# Stochastic Cusp Catastrophe Models with Traffic and Weather Data for Crash Severity Analysis on Urban Arterials Athanasios Theofilatos, George Yannis, Eleni Vlahogianni, John Golias

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# Introduction

- The effective treatment of crashes and the proactive transportation safety is a major concern
- Much research that utilized real-time collected traffic and weather data in freeways has beer
- Crash injury severity is underrepresented.
- Alternative modeling techniques should also be considered.

# **Objectives**

- The main objective is to propose cusp catastrophe models for modeling crash injury set
- Cusp catastrophe models are applied and compared with traditional statistical models.
- The potential existence of non-linearity in the system is examined.
- Real-time traffic and weather data from two major urban arterials in Athens, Greece are con
- The findings of the study are expected to extend previous research and add to current know

### Data preparation

Within this research, a large collection and processing of data took place:

- The available dataset refers to the period 2006-2011 and come from two high demand urba of Athens (Greece).
- $\checkmark$  These two arterials have similar geometrical and traffic characteristics.
- Crash data were collected from the Greek accident database, SANTRA, which is pro Technical University of Athens.
- ✓ Traffic data were extracted from the Traffic Management Centre (TMC) of Athens, which since 2004 and covers several major roads in Athens. The TMC data included traffic flow time speed every 1 minute.
- $\checkmark$  Traffic data from the adjacent upstream loop detector were considered.
- Data were further aggregated to 1-hour traffic information to obtain averages, standard dev to a crash occurrence.
- ✓ Weather data were collected from the Hydrological Observatory of Athens, which is database, covering more than 10 meteorological stations located in the greater Athens area.
- ✓ Data include rainfall, temperature, relative humidity, solar radiation, wind direction and wind Each crash case was assigned to the closest meteorological station and then the relevant
- extracted.
- $\checkmark$  The 10-min raw weather data were aggregated over hour in order to obtain maxima, deviations, in the time-slice of 1-hour, 2-hours, 6-hours and 12-hours prior to the time of the
- Crash severity is defined in two ways:

Severity\_1 =  $\frac{Number \ of \ severely \ injured \ and \ killed}{1}$ Total number of persons invovled

Severity\_2 =  $\frac{Total number of persons invovled}{Total number of vehicles involved}$ 

## Method of Analysis

- The core analysis of this study is the **catastrophe theory.**
- **Cusp catastrophe** models are the most widely applied.

 Catastrophe theory examines the qualitative changes in the behavior of systems when the control factors that influence their behavioral state face smooth and gradual changes

- It assumes the existence of a dynamic system
- It explains the sudden transition between the system states.
- Two critical control parameters exist, namely  $\alpha$  and  $\beta$ :
- $\alpha = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_n X_n$
- $\beta = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_n X_n$



Note: Figure by <u>Tao et al. 2013</u>, A cusp catastrophe model of mid-long-term landslide evolution over low latitude highlands of China. Geomorphology 187 (2013) 80–85. Copyright 2013, Elsevier. Under the Creative Common License.

where  $X_1, X_2, \dots, X_n$  is a set of measured independent variables

- The dependent variable can be a combination of other dependent variables  $Y_1, Y_2, \dots, Y_n$
- $y = w_0 + w_1 Y_1 + w_2 Y_2 + \dots + w_n Y_n.$
- Due to the nature of the dependent variable (censored) the traditional linear regression model is not appropriate
- Comparison of results with the cusp models will reveal potential non-linearity in the system.

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n to societies.								
n carried out recently.	<ul> <li>Descriptive sta</li> </ul>	tistics						
		Variable	Description			Unit	Mean	Std. deviation
		Severity_1	Number of severely Total number of pers	injured and kill sons involved	ed divided by	unitless	0.086	0.259
		Severity 2	Total number of pers	sons involved o involved	livided by Total	unitless	0.885	0.500
			Acc.Type1 (Off road)	/Fixed object/C	Other)	unitless		155*
everity.		Acc.Type	Acc. Type2 (Head-or Acc. Type3 (Rear-en	ו) d)		unitless unitless		36* 73*
			Acc.Type4 (Side)	,		unitless		53*
		O avg 1h up	Acc.Type5 (Sideswi	pe) Jane unstream		unitless veb/bour/lane	810 /50	36* 301 719
		Q_avg_m_up Q_stdev_1h_up	1h st.deviation of flor	w per lane ups	tream	veh/hour/lane	264.330	339.374
		Q_median_1h_up	1h median of flow pe	er lane upstrear	n	veh/hour/lane	628.600	437.337
nsidered.		Q_cv_1h_up V_avg_1h_up	1h coefficient of varia	ation of flow pe instream	r lane upstream	unitless km/h	0.109 47 340	0.085 18 959
		V_stdev_1h_up	1h st.deviation of sp	eed upstream		km/h	5.333	5.591
vledge.		V_cv_1h_up	1h coefficient of varia	ation of speed	upstream	unitless	0.154 15 720	0.175
		Occ_avg_m_up Occ_stdev_1h_up	1h st.deviation of oc	cupancy upstream	am	percentage %	4.097	4.917
		Occ_cv_1h_up	1h coefficient of varia	ation of occupa	ncy upstream	unitless	0.248	0.216
		T_1h_max	1h maximum temper	rature		°C	19.240	7.710
an arterials in the center		T_1h_avg	1h average tempera	ture		°C ℃	18.700	7.714
		Rain 1h sum	Th sum of rainfall	nperature		mm	0.397	0.335
		Rain_1h_st.dev	1h st.deviation of rai	nfall		mm	0.004	0.031
		Rain_2h_sum	2h sum of rainfall			mm	0.068	0.618
ovided by the National		Rain_2n_st.dev	6h sum of rainfall			mm	0.152	0.094
		Rain_6h_st.dev	6h st.deviation of rai	nfall		mm	0.013	0.083
has been in operation		Rain_12h_sum Rain_12h_st.dev	12h sum of rainfall 12h st deviation of ra	ainfall		mm mm	0.252 0.014	1.142 0.068
v, traffic occupancy and		W.Sp_1h_max	1h maximum wind sp	beed		m/sec	2.759	1.836
		W.Sp_1h_avg	1h average wind spe	eed		m/sec	2.204	1.688
		W.Sp_1h_stdev	1h st.deviation of wir	nd speed		m/sec	0.387	0.223
viations and so on, prior		Sol_1h_max Sol_1h_avg * Distribution of crash tv	1h average solar rac	liation		W/m <sup>2</sup>	307.550	321.884
an online open-access	Severity_1 (Numb	per Of Severely	y Injured and <b>F</b>	Killed By 1	Total Numbe	er Of Perso	ns Invo	olved)
speed.	Cusp catastrop	he						
weather data had to be	Assymetry factor a	Variable	Coefficient	Std. error	p-value	∞ - <b>Г</b> ~		8)
	a <sub>0</sub>	Constant term	ı -0.200	0.093	0.032**			200
averages and standard	a <sub>1</sub>	V_cv_1h_up	-0.720	0.372	0.052*	: <b>7</b> :0 <del>1</del>	$\sim$	
crash occurrence.	a <sub>2</sub>	Acc.type1	-0.417	0.228	0.067*	~ -	× ×	$\langle   \rangle$
	a1	Acc.type2	-0.280	0.144	0.052*	0		$\sim$
	a	Acc type3	-1 021	0 420	0 015**	p		
	9 <sub>4</sub>	Acc type4	-0.493	0.286	0.084*	9 -		
		W Sn 1h ma	v 0.068	0.032	0.031**	-		
	ся <sub>6</sub>	w.op_m_ma	A -0.000	0.002	0.001			
	Bifurcation factor β					-6	4 -2	å <sup>2</sup>
	b0	Constant term	-	-	-			
	b1	log(Q_avg_1l	n_up) 0.755	0.034	0.000**			
	Dependent variable y							
	w0	Constant term	-2.342	0.047	0.000**	]		K
A'B'	w1	Severity_1	4.732	0.101	0.000**			a t
Catastrophe	McFadden R <sup>2</sup>	0,789				Ļ		
	pseudo-R <sup>2</sup>	0.845						1 million
	Logistic model R <sup>2</sup>	0.095					\	$\square$
		0.000					¥	• • • • • • • • • • • • • • • • • • •

\*\*=95% significance level

\*=90% significance level

### Censored regression

Variable	Coefficient	Std.error	p-value
Constant term	7.078	2.943	0.016**
V_cv_1h_up	-1.975	1.627	0.225
Acc.Type1	-1.731	1.049	0.098*
Acc.Type2	-1.225	0.712	0.085*
Acc.Type3	-12.729	563.132	0.982
Acc.Type4	-1.763	1.075	0.101
W.Sp_1h_max	-0.302	0.169	0.074*
log(Q_avg_1h_up)	-1.312	0.498	0.008**
Madalla R <sup>2</sup>	0.119		

\*\*=95% significance level

\*=90% significance level

Control Panel



# Findings

# Severity\_2 (Total Number Of Persons Involved By Total Number Of Vehicles Involved)

### • Cusp catastrophe

Assymetry factor a	Variable
a <sub>0</sub>	Constant term
a <sub>1</sub>	V_cv_1h_up
a <sub>2</sub>	log(Q_avg_1h_up
a <sub>3</sub>	Sol_1h_max
Bifurcation factor β	
b <sub>0</sub>	Constant term
b <sub>1</sub>	Acc.Type1
b <sub>2</sub>	Acc.Type2
b <sub>3</sub>	Acc.Type3
b <sub>4</sub>	Acc.Type4
Dependent variable v	
w0	Constant term
w1	Severity_2
McFadden R <sup>2</sup>	0.251
pseudo-R <sup>2</sup>	0.303
Logistic model R <sup>2</sup>	0.313
**=95% significance level	
*=90% significance level	

### Censored regression

Variable Constant term V\_cv\_1h\_up log(Q\_avg\_1h\_ Sol\_1h\_max Acc.Type1 Acc.Type2 Acc.Type3 Acc.Type4 Madalla  $R^2$ 

\*=90% significance level

# **Conclusions - Discussion**

- Promising fit of the cusp models.
- and independent variables for Severity\_1.
- The cusp catastrophe model is superior for Severity\_1.
- sudden changes to crash severity.
- All crash cases lie inside the instability area.
- model does not outperform the traditional linear model.
- crash (Severity\_2), it seems that the linearity of the system is preserved.
- be nonlinear in nature.

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	Coefficient	Std.error	p-value
	1.484	0.291	0.000**
	0.057	0.132	0.663
up)	-0.041	0.000	0.367
	0.000	0.000	0.009**
	-0.259	0.078	0.000**
	-0.500	0.060	0.000**
	-0.571	0.068	0.000**
	-0.543	0.078	0.000**
	0.300		

\*\*=95% significance level

• Possible evidence of presence of cusp and imply strong nonlinear relationships between crash injury severity

• It is found that small changes to crash type, maximum wind speed, traffic flow and variation of speed leads to

• For Severity\_2, the cusp model has a reasonable fit but is not superior to the traditional linear models.

• Although some traffic and weather variables have strong non-linear relationships with crash severity, the cusp

• When severity is expressed as the number of severely injured and killed divided by the total number of persons involved in a crash (Severity\_1), the safety system is highly non-linear and sudden transitions from unsafe (high severity) to safe regions (low severity), due to small changes of traffic and weather parameters.

• When severity is expressed as the total number of persons involved by total number of vehicles involved in the

• The findings indicate that the dynamic change in urban road safety levels expressed by crash severity is likely to