the actual and predicted output is minimized (Tu, 1996).

A MLP with one hidden layer and a logistic output activation function provides an output value y_p of the p-th data example of the form (McNelis 2005):

$$y_p = \frac{1}{1+e^{-net_j}}, \tag{1}$$

$$net_j = \sum_k w_{kj} h_k + \theta_j \tag{2}$$

where w_{kj} is the connection weight between the k_{th} neuron in the hidden layer and the j_{th} neuron in the output layer and θ_j is the bias term. The term h_k presents the output of the hidden neuron and is given by: $h_k = \frac{1}{1+e^{-net_k}}$, with $net_k = \sum_i w_{ik} x_i - \theta_i$, where w_{ik} is the connection weight between the k_{th} neuron in the hidden layer and the i_{th} input variable. θ_i is the bias term. The output of the MLP for a discrete choice model can be described by (McNelis 2005):

$$\tilde{p}_i = \sum_j \gamma_j net_{j,i} \tag{3}$$

$$\sum_{j=1} \gamma_j = 1, \gamma_j \geq 0 \tag{4}$$

where probability $\tilde{p}_i$ is the weighted average of the logsigmoid function for neurons bounded between 0 and 1. The functional form described in Eq(1) resembles a logistic regression model which can be considered as a special case of a neural network regression for binary choice, since the logistic regression represents a neural network with one hidden neuron (McNelis 2005). The difference is in the existence of the hidden layer; the nonlinearity induced in the hidden layer - the output h_k is usually a nonlinear function of the input patterns - provides the NN model with enhanced flexibility compared to Logit models (Tu, 1996). Tu (1996) summarizes the advantages and disadvantages of neural networks models when compared to logit models; current literature in neural network applications for transportation problems emphasizes that, although neural networks may result to more flexible and robust models when compared to similar statistical structures, they may not be considered as a stand-alone modeling choice, as they require statistics for increase their transparency and explanatory power (Karlaftis and Vlahogianni 2010).

Neural Networks as Explanatory Models

One of the fundamental differences between MLPs and statistical modeling is the lack of an inherent mechanism for explicitly describing the learnt relationship between the input and output space. Most researchers implementing NN models perceive them as “black-boxes” and focus on improving the accuracy of modeling disregarding the explanatory power that NNs may have (Zobel and Cook, 2011).The need for developing NN models with explanatory power is related to the decision-making process in transportation. Intuitively, any decision in transportation and traffic operations should be based on a solid understanding of the mechanism by which different factors interact and influence transportation phenomena.

Various methods to extract the significance of input variables in neural network modeling have been proposed; Zobel and Cook (2011) provide a comprehensive discussion regarding several sensitivity analysis techniques and categorize them into two classes: the general measures, which provide an estimate for each variable’s influence on the overall behavior of the network and, the specific measures, which estimate each variable’s influence on the network’s output for a particular instance of an input vector. Such approaches can be further divided on whether they are implemented before or after training. When testing for variable importance before neural network training, information theoretic measures form a solid alternative (Papadokonstantakis et al., 2006):

$$I(Y \mid \vec{X}) = \frac{H(Y) - H(Y \mid \vec{X})}{H(Y)} \times 100 \tag{5}$$

where $H(Y)$ and $H(Y \mid \vec{X})$ are the entropy and conditional entropy of the dependent variable Y , and $\vec{X}$ is the input space used to predict Y. Mutual information quantifies the strength of the relationship between input and output; the higher the value of $I(Y \mid \vec{X})$ the greater the information transfer between $\vec{X}$ and Y and the greater the contribution of $\vec{X}$ to the knowledge of Y. Mutual information may account for the relationship between different input variables and the output, regardless of whether the relationship is linear or nonlinear (Vlahogianni et al., 2006).

A class of variable significance measures, that has attracted considerable attention, is those resulting from the partial derivative of the output with respect to the input variable (an example of such measure is the relative strength of effects measure proposed by Yang and Zhang, 1997). The first order partial derivative of the output variable *y* to the input variable *x* for the jth variable in a neural network is given by:

$$\frac{\partial y_j}{\partial x_i} = \sum_k \frac{\partial y_j}{\partial net_j} \frac{\partial net_j}{\partial h_k} \frac{\partial h_k}{\partial net_k} \frac{\partial net_k}{\partial x_i} = \sum_k f_k' w_{kj} f_k' w_{ik} \tag{6}$$

where f_j' and f_k' is the first order partial derivative of the jth variable of the output layer and the k_{th} variable in the hidden layer. Using a logistic transfer function we get: $f_j' = y_j\left(1 - y_j\right)$ (we can use the same for f_k'). For the calculation of partial derivatives, a finite differences approach may be implemented (details may be found in McNelis 2005).

The significance input variables may be established based on partial derivatives and bootstrapping (McNelis 2005). From the calculated set of residuals $\hat{e} = y - \hat{y}$, where $\hat{y}$ and y are respectively the predicted and actual values of the output obtained by the best fitted MLP, a first set of shocks for the first bootstrap experiment, $\hat{e}^{b1}$, is obtained and a new dependent variable for the first bootstrap experiment is generated. Then, $y^{b1} = \hat{y} + \hat{e}^{b1}$ is generated and, from the new dataset $\left(y^{b1}, x\right)$, the MLP is re-estimated and the partial derivatives are obtained. The above procedure is repeated several times. The bootstrap p-values for each of the derivatives, giving the probability of the null hypothesis that each of these derivatives is equal to zero, are calculated by ordering the set of estimated partial derivatives (as well as other statistics) from lowest to highest values, and obtaining a probability distribution for these derivatives. The disadvantage of the bootstrap approach to extract the significance form the partial derivatives is that it is more time-consuming than likelihood ratio statistics, as the modeler has to resample from the original data and re-estimate the MLP multiple times (McNelis 2005).

In this paper two types of sensitivity measures are implemented; the first is mutual information and the second is partial derivatives. These measures will be used to rank the importance of the independent variables in the modeling of the probability of having as secondary accident. Both measures may significant managerial implications. Based on mutual information, a transportation engineer may acquire information on the overall significance of certain variables on the secondary accident likelihood under the prevailing roadway and traffic conditions, whereas, using the partial derivatives based ranking the engineer may have direct information on which variable to alter in order to affect immediate change to the secondary accident likelihood. Table 1 depicts a short interpretation of the joint consideration of partial derivatives and mutual information on the impact of each input variable to the output.

<Table 1>

Evidently, the joint consideration of these measures should provide useful and sophisticated information in terms of modeling and managerial perspectives. For example, one could omit from modeling those variables that have low mutual information and low partial derivative. Moreover, in the case of secondary incident likelihood control, given the prevailing roadway and traffic conditions, a transport engineer may develop policies that aim at altering the state of those variables that rapidly affect the increase of the secondary accident likelihood, or identify which specific characteristic of primary incident may not critically affect the probability of having a secondary incident. Nevertheless, expert knowledge is required for setting numerical boundaries for the ranges of both influence measures.

APPLICATION AND RESULTS

Available Data and Secondary Incident Detection

The available data come from Attica Tollway, a 65.2 km urban motorway connecting 2 major interurban motorways, the Athens international airport and the city center. Entry to the freeway is through 39 toll plazas with 195 toll lanes. On a daily basis, more than 370,000 daily entries are recorded with an average annual increase of 8%. In the central section, traffic congestion is frequently observed increasing the likelihood of severe impacts from a “routine” event (e.g. lane closure for maintenance) developing into a wider scale incident. Apart from the extensive loop detector system, traffic monitoring and management is conducted via a broad ITS equipment network encompassing CCTV cameras and inductive loops, Emergency Roadside Telephones (ERT), Carbon monoxide and opacity sensors detectors in bored and cut & cover tunnels, and Variable Message Signs (VMS).

The available data consist of a total of 3,500 incident records for the period between 2007 and 2010. For each incident record, two categories of characteristics are considered: incident related information and traffic related information. Incidents are described by their exact location including the lane(s) blocked and the start/end time of the incident that is used to extract the total duration of the event. Total incident duration refers to all phases of the incident from detection to roadway clearance. It is generally assumed that the total duration of the incident may increase the risk of secondary incident occurrence (Karlaftis et al., 1999). Additional incident related information incorporated in the dataset refer to vehicle type and number of vehicles involved in the incident. Vehicle type influences clearance time since larger vehicles, trucks for example, require longer clearance time. In this study, 3 categories are considered: a) passenger cars (PC), b) power-two-wheelers (PTW; i.e. motorcycles), and c) heavy vehicles. Regarding traffic related information, data such as hourly lane volume and travel speed were also included in the analysis. However, reliable traffic information was present for only 1465 incident records that will be further used to the proposed analysis.

The above data was further enhanced by integrating information on the rainfall intensity collected every 10 minutes. The weather conditions in the entire Attica toll way are monitored by four meteorological stations; these data are available from the METEONET network (http://meteonet.chi.civil.ntua.gr/en/divs.html) developed by the National Technical University of Athens. For this analysis, speed and volume at the beginning of an incident were associated with rainfall intensity information expressed in mm per 10 minutes. As the rainfall is a local phenomenon, an inverse distance weighting multivariate interpolation algorithm was applied in order to acquire accurate rainfall intensity in every incident location weighted to the distance from the closest meteorological sections (Segond et al., 2007).

For the detection of secondary incidents a methodology that calculates the dynamic thresholds of the influence area of a primary incident using detailed real-time collected traffic data from upstream loop detectors is used (Orfanou et al., 2011). The methodology is based on the ASDA model (Automatische Staudynamikanalyse: Automatic Tracking of Moving Traffic Jams), a robust approach for automatically tracking the propagation of moving traffic jams

(Kerner et al. 2004). Let (Q_o, Q_n) be two consecutive loop detectors on a freeway road section and let L be their respective distance. After the moving jam has been observed at detector Q_0 at time t_o, the ASDA model begins by continuously calculating the positions of the upstream front $x_{up}^{(jam)}(t)$. After the downstream front of the moving jam is registered at detector Q_n at a later time t_1, the ASDA model starts calculating the positions of the downstream front, $x_{down}^{(jam)}(t)$.

The positions of both fronts of the formulated moving jam, caused by the primary incident, are defined by using the following two equations (Kerner et al. 2004):

$$
\begin{aligned}
x_{up}^{(jam)}(t) &= L_{i+1} - \int_{t_o^{(i+1)}}^{t} \frac{q_0^{(i)}(t) - q_{min}}{\rho_{max} - \left(q_0^{(i)}(t) / w_0^{(i)}(t)\right)} dt \\
x_{down}^{(jam)}(t) &= L_j - \int_{t_1^{(j)}}^{t} \frac{q_{out}^{(j)(jam)}(t) - q_{min}}{\rho_{max} - \left(q_{out}^{(j)(jam)}(t) / w_{max}^{(j)}(t)\right)} dt
\end{aligned}
\qquad (7)
$$

with index i and j for the detectors whose time values at time t have to be used, L_{i+1}, L_j are the distances of the corresponding detectors from the location of interest, $t_0^{(i+1)}$ indicates the time when the upsteram front of the moving jam has been observed at detector i+1, $t_1^{(j)}$indicates the time when the downstream front of the jam has been observed at detector j, $q_0^{(i)}(t)$ and $w_0^{(i)}(t)$ are the measured flow rate and average vehicle speed at the I detectors upstream of a moving jam, $q_{out}^{(j)(jam)}$ and $w_{max}^{(j)}$ are the measured flow rate and the average vehicle speed at detector j downstream of the moving jam, q_{min} and ρ_{max} are the measured flow rate and density inside the moving jam (Kerner et al. 2004).

The algorithm described by Equation 7 is the simplest version of the ASDA algorithm and is based on the use of the shockwave formula. This algorithm differs from other widely applied methodologies for spatio-temporal congested patterns tracking in that it uses not only speed but also traffic rates for detecting the spatio-temporal evolution of traffic and potentially more robust in defining traffic states. The ASDA algorithm has been applied and evaluated for tracking congestion against other techniques in Li and Bertini (2010); the authors discuss the difficulty of the specific technique in detecting the random fluctuations of traffic flow induced either by special roadway or local extreme traffic conditions.

To assist the ASDA algorithm, a speed threshold technique is implemented similar to the one in Li and Bertini (2010). In particular, the time when the upstream and downsteram front are observed at each detector is estimated based on the speed threshold algorithm. Because high speeds were observed, a maximum speed threshold equal to 60 kph was set; additionally, the speed differential between two successive detectors was set to 20 kph. The upstream front of the moving jam has reached a given detector at some point in time if the following criteria are observed:

1. The speed at the detector is below the maximum speed threshold,
2. The speed drop at the detector is higher than 35%,
3. The difference between the speeds at the detector and the next downstream detector is greater than the speed differential.

If congestion occurs, only the speed drop criterion is applied since the speeds are already below 60kph and the speeds between successive detectors range at the same levels.Using Eq. (7), it is possible to accurately calculate the position of the upstream and downstream front of the wide moving jam at any time. Consequently, it is also possible to estimate the jam width $L_s = x_{down}^{(jam)} - x_{up}^{(jam)}$ at any time, as well as queue duration and maximum queue length caused by the primary incident occurrence. Therefore, the spatiotemporal boundaries of the influence area are fully defined. The application of the methodology results in defining a curve of the form of Figure 1 for each incident record in the available incident dataset; any incident falling within this area is considered as secondary.

<Figure 1>

The above methodology is applied to the available incident dataset and results suggest that approximately 3.5% of total 1465 incidents can be regarded as secondary. This percentage matches those presented in previous research studies on secondary incident detection (Raub, 1997; Moore et al., 2004). Details of the results comparative study of the different secondary detection methodologies including the proposed approach can be found in Orfanou et al. (2011)

Developing Classifiers for Secondary Incident Risk Modeling

Neural classifiers as described by the Equations 1 to 4 are developed and compared to Logit, Probit and Gompit models with respect to their accuracy and explanatory power. Probit models use the cumulative Gaussian normal distribution rather than the logistic function - used by the Logit model - for calculating the probability of belonging to either of two categories (Washington et al., 2010):

$$p_i = \mathbf{\Phi}(x_i\beta + \beta_0) == \int_{-\infty}^{x_i\beta+\beta_0} \phi(t)dt \quad (8)$$

where $\mathbf{\Phi}$ is the cumulative standard distribution and ϕ represents the standard normal density function. The Gompit model uses the Weibull distribution that is asymmetric and strongly negatively skewed and approaches zero only slowly and 1 more rapidly (compared to the Probit and Logit models; Washington et al., 2010):

$$p_i = 1 - \exp(-\exp(x_i\beta + \beta_0)) \quad (9)$$

The dependent variable is incident type; y=1 if it is secondary and 0 otherwise, βi are the coefficients. The independent variables are shown in Table 2. Those variables are selected based on previous studies. Moreover, the detailed traffic information as well as weather information on precipitation at the emergence of a primary accident is introduced.

<Table 2>

Table 3 shows the estimated mutual information conditioned on the observed output values y. As can be seen, traffic conditions at the occurrence of an incident (travel speed and hourly lane volume), as well as weather conditions in terms of rainfall seem to significantly contribute to an incident categorization. Moreover, incident duration is also highly contributing to the secondary accident's likelihood. Variables such as upstream geometry, blocked lanes, vehicles involved in the incident and the existence of curves are less critical, whereas the geometry conditions downstream of an incident have the least contribution to the likelihood of having a secondary incident.

<Table 3>

Prediction results are depicted in Table 4 and Table 5, where the false positives and negatives are presented for the five models and for in- and out-of-sample accuracy respectively; the in-sample performance will evaluate how well the model is specified, whereas the out-of-sample performance will evaluate the ability of a well-specified model to generalize to unseen data patterns. The out-of-sample performance is critical to the predictability of the model (Vlahogianni et al. 2005).

A false positive occurs when the predicted variable is incorrectly labeled as being a secondary, whereas a false negative occur when a true secondary is labeled as a primary incident. The out-of-sample accuracy of the different models results through a bootstrapping procedure; an iterative process repeated 100 times was undertaken where each time 1000 draws from the original sample, with replacement, where used for estimation; the remainder of the data were used to evaluate the out-of-sample forecast performance. The resulting statistics of true and false positives are produced by examining the mean and distribution of the error-percentages of the alternative models.

<Table 4>

Results indicate that the MLP and the Logit have similar performance in classifying the incidents as secondary, as well as in forecasting the occurrence of secondary incidents using out-of-sample data. An MLP with few hidden layers has exactly the same performance as the Logit model; this may be expected considering the Logit as a special class of MLP with 1 hidden neuron.

<Table 5>

Interestingly, when the number of hidden neurons increases the model's performance in the out-of-sample data increases and outperforms the Logit model without showing signs of over-fitting (because of increased hidden neurons). Moreover, the comparison of the models in the out-of-sample data shows that both the MLP and the Logit outperform the Probit and Gompit models.

TABLE 6Table 6 summarizes the results with respect to the partial derivatives and the corresponding p-values for the different models considered. MLP's explanatory power converges to the one of the Logit model. The same does not apply for the rest of the models. For example, although the collision type seems to be significant in the MLP and Logit models, in the Probit and Gompit models this variable is not significant.

<Table 6>

Changes in speed and volume, number of blocked lanes and vehicles involved, as well as the upstream geometry are found critical regarding the probability of having a secondary incident, whereas changes in rainfall intensity does not greatly influence secondary incident likelihood. More specifically, results suggest that decreases in speed and increases in lane volume increase the probability of having a secondary incident. Moreover, an increase in rainfall may result in increased secondary incident likelihood. However, it should be noted that all rainfall incidents coinciding with incidents in the available database were light rain, limiting the model's transferability to heavier rain instances. Further, increased road geometry complexity upstream of a primary incident seems to increase the likelihood of having a secondary incident, and the probability of having a secondary incident is higher when the number of vehicles involved increases. The results also indicate that secondary incident likelihood is negatively related to changes in the number of lanes that are blocked due to the primary incident, to the existence of a curved section at the location of the primary incident, and the involvement of heavy vehicles (similar findings were reported by Zhang and Khattak, 2010). Interestingly, in all models, small changes in downstream geometry and duration of the incident were not found significant with respect to the likelihood of a secondary incident.

The joint consideration of both sensitivity measures is graphically depicted in Figure 2, where the x axis is the ranking of the variables using the partial derivatives measure *PD(x)* and the y axis represents the ranking of the variables using the mutual information measure *I(x)*. In Figure 2, two distinct areas are observed: the high contribution variables area and the area of variables whose small changes may impose changes to the probability of having a secondary accident.

<Figure 2>

As can be observed, the joint consideration - when using some expert knowledge to set the boundaries of high/low ranking - may clarify the ambiguities resulting for separately considering each influence measure separately. It also provides some useful managerial tools for alleviating the effects of a primary incident in traffic and, thus, in reducing the likelihood of having a secondary accident. From Figure 2 it is evident that it is important to know the speed and volume at the occurrence of the primary incident, the duration of the primary accident, and rainfall intensity to define the probability of having a secondary accident. Moreover, critical variables to the knowledge of the probability of secondary accidents are the number of blocked lanes and vehicles involved, and upstream geometry. Further, if one would like to reduce in the probability of having a secondary accident, he/she should focus on managerial actions that would lead to controlling the speed and volume in the area of the accident, shift the number of blocked lanes (primarily by speeding-up the clearance procedures), and redirecting heavy vehicles. The above joint consideration of the proposed influence measures may be used to identify and structure a set of action plans that may be used to mitigate the effects of primary incident on freeway operations.

CONCLUSIONS

Identifying influential roadway, traffic and incident characteristics that increase the likelihood of secondary incident occurrence is critical to the development and implementation of efficient traffic management strategies. This paper extended past knowledge by comparing different structures of MLPs to the classical statistical models such as Logit, Probit and Gompit models, for secondary incident likelihood modeling. The comparison focused on both the accuracy and the explanatory power of the models evaluated. Results indicate that the MLP with a logistic activation function that acts as a general Logit model, along with the Logit model, outperform the rest of the methods evaluated. Regarding influential factors, we found that traffic conditions at the occurrence of an incident as well as weather conditions in terms of rainfall, seem to significantly contribute to secondary accident occurrence. Changes in speed and volume, number of blocked lanes and percentage of heavy vehicles, as well as upstream geometry were found to significantly influence the probability of having a secondary incident, whereas changes in rainfall intensity do not critically influence secondary incident likelihood. Interestingly, for all models, changes in downstream geometry and duration of an incident were not found significant with respect to the likelihood of having a secondary incident.

From a methodological perspective, the paper contributes towards two distinct directions: first, it provides neural network models for transportation applications with tractable explanatory power, as well as a methodological framework for comparing neural network and classical statistical models. Second, the potential benefits of a decision making framework that describes which variables to monitor and how to change those variables in order to control the probability of having a secondary accidents are evaluated and discussed. The proposed neural network approach to modeling the secondary accident likelihood may be considered as a step forward to using neural networks as a transparent managerial tool for decision making and can be easily extended to other transportation applications.

ACKNOWLEDGEMENTS

Research in this paper was supported by the Basic Research fund of the National Technical University of Athens (Greece). The data used are a courtesy of Attica Tollway Operations Authority. The development and training of the different models was based on the codes found in McNelis P. (2005).

REFERENCES

Chen, C., Skabardonis, A. and Varaiya, P. (2004). Systematic Identification of Freeway Bottlenecks. In Transportation Research Record: Journal of the Transportation Research Board, 1867, *Transportation Research Board of the National Academies*, 46-52.

Cheng, B., and D.M. Titterington, Neural networks: a review from a statistical perspective. *Statistical Science* 9, 1994, 2–54.

Hirunyanitiwattana, W., and S. Mattingly. Identifying secondary crash characteristics for California highway system. CD-ROM. Transportation Research Board of the National Academies, Washington, D.C.,2006.

Karlaftis, M. G., and E. I. Vlahogianni. Statistics versus Neural Networks in Transportation Research: Differences, Similarities and Some Insights, Submitted to *Transportation Research Part C: Emerging Technologies*, Vol. 19, No. 3, 2011, pp. 387-399.

Karlaftis, M. G., S. Latoski, P. Richards, J. Nadine, and K. C. Sinha. ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes. *Journal of Intelligent Transportation Systems*, Vol. 5, No.1, 1999, 39-52.

Kerner, B., S., Rehborn, H., Aleksic, M. and Haug, A. (2004). Recognition and tracking of spatial–temporal congested traffic patterns on freeways, Transportation Research Part C: Emerging Technologies, 12(5), 369-400.

Khattak A., Wang, X., and Zhang H. (2009). Are incident durations and secondary incident occurrence interdependent? In Transportation Research Record 2099, 39-49.

Khattak, A. J., Wang, X., Zhang, H. and Cetin M. (2011). Primary and Secondary Incident Management: Predicting Durations in Real Time, Report No.: VCTIR 11-R11, April, Virginia Center for Transportation Innovation and Research, Charlottesville, VA.

Li, H. and Bertini, R. L. (2010). Comparison of Algorithms for Systematic Tracking of Patterns of Traffic Congestion on Freeways in Portland, Oregon, Transportation Research Record 2178, 101-110.

McNelis P. (2005). Neural Networks in Finance: Gaining Predictive Edge in the Market. January 2005. Elsevier Acadmic Press.

McNelis P., and P. McAdam. Forecasting Inflation with Forecast Combinations: Using Neural Networks in Policy, Complexity Hints for Economic Policy New Part V, Economic Windows, 2007,pp. 253-270, Springer Milan.

Moore, J.E., G. Giuliano, and S. Cho.Secondary Accident Rates on Los Angeles Freeways,*Journal of Transportation Engineering.* Vol.130, No. 3,2004, pp.280–285.

Orfanou, F. P., E. I. Vlahogianni, and M. G. Karlaftis. (2011). Detecting Secondary Accidents in Freeways.To Appear in the forthcoming 3rd International Conference on Road Safety and Simulation (RSS2011), Indianapolis, Indiana, September 14-16.

Papadokonstantakis, S., A. Lygeros, and S. P. Jacobsson. Comparison of recent methods for inference of variable influence in neural networks.*Neural Networks,* Vol.19, No. 4, 2006, pp. 500–513.

Raub, R. A. Secondary crashes: An important component ofroadway incident management, *Transportation Quarterly*, Vol. 51, No. 3,1997, pp. 93–104.

Sarle, W.S. Neural networks and statistical models. In: Proceedings of the Nineteenth Annual SAS Users Group International Conference (April 1–13), 1994.

Segond, M.-L., N.Neokleous, C.Makropoulos, C.Onof, andC.Maksimovic, (2007).Simulation and spatio-temporal disaggregation of multi-site rainfall data for urban drainage applications *Hydrological Sciences Journal*, Vol. 52, No. 5, 2007, pp. 917-935.

Sun, C., and V. Chilukuri. Dynamic Incident Progression Curve for Classifying Secondary Traffic Crashes.*Journal of Transportation Engineering*, Vol. 136, No. 12, 2010, pp. 1153-1158.

Tsirigotis, L., E.I. Vlahogianni, and M. G. Karlaftis. Does Information on Weather Affect the Performance of Short-term Traffic Forecasting Models? *Journal of Intelligent Transportation Systems Research*, Vol. 9, No. 3, 2011, forthcoming.

Tu, J. V. Advantages and Disadvantages of Using Artificial Neural Networks versus Logistic Regression for Predicting Medical Outcomes. *Journal of Clinical Epidemidemiology*, Vol. 49, No. 11, 1996, pp. 1225-1231.

Vlahogianni E., M.G. Karlaftis, J. C.Golias, and B. Halkias. Freeway Operations, Spatiotemporal Incident Characteristics and Secondary Crash Occurrence. In *Transportation Research Record: Journal of the Transportation Research Board*,No. 2178,Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 1-9.

Vlahogianni, E. I., Karlaftis, M. G, and Golias, J. C. (2005). Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach, Transportation Research Part C: Emerging Technologies, 13(3), 211-234.

Vlahogianni, E. I.,M. G. Karlaftis, and J. C. Golias. Statistical Methods for Detecting Nonlinearity and Non-Stationarity in Univariate Short-term Time-series of Traffic Volume.*Transportation Research Part C: Emerging Technologies*, Vol. 14, No. 5, 2006, pp. 351-367.

Washington, S.P., M.G.Karlaftis, F.L. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis - 2nd Edition*, Chapman & Hall / CRC Press, Boca Raton, FL, 2010.

Yang, Y., and Q.Zhang. A hierarchical analysis for rock engineering using artificial neural networks. *Rock Mechanics and Rock Engineering*, Vol. 30, No. 4, 1997, pp. 207–222.

Zhan, C., Gan, A., Hadi, M., (2009). Identifying Secondary Crashes and Their Contributing Factors, Transportation Research Record: Journal of the Transportation Research Board, 2102, 68-75.

Zhan, C., L. Shen, M. Hadi, and A. Gan. “Understanding the characteristic of secondary crashes on freeways,” CD-ROM. Transportation Research Board of the National Academies, Washington, D.C., 2008.

Zhang, H. and Khattak. A. (2001). What Is the Role of Multiple Secondary Incidents in Traffic Operations?*Journal of Transportation Engineering*, 136(11), 986-997.

Zobel, C. W. and D. F.Cook. (2011). Evaluation of neural network variable influence measures for process control, Journal of Engineering Applications of Artificial Intelligence, 24(5), 803-812.

TABLE 1: Interpretation of the joint consideration of partial derivatives and mutual information on the impact of each input variable on the output.

		Partial Derivative	
		High	*Low*
Mutual Information	*High*	Small changes in the variable’s value can have a high impact on the magnitude of the response. The variable has a high contribution to the response value.	Small changes in the variable’s value have limited or no effect on the magnitude of the response, but its absence would have a large impact.
	Low	Although the variable contributes less to the magnitude of the response, changes to the variable’s value might have an impact on the magnitude of the response.	The variable has low contribution to the response, and offer limited opportunity to effect change to the magnitude of the response.

TABLE 2: Description of the input variables.

Variable	Type	Description
Duration	Continuous	The incident duration in minutes
Collision Type	Categorical	0 to 4, from less to more severe
Nr. Lanes	Categorical	1 to 3, 1:1 lane, 2: two, 3: more than 2
Nr. Vehicles	Categorical	1 to 3, 1:one vehicle, 2: two vehicles, 3: more than 2 vehicles involved
Heavy Vehicle	Categorical	0 to 1(Heavy Vehicle involved)
Travel Speed	Continuous	Travel speed (km/h) at the occurrence of the incident
Hourly volume	Continuous	Hourly volume (veh/h/lane) at the occurrence of the incident
Rainfall	Continuous	Rainfall at the occurrence of the incident in mm/10min
Alignment	Categorical	0 to 1(curve)
Downstream Geometry	Categorical	0 to 4, 0: no special geometry, 1: adjacent to tunnel, 2: adjacent to toll, 3: adjacent to entrance/exit, 4: more than one
Upstream Geometry	Categorical	0 to 4, 0: no special geometry, 1: adjacent to tunnel, 2: adjacent to toll, 3: adjacent to entrance/exit, 4: more than one

TABLE 3: Variable contribution to the incident category *y* with respect to the conditional mutual information.

Variable	$I(Y \mid \vec{X})$	Normalized $I(Y \mid \vec{X})$
Speed	0.17	1.00
Duration	0.12	0.72
Hourly volume	0.12	0.69
Rainfall	0.11	0.67
Nr. Vehicles	0.09	0.51
Upstream Geometry	0.08	0.45
Nr. Lanes	0.08	0.45
Collision Type	0.07	0.39
Alignment	0.07	0.38
Heavy Vehicle	0.06	0.33
Downstream Geometry	0.05	0.27

TABLE 4: Error percentages for in-sample classification.

Model[1]	Likelihood	False Positive	False Negative	Weighted Average
MLP(11-6-2)	425.52	0.037	0.091	0.064
MLP(11-12-2)	425.52	0.036	0.091	0.064
Logit	425.52	0.037	0.091	0.064
Probit	428.99	0.037	0.090	0.063
Gompit	442.96	0.040	0.090	0.065

[1] *The numbers in parentheses signify the number of neurons of the input, hidden and output layerof the MLP.*

TABLE 5: Error Percentages for out-of-sample forecasting.

Model[1]	False Positive	False Negative	Weighted Average
MLP(11-6-2)	0.042	0.102	0.072
MLP(11-12-2)	0.050	0.089	0.069
Logit	0.042	0.102	0.072
Probit	0.705	0.002	0.353
Gompit	0.764	0.000	0.382

[1] *The numbers in parentheses signify the number of neurons of the input, hidden and output layer of the MLP.*

TABLE 6: Input variable significance with respect to partial derivatives and p-values[1].

Variable	Partial Derivative (p-value)			
	MLP(11-12-2)[2]	Logit	Probit	Gompit
Duration	0.014*	0.014*	0.012	0.013
Collision Type	0.023*	0.023*	0.019	0.014
Nr. Lanes	0.065**	0.065**	0.065**	0.061**
Nr. Vehicles	0.063**	0.062**	0.071**	0.073**
Heavy Vehicles	0.091**	0.091**	0.094**	0.094**
Speed	-0.098**	-0.097**	-0.089**	-0.068**
Lane Volume	0.053**	0.053**	0.053**	0.053**
Rainfall	0.021**	0.018**	0.030**	0.039**
Alignment	0.033**	0.036**	0.039**	0.037**
Downstream Geometry	0.003	0.003	0.003	0.001
Upstream Geometry	0.034**	0.035**	0.032**	0.026**

[1] *Significance is calculated from bootstrapped distributions*
[2] *The numbers in parentheses signify the number of neurons of the input, hidden and output layer.*
**significance at 95% level, ** significance at 99%level*

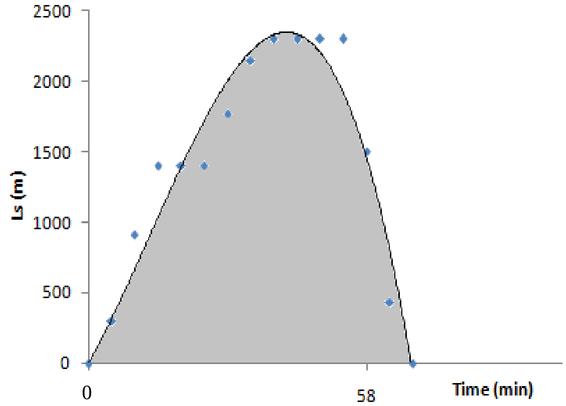

FIGURE 1: Boundaries of the length L_s of the influence area upstream of an incident with duration equal to 58 min using as proposed method of analysis based on the ASDA algorithm.

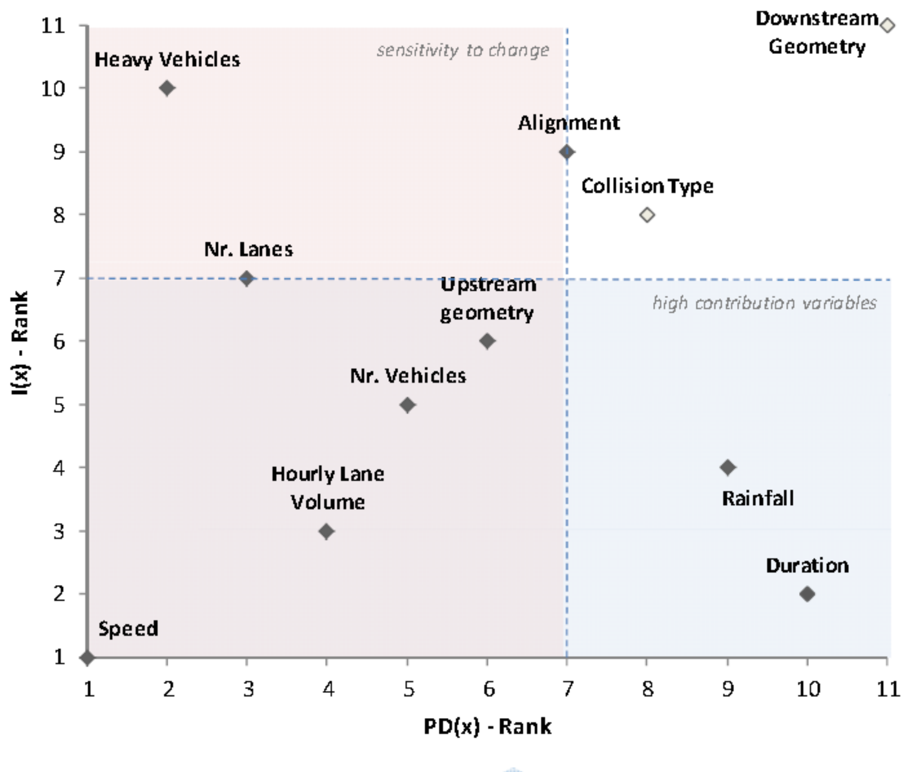

FIGURE 2: Graphical representation of the influence of input variable with regards to the partial derivative versus the inputs' influence based on the conditional mutual information.