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Time series modeling in traffic safety research

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ABSTRACT

The use of statistical models for analyzing traffic safety (crash) data has been well-established. However, time series techniques have traditionally been underrepresented in the corresponding literature, due to challenges in data collection, along with a limited knowledge of proper methodology. In recent years, new types of high-resolution traffic safety data, especially in measuring driver behavior, have made time series modeling techniques an increasingly salient topic of study. Yet there remains a dearth of information to guide analysts in their use. This paper provides an overview of the state of the art in using time series models in traffic safety research, and discusses some of the fundamental techniques and considerations in classic time series modeling. It also presents ongoing and future opportunities for expanding the use of time series models, and explores newer modeling techniques, including computational intelligence models, which hold promise in effectively handling ever-larger data sets. The information contained herein is meant to guide safety researchers in understanding this broad area of transportation data analysis, and provide a framework for understanding safety trends that can influence policy-making.

1. Study objectives and methodology

Within transportation safety research (herein referred to as traffic safety research), data modeling has long been dominated by cross-sectional methods. These models consider the combined effects of various external factors on one or more safety measures within a single period. Despite their ubiquity, however, cross-sectional models can misinterpret the effects of a variable observed repeatedly over time − so-called “time series” data. Time series models, by contrast, facilitate the study of longitudinal changes in crash exposure, crash risk, and crash outcomes for a single subject (or group of subjects), to better establish estimates of their future values. For this reason, time series analysis is a powerful tool for analyzing transportation and traffic engineering datasets that may include an underlying temporal structure (Chatfield, 2010).

The use of time series models in traffic safety research is scarce, relative to the use of cross-sectional models. This may be attributed to numerous factors, including the lack of relevant data, as well as the complexity in the data structures of the safety issues in question. Nevertheless, in the current age where detailed real-time or near-real-time information may be acquired for individual vehicles or infrastructure elements at low cost, time-series modeling is well suited to lend a new perspective on classic safety issues.

Within the larger body of traffic safety research, there are several areas that have seen modest use of time series methodological techniques. These areas include, but are not necessarily limited to, driver behavior and education, pedestrian safety, alcohol use and driving, and roadway environmental factors. This paper critically reviews the current literature on time series analysis in these areas, details some of the common challenges in applying time series models, and explores future directions for data and methodological development.

The methodological strategy used for this publication was a non-exhaustive search of various peer-reviewed journals pertaining to traffic safety, economics, and human factors. From this review, publications which used time series analysis as their primary methodological component were catalogued, and the different elements of the research were identified. The following elements were used to categorize each reviewed publication:

- Research Topic
- Modeling Methodology
- Surrogate Measure of Safety (i.e., the response variable)
- Geographic Scope of Analysis
- Time Scale/Interval of Collected Data

The results of this identification process are a select number of publications, 53 in total, contained in Table 1. Note that not every

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Table 1
Overview of case studies in time series modeling in transportation safety research.

Author Year	Study Period	Topic								Method							
		Alcohol Use	Photo Enforcement	Safety Belt Use	Speed Limits	Weather Impacts	Pedestrians	Driver Behavior	Other	ARIMA	ARCH/GARCH	GLM	SEM	VAR	Frequency Domain	Comp. Intelligence	Markov
Abdel-Aty and Abdalla (2004)	1999				X												
Ahangari et al. (2016)	1990–2010								X			X					
Ameen, et al. (2001)	1978–1995								X			X					
Bergel-Hayat et al. (2013)	1975–2005					X							X				
Blose and Holder (1987)	1973–1982	X								X							
Boroujerdian et al. (2014)	2004–2007														X		
Brijs et al. (2008)	2001					X											
	2004–2013								X								
Campbell et al. (1991)	1984–1988			X						X			X				
Carnis and Blais (2013)	1999–2010		X							X							
Chi et al. (2013)	1998–2007								X								
Commandeur et al. (2013)	1969–1985								X	X							
Figlio (1995)	1976–1993	X								X							
Foss et al. (2001)	1991–1996	X											X				
García-Ferrer et al. (2006)	1975–2003	X								X							
Giuffre (2014)	2006–2012								X								
Hadayeghi (2007)	2000–2004		X														
Holder and Blose (1987)	1973–1982	X								X							
Holder and Wagenaar (1994)	1976–1989	X								X							
Houston and Richardson (2002)	1988–1997			X						X							
Huitema et al. (2014)	2001–2010							X									
Ko et al. (2004)	2003							X			X						
Kopits et al. (2005)	1963–1999								X			X					
Kweon et al. (2009)	1980–2005						X										
Lavoie (2017)	2001–2013	X															
Lord and Persaud (2000)	1990–1995								X								
Lu (1992)	*Not stated*								X						X		
Ma (2010)	2004–2007				X		X		X								
Malyshkina et al. (2009)	1995–1999					X											X
Masten (2007)	1994–2004			X						X							

(continued on next page)

Table 1 (*continued*)

Author Year	Study Period	Topic								Method							
		Alcohol Use	Photo Enforcement	Safety Belt Use	Speed Limits	Weather Impacts	Pedestrians	Driver Behavior	Other	ARIMA	ARCH/ GARCH	GLM	SEM	VAR	Frequency Domain	Comp. Intelligence	Markov
Masten et al. (2013)	1986–2011								X								
Meyerhoff (1977)	1973–1974								X						X		
Neyens et al. (2008)	1995–2005								X	X							
Quddus (2008)	1950–2005							X		X							
Quddus (2016)	2009–2014								X	X							
Ray (1989)	1978–1985	X							X			X					
Rock (1995)	1982–1991				X					X							
Sandt (2016)	2013–2014						X										
Scuffham and Langley (2002)	1970–1994								X				X				
Sebego et al. (2014)	2004–2011	X								X		X					
Serhiyenko et al. (2014)	1995–2009						X							X			
Tefft (2014)	1986–2011			X													
Thomas et al. (2011)	2009			X													
Vaca (2016)	2009	X															
Vanlaar et al. (2014)	1994–2008		X							X							
Vernon et al. (2004)	1992–1999				X					X							
Vingilis et al. (2005)	1992–1998	X										X					
Wagenaar et al. (1988)	1976–1986			X						X							
Wagenaar and Margolis (1990)	1980–1986			X						X							
Wagenaar et al. (2007)	1976–2002	X								X							
Zaki and Sayed (2013)	*Not stated*								X						X		
Zhang, et al. (2011)	2010	X													X		
Zhang, et al. (2013)	2012					X								X			

Author Year	Study Period	Method	Measure			Scope				Data Time Scale							
		GEE	Crash Frequency	Crash Severity	Other	International	National	State	Local	Second	Hour	Day	Week	Month	Quarter	Year	Other
Abdel-Aty and Abdalla (2004)	1999	X	X					X									x

(*continued on next page*)

Table 1 (*continued*)

Author Year	Study Period	Method	Measure			Scope				Data Time Scale							
		GEE	Crash Frequency	Crash Severity	Other	Internati-onal	National	State	Local	Second	Hour	Day	Week	Month	Quarter	Year	Other
Ahangari et al. (2016)	1990–2010		X			X	X					X					
Ameen, et al. (2001)	1978–1995		X			X						X					
Bergel-Hayat et al. (2013)	1975–2005		X			X			X					X			
Blose and Holder (1987)	1973–1982		X					X						X			
Boroujerdian et al. (2014)	2004–2007		X						X								X
Brijs et al. (2008)	2001		X			X						X					
	2004–2013			X		X						X					
Campbell et al. (1991)	1984–1988		X	X				X						X			
Carnis and Blais (2013)	1999–2010		X				X							X			
Chi et al. (2013)	1998–2007		X					X						X			
Commandeur et al. (2013)	1969–1985		X			X						X					
Figlio (1995)	1976–1993		X					X	X					X		X	
Foss et al. (2001)	1991–1996		X					X						X			
García-Ferrer et al. (2006)	1975–2003		X	X			X							X			
Giuffre (2014)	2006–2012	X	X			X										X	
Hadayeghi (2007)	2000–2004	X			X	X										X	
Holder and Blose (1987)	1973–1982							X						X			
Holder and Wagenaar (1994)	1976–1989		X					X						X			
Houston and Richardson (2002)	1988–1997		X	X				X						X			
Huitema et al. (2014)	2001–2010		X						X					X			
Ko et al. (2004)	2003							X		X							
Kopits et al. (2005)	1963–1999		X			X										X	
Kweon et al. (2009)	1980–2005		X					X								X	
Lavoie (2017)	2001–2013	X			X			X									
Lord and Persaud (2000)	1990–1995	X	X			X										X	
Lu (1992)	*Not stated*							X		X							
Ma (2010)	2004–2007	X		X		X										X	
Malyshkina et al. (2009)	1995–1999		X					X					X				
Masten (2007)	1994–2004		X					X						X			
Masten et al. (2013)	1986–2011	X	X				X								X		
Meyerhoff (1977)	1973–1974			X			X				X						
Neyens et al. (2008)	1995–2005		X					X						X			

(*continued on next page*)

Table 1 (*continued*)

Author Year	Study Period	Method	Measure			Scope				Data Time Scale							
		GEE	Crash Frequency	Crash Severity	Other	Internati-onal	National	State	Local	Second	Hour	Day	Week	Month	Quarter	Year	Other
Quddus (2008)	1950–2005		X			X										X	
Quddus (2016)	2009–2014		X			X							X	X			
Ray (1989)	1978–1985		X					x						x			
Rock (1995)	1982–1991							X						X			
Sandt (2016)	2013–2014	X			X			X									X
Scuffham and Langley (2002)	1970–1994		X				X								X		
Sebego et al. (2014)	2004–2011						X							X			
Serhiyenko et al. (2014)	1995–2009			X				X						X			
Tefft (2014)	1986–2011	X	X				X									X	
Thomas et al. (2011)	2009	X			X			X									X
Vaca (2016)	2009	X			X		X										X
Vanlaar et al. (2014)	1994–2008		X						X					X			
Vernon et al. (2004)	1992–1999							X								X	
Vingilis et al. (2005)	1992–1998							X						X			
Wagenaar et al. (1988)	1976–1986							X						X			
Wagenaar and Margolis (1990)	1980–1986							X						X			
Wagenaar et al. (2007)	1976–2002							X						X			
Zaki and Sayed (2013)	*Not stated*								X								X
Zhang, et al. (2011)	2010								X	X							
Zhang, et al. (2013)	2012						X					X					

reviewed publication is included in this table. For example, numerous published papers on safety have utilized some form of the autoregressive integrated moving average (ARIMA) methodology. The intent of cataloguing a select few of those publications is to highlight the methodology as a commonly used tool within time series analysis and traffic safety, as well as to underscore the research topic(s) that have most prominently benefited from its use.

The intent of this cataloguing and review process is to identify commonly cited time series methodological tools and techniques; consequently, the goal is for this publication to serve as a starting point in understanding how to apply time series analysis in traffic safety research. Its audience is those who understand basic elements of econometric modeling, but have not previously used time series models in research data analysis. A particular focus for this audience is on the use of so-called "classic" time series models, which are based on a series of exogenous and endogenous variables drawn from historic data, and follow similar conventions with many other econometric models. All concepts and modeling techniques contained herein reference extensive outside publications, to provide the reader with a path to deeper understanding of individual techniques.

2. Time series models: the 20,000-foot level

Principal considerations in modeling for traffic safety include understanding safety-related phenomena, as well as acquiring proactive (and actionable) insight into the factors affecting traffic safety. Traffic safety modeling for planning and policy-making may entail a high degree of complexity, especially in the preliminary stages of concept formulation and model selection. This is because many safety phenomena entail strong behavioral and cognitive aspects that are difficult to isolate; for example, consider the set of safety issues related to the driving task. Each driver/rider has their personal stock of values, ideas, and practices, reflecting rigorously on their behavior on the road; this includes braking, passing, and so on, and may not always converge to "typical rider behavior" (Vlahogianni et al., 2013; Wang et al., 2013). These complex interrelationships frequently evolve over time, and may reflect irregular and strongly nonlinear observations of measured indicators and influential factors. In this framework, time series modeling can be viewed as a tool for revealing the underlying mechanism of such complex phenomena, as well to forecast future outcomes of these relationships.

Time series data consist of one or more series of repeated observations on a single subject, with the nature of the observations (particularly those data elements matching with a phenomenon, or dependent variable, of interest) guiding appropriate modeling technique(s). Typically, each observation is dependent on its own past observations, otherwise referred to as serial correlation (Washington et al., 2011). Serial correlation may be present in various forms, including univariate (autocorrelation), multivariate (cross-correlation), or some combination of the two. This serial dependency may also change with time and space. For cross-sectional econometric models, serial correlation is frequently problematic. This is because basic modeling and estimation techniques, such as ordinary least squares (OLS) linear regression, assume independence of error terms. If observations in the data are correlated, then the error terms resulting from a model built around that data will also be correlated (recall that the output for any econometric model is an estimated, or predicted, value, differing from its observed value by the amount of the error term). This correlation of errors can lead to incorrect model inferences and an overstating of the significance of certain variables. The ability to demonstrate accurate, reliable, and defensible relationships between variables that exhibit serial correlation is one of the major advantages of time series models.

2.1. The "Big two": time domain & frequency domain models

On the question of serial correlation, there is some ambiguity as to what is meant by an observed sample being reliant on "past" observations. While this can refer to an observation (or series of observations) that was made at an earlier point in time, it can also refer to dependence on observations in a different part of the frequency spectrum (as is the case with periodic phenomena, such as traffic volumes, which cycle through a limited range of values). Depending on this definition, time series models are can fall within one of several "domains".

One such category is the *time domain*. Time-domain models estimate patterns in the data as a function of time, and include past observations of the dependent variable as regressors (Shumway and Stoffer, 2010). Note here that *regressor* is not used interchangeably with *exogenous variable* − the typical convention in most time domain models is to refer to exogenous, or truly independent, variables separately from variables that are based on past observations of the phenomena being modeled. These past observations are referred to as *lagged variables*. Time-domain techniques comprise most existing time series modeling in traffic safety literature, largely due to their (relative) ease of application, as well as the intuitiveness of the results.

In contrast to time domain models, *frequency domain* models consider specific phenomena over a range of observed magnitudes or frequencies (as opposed to a range of time periods). Frequency domain models are especially popular in traffic operations research, where traffic patterns follow predictable daily or weekly fluctuations, but have found limited foothold in traffic safety literature (Washington et al., 2011). Frequency domain outputs can be converted to time domain outputs using a variety of transformations. The most widely used of these is the Fourier transform; the reader is referred to external literature for its use (Cohen, 1994).

3. Current applications & methodological approaches

To date, time series methods in traffic safety research have largely focused on the effects of driver risk factors or policies on some surrogate measure of safety (e.g., crash rates, frequency, or severity). Such policies include the implementation of laws meant to discourage driving while intoxicated or not wearing a seat belt. Historical crash frequencies are often used to assess the impact of these laws, *ceteris paribus* − that is, with all other factors held constant. In practice, this assumption is necessary, but often overly-restrictive; it is beyond the capacity of the researcher to control all external factors associated with crash risk, given the wide-ranging nature of such influences. However, such an assumption allows the researcher to make reasonable inferences about policy implications, in the face of a variety of unknown covariates.

The reliance on the *ceteris paribus* assumption is particularly strong in time-domain models, such as autoregressive moving average (ARMA) and ARIMA methods. The implicit limitations have also prompted the development of methodologies that can better account for the inherent stochastic nature of multiple variables simultaneously, such as vector autoregression (VAR) models.

Table 1 summarizes existing literature to provide some guidance in the selection of appropriate modeling techniques based on the data collected. It considers the general subject of the research (e.g., speeding, enforcement, alcohol use), the scope of implementation (international, national, state and local), the safety measure considered (crash frequency or severity), the available data resolution (daily, monthly, annually), and finally, the modeling technique used. The following sections layout some of the most common applications for time series analysis in traffic safety research, grouped by subject area, data type, and methodology. The descriptions of these application areas are necessarily brief, and the reader is directed to the cited literature for detailed information around the methodological techniques and steps for analysis.

3.1. Driver behavior & education research

In this area of research, researchers attempt to model the relationships between safety measures, such as crash rates or crash counts, and one or more driver behaviors (e.g., speeding, seat belt use). Typically, of primary interest is the effect of some external policy or law enforcement change intended to alter driver behavior, oftentimes for the sake of improved safety. Data collected with this objective in mind tends to lend itself well to time series analysis, since in the absence of these external influences, driver behavior tends to remain the same over time (controlling for certain socioeconomic characteristics, such as age or income). The resultant time series models often establish a "before" period of data collection, including the period in which the policy shift occurs, and continue to collect data for some period "after" the new policy is enacted. Traditionally, ARMA and ARIMA models have found success here. For example, ARIMA models have been used extensively in safety belt studies to investigate the effects of switching from secondary to primary enforcement. These models tend to consider monthly counts of crashes or fatalities as a surrogate measure for traffic safety (Houston and Richardson, 2002; Masten, 2007; Wagenaar et al., 1988). Other studies have considered changes in hospital admissions following a mandatory safety belt law (Wagenaar and Margolis, 1990). ARIMA methods have also been used for studies on speed limit changes (Rock, 1995; Vernon et al., 2004), pedestrian stop vs. yield policies at crosswalks and intersections (Kweon et al., 2009), the implementation of photo enforcement at intersections (Carnis and Blais, 2013; Vanlaar et al., 2014), and enhanced driver licensing policies (Neyens et al., 2008).

Like single-equation autoregressive methods, simultaneous equation models, such as VAR, are increasingly being used as computational power becomes less of an issue. Past studies using VAR include the investigation of changes in pedestrian crash injury levels (Serhiyenko et al., 2014), along with the modeling of global trends in traffic safety to separate general technological innovations from country-specific policy effects (Beenstock and Gafni, 2000).

The effects of graduated driver licensing and education on traffic safety has also been a topic of exploration for time series analysis. One particular area of recent development in assessing these effects has been the use of generalized estimating equations (GEEs). GEEs are a semi-parametric extension of generalized linear models (GLM) used when there are possible unknown correlations between dependent variables. Unlike random effects panel models, GEE estimates the average response of the population to a particular treatment rather than predicting the effect of a treatment on an individual (Lord and Persaud, 2000; Wang, 2014). Because the GEE is not likelihood based, one can use quasi-Akaike Information Criterion (QIC) to aid in model selection (Pan, 2001). Most commonly found in the public health literature, GEEs have also been argued to provide useful information on how driver education policies for teens and older drivers can affect the number of fatal crashes on the roadway (Masten et al., 2013; Tefft, 2014), as well as how various enforcement and community safety tools can improve driver behavior (Hadayeghi, 2007; Sandt, 2016; Thomas et al., 2011).

Last, some studies have used a combination of models to more accurately represent the data. Sebego et al. (2014) estimated a combination of ARIMA, Poisson and negative binomial regression models to examine the effect of several safety-related policies on crash rates and single-vehicle fatalities in Botswana (Sebego et al., 2014). Another study examined the effect of seatbelt laws in nine states on crash frequency using ARIMA and structural equation models (SEMs) (Campbell et al., 1991).

3.2. Alcohol-related crashes

Like behavior-based research on traffic safety, time series models have been used extensively to investigate the safety effects of legislative changes on alcohol consumption. Here, alcohol-related crash counts are often the dependent variable, although total crash counts or crash rates immediately before/after the policy intervention are sometimes considered. Such studies have examined the effects of adopting new liquor service policies (Blose and Holder, 1987; Holder and Blose, 1987; Holder and Wagenaar, 1994), shifts in the legal drinking age (Figlio, 1995; Wagenaar et al., 1988), and decreases in the legal blood alcohol content (BAC) for drivers (Wagenaar et al., 2007).

SEMs have also been used to assess the effects of various alcohol-related policies on driver behavior (Foss et al., 2001; Vingilis et al., 2005). It is important to note that SEMs differ from VAR; while VAR considers lagged observations of the dependent variables for multiple systems simultaneously, contemporaneous (or interactive) effects between these systems are not explicitly modeled, and instead are captured in the error terms. SEMs, by contrast, do not consider lagged observations of the dependent variable, but instead include the interaction variables for multiple systems directly in the model. Finally, a handful of studies have applied frequency domain analysis to examine driver and vehicle characteristics in drunk driving scenarios (Lu, 1992; Zhang et al., 2011).

Finally, in similar fashion to questions around the effectiveness of driver education programs and behavior, GEEs have found growing success in recent years when evaluating the impacts of alcohol use on traffic safety (Lavoie, 2017; Vaca, 2016)

3.3. Changing roadway environments

While a sizable portion of time series modeling in traffic safety research has focused on driver-level characteristics and behavior policies, there is another side of the traffic safety question that must be given due consideration: the effects of environmental and roadway design characteristics.

Some studies in this area have estimated autoregressive conditional heteroscedasticity (ARCH) models to focus on changes in driver behavior due to specific roadway environments and vehicle technologies. These factors often have a significant impact on not only mean values of safety indicators, but their variance over time as well − aka, heteroscedasticity (Bengtsson, 2001; Ko et al., 2004). A more advanced form of autoregressive model is the dual memory model, which includes both an ARIMA and generalized autoregressive conditional heteroscedasticity (GARCH) component; these models have been previously applied in traffic forecasting (Karlaftis and Vlahogianni, 2009).

Weather and road condition factors have also been explored using VAR techniques (Zhang et al., 2013). Similarly, SEMs have been used in the time series safety literature to assess the impacts of weather on crash counts (Bergel-Hayat et al., 2013), and the relationship between various economic indicators and crash fatalities (Scuffham and Langley, 2002). Similar to driver behavior and alcohol-related effects, GEEs have also been used to explore linkages between safety and roadway conditions (Abdel-Aty and Abdalla, 2004; Giuffre, 2014; Ma, 2010).

On the question of safety in a changing roadway environment, several types of frequency domain models, include spectral and wavelet analysis, have been utilized. This includes the identification of crash "hot spots" (Boroujerdian et al., 2014) and assessing the impact of daylight savings time on fatal crashes (Meyerhoff, 1977). More general applications of frequency domain analysis to vehicle trajectories, with safety implications in automated vehicle control and positioning systems, have also been explored (Zaki and Sayed, 2013). Other research has focused on examining temporal patterns associated with fatal crashes, to determine whether certain times of the day, week, or year are associated with a higher crash risk (Green, 1971).

4. Data considerations

Time series analyses, either univariate or multivariate, are dependent on the availability and quality of data with temporal structure; the lack of such data, or the inability to control their quality, may lead to erroneous results with far reaching implications to policy-making. Data errors may be due to specific collection mechanisms or general difficulty in monitoring the phenomena under study. Note that the term "data" used herein refers to quantitative data only; qualitative data must often be converted to some type of quantitative scale before it can be used in time series or most other types of econometric analyses (Washington et al., 2011).

4.1. Study design

As one explores time series analysis in traffic safety research, it is important to understand how different data collection methods can affect the quality of results, and for the researcher to be able to view the resultant analysis in the proper context and level of transferability. Failing to do so would attribute undue importance to results that may be based on subjective data, or otherwise draw erroneous conclusions and statements of certainty from what is invariably an empirical and dynamic process. For example, to develop effective crash safety countermeasures and policies, it is often beneficial to acquire high-resolution data for the full spectrum of the crash phenomenon (meaning pre-, during- and post- event information). However, researchers relying on conventional collection methods usually draw heavily on police reports that entail a subjective set of aggregated information deprived of critical exposure data. Such data are typically deprived of the necessary spatiotemporal coverage to support the use of proper time series methods. The risk of overreliance on such subjective data is that importance of certain environmental or behavioral factors may be overstated in the model, or conversely, that critical determinants in the crash injury process are missed (Mannering and Bhat, 2014).

Several particular data collection issues are worth mentioning. The first is that of naïve before/after data collection and analysis. In general, such a study is conducted by considering crash data at a single site or multiple sites for some period before and after the implementation of a safety countermeasure. While such an analytical approach may seem intuitive, in practice it suffers from issues such as regression-to-the-mean (RTM) and various biases through violation of the *ceteris paribus* assumption. As such, conclusions drawn from these kinds of studies, particularly those based on data modeled using time series techniques—where the challenge of holding other factors constant increases greatly with the passage of time—should be carefully considered. Detailed approaches and issues associated with before/after studies and data collection are widely documented in the traffic safety literature (AASHTO, 2010; Hauer, 1997, 1980; Maher and Mountain, 2009). Extensive past work has shown that the Empirical Bayes approach addresses RTM and small sample size problems by considering information from both a site in question (where data may be sparse) and a set of similar sites (where more data can be modeled to obtain an expected value) (Cheng and Washington, 2005; Gkritza et al., 2014; Hauer, 1996; Hauer et al., 2002; Persaud and Lyon, 2007)

Another potential alternative method of data collection and study design which is gaining use in the traffic safety field is that of the randomized controlled trial (RCT). These studies rely on the use of a treatment group and control group (which does not receive the "treatment"), with participants randomly assigned to either group to minimize the effects of any contemporaneous correlations in participant behaviors or environmental conditions. RCTs, even those which rely on the self-reporting of data, tend to result in fewer biases than those found in data collected through before/after studies (Boufous et al., 2010; Hauer, 1997).

4.2. Data gaps

A related challenge with developing data sources for time series analysis is the problem of unevenly-spaced (in time) observations. Many time series models assume that observations follow a regularly-spaced interval; however, real world data may not necessarily abide by this convention. A natural disaster, for example, could alter the availability of time series measurements on a transportation system within a short- or medium-term interval. Additionally, time series measurements of transportation data in many developing countries are only sporadically available. Furthermore, it may be that different phenomena of interest are measured using different time intervals.

To establish meaningful cause-and-effect relationships, these discrepancies in data availability must be addressed. One of the most common methods to fill in the missing data gaps is to use interpolation between known values in the time series data. However, the analyst must weigh this technique against the implications of using "estimated" data values rather than observed ones (which may have considerable variation) (Fung, 2006).

5. Common methodological issues

The following sections present common methodological issues that researchers must consider when starting out with time series modeling. This list is not necessarily exhaustive, and the reader is referred to the additional cited literature for detailed information on how to address the specifics. However, it is unlikely that a time series model will result in correct inferences if the following items are not given at least a cursory consideration.

5.1. Stationarity

Stationarity, or the ability to remain constant over time, is a requirement in classical time series models in both the mean and variance of the collected data (Karlaftis and Vlahogianni, 2011). The existence of *non-stationary* variables has significant implications: non-stationary variables may lead to spurious, or falsely significant, parameter estimates (Washington et al., 2011). Most transportation time series exhibit trends, as well as seasonal and irregular components, or may be *co-integrated*, whereas many models require data with stationary features. Therefore, time series should be tested against stationarity and long memory prior to modeling, and if non-stationary features exist, these should be alleviated using techniques such as filtering, differencing, or fractional differencing (Karlaftis and Vlahogianni, 2011).

5.2. Linearity

(Non)linearity is a property met in numerous kinds of transportation phenomena, and especially those that incorporate behavioral aspects. The existence of nonlinear relationships between variables is difficult to account for using classical time series models, such as the ARMA family of models. As such, the ability to identify the nature of the series is essential in improving the understanding of the process involved and in providing an accurate approximation of complex data structures. A popular test of nonlinearity is the surrogate time series test (Theiler et al., 1992).

5.3. Goodness of fit

Applying statistical diagnostics for testing the goodness of fit (GOF) has been largely disregarded in transportation time series modeling, especially when forecasting is the focal point (Karlaftis and Vlahogianni, 2009). In the classical statistics framework, if a model is of adequate structure, the residuals should behave like white noise; that is, an independent identically distributed (i.i.d.) process with zero mean and constant variance. This implies that any "strong" properties in the error term − serial correlation, volatility and so on − may hint at some specification bias such as omitted variables or misspecification of the functional form. Classical time series analysis includes an abundance of GOF diagnostics tools. Some examples include the Ljung-Box Q-statistic for serial correlation in residuals (Ljung and Box, 1978), the McLeod − Li test for serial dependence in the square residuals (McLeod and Li, 1983), the Jarque-Bera statistic for normality (Jarque and Bera, 1980) and the Brock, Deckert, and Scheinkman (BDS) test for neglected nonlinearity (Brock et al., 1996). Several methods, including the generalized linear ARMA (GLARMA) (Quddus, 2016) and the integer-valued AR (INAR) (Quddus, 2008) models, hold promise in more accurately accounting for the non-normal distribution of observed crash data and the associated model prediction errors.

The presence of serial correlation in time series data can cause standard errors to be biased downwards, obscuring the true significance of independent variables. Serial correlation may be detected several ways, including the Durbin-Watson or Breusch-Godfrey tests. Once detected, serial correlation can be addressed in several ways. One can opt to change the functional form, such as taking the natural log of all variables, using first differences, or adopting generalized least squares (GLS) methods, such as the Prais-Winston or Cochrane-Orcutt. The Newey-West standard error structure may be used to fix higher order serial correlation problems, as it adjusts standard errors upwards but does not alter estimated beta coefficients (Wooldridge, 2015). An alternative method to handle higher orders of serial correlation is to eschew static approaches in favor of a distributive lag or autoregressive (dynamic) model. Distributive lag models use lags in independent variables as additional independent variables, allowing one to track the effects of independent variables on the dependent variable for more than one period.

5.4. Stochastic processes

Another broad consideration is the manner in which irregularities in the time series are accounted for (Kantz and Schreiber, 2003). The conventional approach to transportation research problems has been the stochastic linear paradigm; this approach assumes that a linear rule with an error term that explains the external random influences will adequately account for irregularities in the data and hypothesized effects. However, unconventional methods, such as nonlinear deterministic (chaotic) models have also been used (Vlahogianni et al., 2006).

5.5. Forecasting and causality

One of the strengths of time series analysis is its ability to generate forecasts on future data trends by drawing inferences from observed past data. Forecasting may refer to a single step ahead, or to an extended prediction horizon (multiple-steps ahead). In the latter case, two distinct approaches exist: 1) the *direct approach*, where based on a time-series of a variable, a model is constructed to estimate the variable state at $t + \Delta$, where Δ is the prediction step, and 2) the *recursive approach*, where given a time-series of a variable, a single step ahead model is constructed to estimate a value at time t, which is then fed back to the model as a new input for the prediction at $t + \Delta$.

Through forecasting, a limited notion of *causality* can be inferred through use of *Granger causality*. Granger causality indicates that the past values of X and the past values of Y have a significant combined effect on the current value of Y, more so than the effect explained by past values of Y alone. Thus, Granger causality may be interpreted as predictive causality—it does not guarantee that X causes Y, but suggests that X *may* be causing, or is at least significantly correlated with Y. In practice, one can show that Granger causality exists by using a series of t-tests and F-tests. VAR model results are often tested for Granger causality, and most relevant computer packages allow for the estimation, testing, and forecasting of VARs automatically (Tsay, 2010).

While Granger causality was originally proposed for use with linear stationary bivariate data (Granger, 1969), it has since been extended to multivariate cases (Arnold et al., 2007; Valdes-Sosa et al., 2005). Furthermore, nonparametric methods of testing for Granger causality have been developed to detect causality in the variance of individual variables (Diks and Panchenko, 2006). To address nonlinear cases, alternative approaches such as GARCH, heuristic additive models, and non-parametric or semi-parametric approaches have been developed (Liu et al., 2009).

Despite the implicit prognostic capability of time series models, the application of such methods in forecasting has been limited. Past work has focused on short-term forecasting of crash fatalities, based on models where other predicted values, such as vehicle-miles traveled, dominate (Ray, 1989). Others have used dynamic-harmonic regression to forecast crash rates from one to twelve months in the future, considering several different policy interventions (García-Ferrer et al., 2006). A number of forecasting studies have focused on traffic volume predictions(Chen et al., 2011; Stathopoulos and Karlaftis, 2003; Vlahogianni et al., 2014a; Zhang et al., 2014), which, while not explicitly linked to crash safety, can impact the measures of safety and crash likelihood.

6. Time series analysis in road safety: the road ahead

There exist several challenges that emerge for the streams on high volume and high complexity transportation data that will most likely influence the road safety science and practice. These are discussed in the following sections with emphasis on novel sources of data and new modeling paradigms.

6.1. Emerging sources of traffic safety-related data

Historically, an important limitation of time series analysis in traffic safety research was the availability of relevant data sources. While crash reports provide a wealth of data and insight into the circumstances surrounding individual crashes, they are time consuming to collect, rely on subjective interpretations of events, and can exhibit significant reporting bias for certain types of crashes, such as no-injury crashes (Troung et al., 2011; Ye and Lord, 2011). The advent of several new high-resolution data sources holds promise in this area. High-resolution data typically refers to data collected at a frequency of 1 s or less (Zhang et al., 2011). New, more precise measurement instruments and enhanced abilities to communicate such measurements to a storage medium or off-site location, have made this type of data more accessible than ever before.

6.2. Vehicle automation and communication systems

One area of safety research in which high-resolution data will flourish in the next several years is vehicle automation and communication systems (VACS). Possible databases that may be considered for time series modeling in safety research are related with “smart” vehicles and infrastructure. VACS can nominally be classified in one of two categories; those that can improve traffic safety, and those that can improve driver convenience (Diakaki et al., 2015). With specific focus on improving traffic safety, collision avoidance systems and lane keeping assistance can measure, for example, the time-–to–last–second–braking (Cabrera et al., 2012). They have also been implemented in driver guidance and cooperative collision warning applications (Shladover, 2012) .

6.3. Infrastructure communication systems

Data like that being generated by VACS can be collected from connected infrastructure systems. One promising source of data in this field is that associated with traffic signal systems. High-resolution traffic signal controller data has been utilized by agencies for several years, and provides detailed information about vehicle arrivals, traffic signal timing, and pedestrian activity (Smaglik et al., 2007; Sturdevant et al., 2012). Currently, high resolution signal controller data is primarily used to evaluate various signal timing interventions and intersection performance measures (Hu and Liu, 2013; Lavrenz et al., 2015), although more recently researchers have started to explore its usefulness in crash safety and crash exposure research (Lavrenz et al., 2016; Lu et al., 2015).

6.4. Behavioral recognition

Over the last decade, several instrumented vehicle studies have been initiated with the goal of better characterizing driving behavior through collection of naturalistic data. Naturalistic data refers to that data which is gathered from drivers in their everyday driving routines, as opposed to specially-structured experiments and driving environments. Such projects include the 100–Car study, the SHRP2 Naturalistic Driving Study (Campbell K., 2012) and Euro-FOT (Csepinszky and Benmimoun, 2010). External events such as crashes and near-crashes, along with measured driver characteristics – speed, acceleration, wheel maneuvers and driver behavior, for example – all present opportunities for researchers to collect high-resolution data (Dingus et al., 2006). Other naturalistic data sets have been used to investigate the allocation of exposure-based risk (Shankar, Jovanis, Aguerde, & Gross, 2008), as well as driver distraction in commercial vehicle operations (Olson, Hanowski, Hickman, & Bocanegra, 2009). Another study proposed a methodology for identifying powered-two-wheeler profiles using time-series data on acceleration, steering, brake activation and wheel speed (Vlahogianni, Yannis & Golias, 2014). The homogeneous nature of these datasets presents significant opportunity for researchers to use time series analysis for unearthing subtle trends that may appear as white noise in the general population.

6.5. User experience mining

A new trend to understanding user habits and revealing their behavior-based crash risk is to use Information and Communication Technologies (ICT) to mine the behavior of road users. ICT may be used in various applications, from advanced in-vehicle warning systems to smart insurance schemes (Parry, 2004; Nichols and Kockelman, 2014). ICT functionality is mainly achieved using location-based technologies or sensor-based information from smartphones (Vlahogianni, 2015a). However, in order for users to allow data sharing to be used for improving safety, they need to have certain incentives with as much personalization as possible, such as eco-friendliness ratings while driving, the quantification of risky behavior (via the frequency and severity of harsh driving events such as braking or acceleration), or other activities, such as cell phone use while driving (Carrel, Lau, Mishalani, Sengupta, & Walker, 2015; Magana & Munoz-Organero, 2015). This interaction between policymakers and road users is achieved through gamification, where users may set goals, quantify their activities and try to improve their performance, to achieve social recognition or other gains (e.g., reduced insurance premiums). The above framework may lead to an abundance of data to be used to quantify risk and provide customized safety countermeasures. Such data may demand new, resource-efficient computational approaches, to be able to provide the information needed to users and authorities in a short timeframe (e.g., safety ratings at the start or end of individual trips).

6.6. New modeling paradigms

Inevitably, with the availability of new forms of data that grow in volume, velocity, veracity, and variety, practitioners will have to leverage the plethora of time series methodologies that have already penetrated other areas of transportation data analysis, but due to the lack of data have not yet flourished in traffic safety. In response to the task of analyzing ever-larger data sets, and the subsequent need to

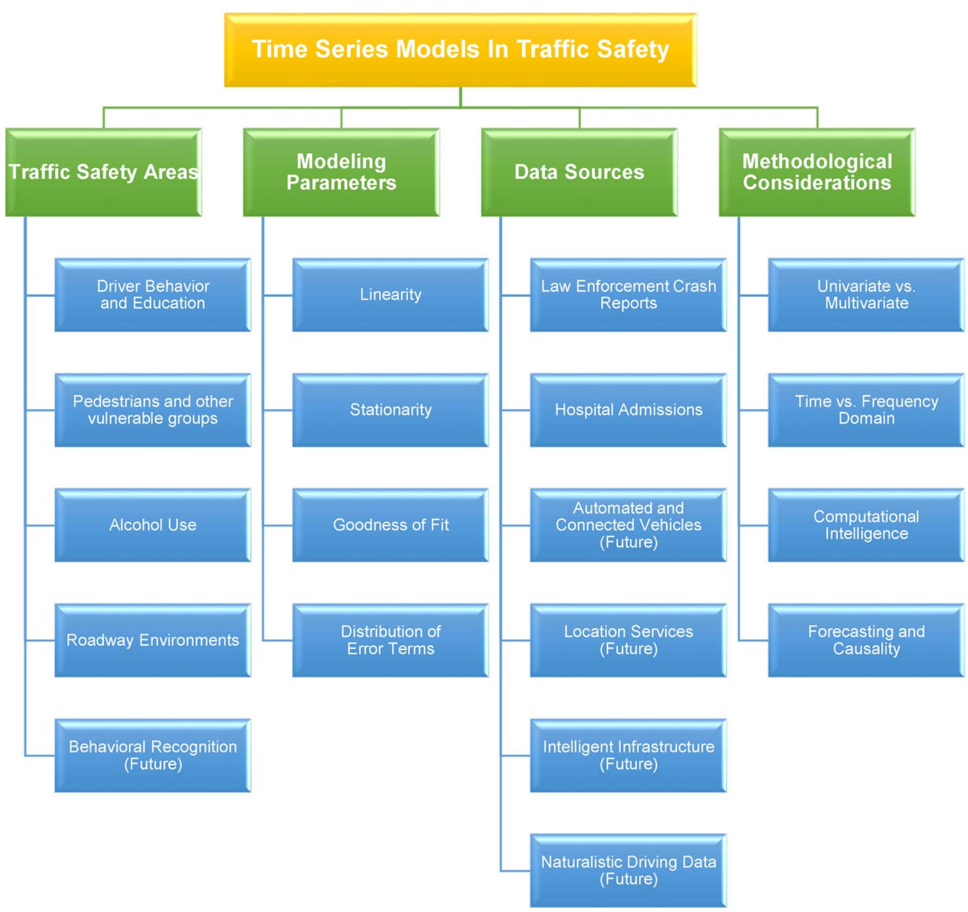

Fig. 1. Overview of the dimensionality of considerations for time series models in traffic safety research.

provide accurate and reliable prediction of safety indicators, machine learning and computational intelligence (CI) models will soon rise as a viable alternative to traditional traffic research and time series models. Such models may efficiently account for several limiting assumptions of classical time series, such as linearity and stationarity. CI models may also provide short-term forecasting models that are more adaptable to sudden shifts in the data (Vlahogianni & Karlaftis, 2013). However, most CI models incorporate a difficult-to-estimate parameterization related to structure and learning mechanisms (Crone & Kourentzes, 2010; Štěpnička, Cortez, Donate, & Štěpnička, 2013; Vlahogianni, 2015b), and it was only very recently that the importance of statistical testing in CI applications has been recognized in traffic engineering time series applications (Vlahogianni and Karlaftis, 2013). Nevertheless, there is significant interdisciplinary literature, which introduces alternative tests for use in CI applications (McNelis, 2005; Medeiros, Terasvirta, & Rech, 2006; Thomaidis & Dounias, 2012).

7. Conclusions

Time-series modeling is widely recognized as a powerful tool for revealing spatiotemporal patterns and predicting future conditions. This paper highlighted several areas of time series analysis where traffic safety research has focused to date, and key elements of these analyses that should be considered. Yet, in recent years, traffic safety research using time series models seems to have become stalled by two major barriers: a lack of knowledge on how to select and apply appropriate modeling techniques, and a dearth of appropriate data sets from users and infrastructure. A summary of the present issues and future challenges that must be considered in time series analysis, along with potential new data sources, is presented as a tree diagram in Fig. 1. In particular, this figure underscores the overreliance of traffic safety modeling on subjective or difficult-to-gather data sources, such as crash reports and hospital admissions, and the potential future application of new data sets. With the abundance of data collected from diverse sources, transport engineers will face a rapid need for tools and methods to aggregate and process this data into safety-altering information.

While classical autoregressive time series models are very useful, due to their well-founded mathematical background and inference mechanisms, CI may lead to models that have certain qualities such as faster analysis of growing data with errors and imperfections, easier data fusion, robustness to uncertainty and data imperfections. Deciding what is the optimum modeling structure in not an easy task. The analyst needs to understand both statistical and machine learning approaches in time series models, and must be able to weigh the advantages and disadvantages of each different model. This may require synergies with other research fields and an interdisciplinary way of thinking.

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