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Advanced Tutorial on Microscopic Discrete-Event Traffic Simulation

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ABSTRACT

Traffic is one of the most important aspects of modern life, both in the developed world and in the developing world. Analysis of traffic systems through modeling and simulation is an essential tool for city planners to optimize traffic flow. Microscopic discrete-event simulation is a natural and powerful method for such analysis. Characteristics of traffic systems that need to be modeled include inter-arrival times, car-following behavior, lane-changing, turning, road structure, intersection structure, and traffic light timing. There are many challenges that must be confronted as well, including the calibration and validation of traffic models, scaling models to larger traffic systems, modeling the continuous nature of traffic in a discrete-event environment, and optimization of traffic system characteristics. An emerging challenge for traffic simulation is the incorporation of autonomous vehicles into traffic systems as not only traditional vehicles, but also as cooperative agents as well.

1 INTRODUCTION

Our busy traffic systems only continue to get more busy as the number of cars on the road increases substantially from year to year. The challenge we all face is to create a safe and efficient road system that can handle the ever-increasing demands we put on it. Both simulation of traffic systems and traffic forecasting can be an essential techniques in developing such a systems, and will be needed to investigate traffic scenarios ahead of time.

Consider the ability to use simulation to predict the consequences of major road construction before a project is even started. With autonomous vehicles on the horizon, there is an opportunity to see the impact of cooperative driving where vehicles are also teammates instead of simply individuals (Sichitiu and Kihl 2008). There are several major steps involved in producing a simulation of a traffic system. For the simulation to be useful, it must be based on real-world data of some kind. There are many types of relevant data and how each is used to build a simulation model will be discussed (Hellinga 1998). Once the data has been secured, processed, and analyzed, models of the various simulation components can be created. These include arrival models, traffic flow models, and the models of the roads themselves. Discrete-event simulations (DES) are well-suited for accurately representing traffic systems since they allow for modeling changes as they are needed, as opposed to discrete-time simulation (DTS), which updates a model at specified times. For instance, when vehicles are created, a DES can produce them at the exact time they should be, while a DTS will have to use a random variable to decide how many cars were produced since the last update, and then also calculate where they should be along their respective roads.

Short term traffic forecasting can be used to help drivers navigating through or around congestions, accidents and other complex traffic situations (Vlahogianni, Karlaftis, and Golias 2014). Traffic parameters of interest for forecasting include travel time, traffic volume, traffic speed, queue length, etc. Traffic apps

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such as Waze, Google Traffic and INRIX are commonly used apps for forecasting traffic. These forecasting techniques are useful for simulation purposes for a few reasons. First, they can provide a basis for modeling certain characteristics of a simulation such as vehicle arrivals, or likely routes through a traffic network. Forecasting can also be used as a means to validate a simulation's structure and results. Traffic forecasting is therefore an indispensable tool for the successful modeling and simulation of traffic networks.

Recently advancements in mobile and wireless technologies have enabled an increased amount of traffic data to be collected (Herrera, Work, Herring, Ban, Jacobson, and Bayen 2010). Increasing numbers of permanent and temporary sensors are also collecting great volumes of data. The availability of large quantities of high-resolution traffic data has greatly facilitated the improvements of both simulation of traffic systems and short term forecasting in recent years.

Predictive modeling of traffic is inherently difficult because of variability in drivers, variability in roads, until recently, a limited amount of data to work with, highly chaotic and dynamic systems. In addition, many factors come into play, including weather, events, accidents, etc. Furthermore, traffic systems become very complex very quickly as the scale of the network is enlarged.

The rest of this paper is organized as follows: Section 2 discusses various types of simulation models. Data collection and analysis are given in Section 3. Section 4 focuses on different short-term traffic forecasting models. Challenges and directions for future work to improve the accuracy and robustness of traffic modeling and simulation are considered in Section 5. Finally, conclusions are in Section 6.

2 TYPES OF SIMULATION MODELS

A traffic simulation model exists in any of three paradigms: macroscopic, mesoscopic, and microscopic. A model can also be implemented using either DTS or DES. (Buss and Al Rowaei 2010) compared the results of discrete-time and discrete-event simulations when using differential equations to calculate changes to the system. They found that the choice of time-step has a large effect on the accuracy of the DTS models, but also that errors resulting from a DES approach were smaller in general than the DTS approach. However, (Lieberman and Rathi 1997) believe that DTS systems are a better choice for large traffic systems that require a great amount of detail. A discrete-event simulation system with thousands of vehicles will likely process many more updates to the system than would a discrete-time simulation. As processors become faster, and parallel and distributed computing techniques continue to improve, the efficiency of DES should get better as well, which along with the better accuracy of such an approach, likely makes DES the better choice for traffic simulation moving into the future.

2.1 Macroscopic Models for Traffic Simulation

Most of the early work in traffic modeling was in the paradigm of macroscopic traffic models. Greenshields' work is the starting point for the traffic flow models that would come later (van Wageningen-Kessels, Van Lint, Vuik, and Hoogendoorn 2015). His work comparing velocity to traffic density led to some of the early breakthroughs in the field and inspired many researchers to pursue traffic modeling.

A notable contribution was provided by (Lighthill and Whitham 1955) and (Richards 1956), with the formulation of the Lighthill-Whitham-Richards (LWR) kinematic wave model of traffic flow. The idea behind this application of kinematic wave theory is that changes in traffic flow propagate backwards through traffic in a wave-like fashion, and that multiple waves can even collide forming kinematic ”shock waves”. However, deficiencies in the basic LWR model were identified (Daganzo 1997) stemming from the fact that the LWR model makes some unrealistic assumptions about traffic flow. First, the original model assumed an instantaneous change of velocity, which would imply an infinite acceleration. Secondly, all vehicles in a geographically defined neighborhood or platoon are assumed to have the same desired velocity. However, real world data has shown that vehicles in a platoon will have their own desired speeds and this will lead to the platoon getting spread out and eventually disentangling (Daganzo 1995).

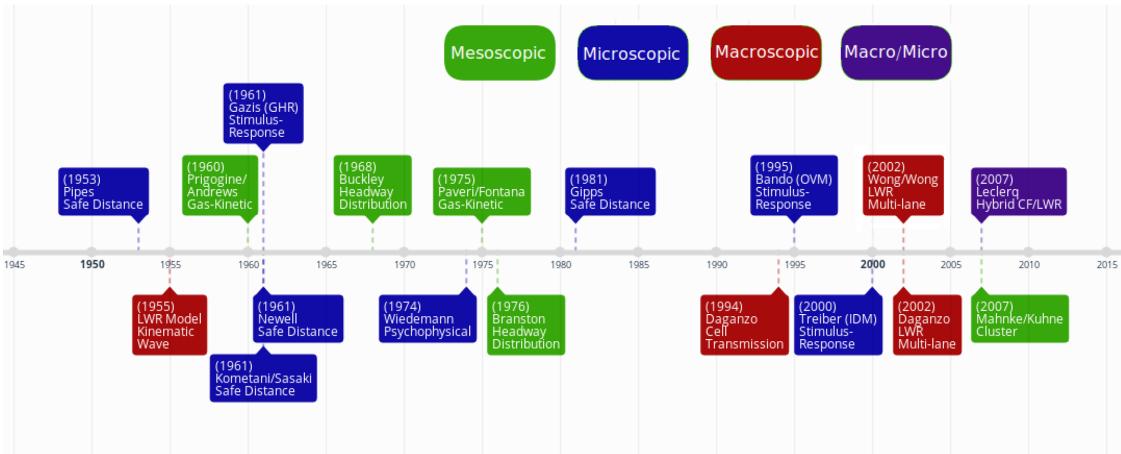

Figure 1: Timeline of traffic simulation models. (Gipps 1981), (Pipes 1953), (Kometani and Sasaki 1961), (Lighthill and Whitham 1955), (Richards 1956), (Newell 1961), (Gazis, Herman, and Rothery 1961), (Prigogine and Andrews 1960), (Buckley 1968), (Paveri-Fontana 1975), (Wiedemann 1974), (Branston 1976), (Bando, Hasebe, Nakayama, Shibata, and Sugiyama 1995), (Daganzo 1994), (Treiber, Hennecke, and Helbing 2000), (Daganzo 2002), (Wong and Wong 2002), (Leclercq 2007), (Mahnke and Kühne 2007).

2.2 Mesoscopic Models for Traffic Simulation

Mesoscopic models utilize elements of both the macroscopic and microscopic paradigms of traffic flow modeling. Specifically, individual vehicles are considered and modeled, but the overall flow is controlled by macroscopic features (Zhou and Taylor 2014). (Buckley 1968) proposed a traffic flow model based on arrival modeling using a semi-Poisson distribution. (Branston 1976) also discussed a traffic flow model based on an arrival model. (Prigogine and Andrews 1960) proposed gas-kinetic traffic models with (Paveri-Fontana 1975) improving on the concepts later. (Helbing 1997) created a multilane version of this model. Later, a generic gas-kinetic model was introduced by (Hoogendoorn and Bovy 2001). The INTEGRATION model (Van Aerde and Yagar 1988) was originally mesoscopic in nature, though it has sen significant evolution since the original formulation (Van Aerde, Hellinga, Baker, and Rakha 1996).

2.3 Microscopic Models for Traffic Simulation

When vehicles are in close proximity in the same lane, then one car is following another car, and must change its own behavior as the car just in front of it also changes. These changes in behavior will result in changes to either the acceleration or velocity of the vehicle. The reasoning behind the changes boils down to either a general response to stimuli, or because of a desire to avoid collisions. When humans make such decisions we either press the accelerator pedal, or the brake (decelerator) pedal. Thus, the decision boils down to what the new acceleration of the vehicle should be. There have been many models proposed for producing new accelerations for following vehicles. The new acceleration value is used to update the velocity of the vehicle, which is then used to update the position of the vehicle. Many car-following models have been proposed with most falling into the classifications below (Brackstone and McDonald 1999).

2.3.1 Stimulus-Response Models

Stimulus-response models assume drivers change their behaviors based on different stimuli. If drivers are not traveling at their own desired velocities then they will choose to either accelerate or decelerate depending on their speeds. Drivers will also adjust their speeds depending on either the spacing between them and the car in front of them, or the relative velocity of the car in front of them.

Some of the earliest work on car-following models was done by (Gazis, Herman, and Rothery 1961), creating the GHR model, which has inspired many other models. For example, Bando et al. proposed the Optimal Velocity Model (OVM) (Bando, Hasebe, Nakayama, Shibata, and Sugiyama 1995), (Bando, Hasebe, Nakanishi, and Nakayama 1998), and Treiber et al. designed the Intelligent Driver Model (IDM) (Treiber, Hennecke, and Helbing 2000), (Kesting, Treiber, and Helbing 2010).

2.3.2 Collision Avoidance Models

Collision Avoidance models work based on the idea that drivers will maintain distances that will prevent collisions with the vehicles in front of them. Some of the earliest work in collision avoidance models was done by (Pipes 1953) and (Kometani and Sasaki 1961). (Gipps 1981) refined the ideas considerably and is still considered to be the leading model in the collision avoidance paradigm (Ciuffo, Punzo, and Montanino 2012). Table 1 shows several models in the Stimulus-Response and Collision Avoidance paradigms.

Model	Formula
GHR	$\dot{v}_n(t+\tau) = p\dfrac{\dot{x}_{n-1}(t)-\dot{x}_n(t)}{[x_{n-1}(t)-x_n(t)]^l}$
IDM	$\dot{v}_n(t+\tau) = a_n\left(1-\left(\frac{v_n(t)}{V_n}\right)^{\delta}-\left(\frac{s^*(v_n(t),\Delta v_n(t))}{s_n(t)}\right)\right)^2$ where $s^*(v_n(t),\Delta v_n(t)) = s_0+v_n(t)T+\frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_n b_n}}$
OVM	$\dot{v}_n(t) = \gamma(v^*(s_n(t))-v_n(t))$ $v^*(s) = v_{\max}(\tanh(s-c_1)+c_2)$
Gipps	$v_n(t+\tau) = min\Big\{v_n(t)+2.5a_n\tau(1-v_n(t)/V_n)(0.025+v_n(t)/V_n)^{1/2},$ $b_n\tau+\left(b_n^2\tau^2-b_n[2[x_{n-1}(t)-s_{n-1}-x_n(t)]-v_n(t)\tau-v_{n-1}(t)^2/b]\right)^{1/2}\Big\}$

Table 1: τ represents a reaction time, p and l, δ, γ, c_1, and c_2 are sensitivity parameters used to fit the models to data, a_n and b_n are the maximum acceleration and deceleration for the n^{th} vehicle, respectively, T is the minimum allowable time to the car in front, s_0 is the minimum allowable spacing between cars, s_n is the current spacing between the n^{th} and $(n-1)^{th}$ car, and V_n is the desired velocity of the n^{th} car.

2.3.3 Cellular Automata Models

Cellular Automata (CA) models are microscopic models because individual vehicles are created for the simulation, but space is no longer continuous, and vehicles move between "cells" that model individual locations on the road, with a small length to allow a single vehicle to occupy a cell at any given point in time. (Nagel and Schreckenberg 1992) showed that the CA approach results in behavior predicted by macroscopic models. Another expansion of the idea was proposed in (Helbing and Schreckenberg 1999) in which the CA model is combined with the Optimal Velocity Model.

3 DATA COLLECTION AND ANALYSIS

Traffic systems produce large volumes of data and it is crucial to know the relevant types, their availability, and how they can be used for traffic modeling (Hellinga 1998). Below are some of these relevant data types.

- **Vehicle Count Data**: Most states provide public access to vehicle count data, usually through a web interface. The frequency of the counts is important for accurate arrival models. Hourly traffic data is very common to find, but is not nearly as accurate as five minute intervals.
- **Speed Limit Data**: Speed limit data can be hard to find, but there are sources available for estimates of the correct values. The Google maps API provides a function for retrieval of speed limits for a particular road segment. Google does not guarantee that these speed limits are accurate. OpenStreetMap can also be used to estimate speed limits, but some advanced work must be done. Each state publishes the maximum speed limit for each type of road they have.
- **Geo-Spatial Data**: Traffic flow is heavily influenced by the shape of the road, especially if collisions are a part of the simulation study. Blind curves, steep hills, narrow lanes, etc. all have an impact on traffic. Much of this data is publicly available, and can be processed using GIS software.
- **Travel Time Data**: Typically, these data provide travel times between two locations. Some governments provide such data, e.g., UK (data.gov.uk), Ireland (data.gov.ie) and Australia (data.qld.gov.au, data.vic.gov.au).
- **Accident Data**: An online system would require accident data to efficiently reroute vehicles. These data are available through web interfaces of state governments or through traffic apps such as Waze.
- **Event Scheduling Data**: In cities, events such as sports, concerts, celebrations, graduations, etc. are usually available ahead of time.
- **Construction Data**: Road construction data are typically posted by state and local governments.

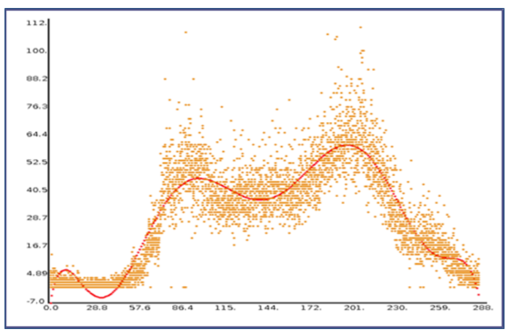

Figure 2: Vehicle counts vs. a polynomial fit

Vehicle counts can be used to determine interarrival times for the system and its sources. Figure 2 shows the vehicle counts on Mondays for 17 weeks and polynomial regression is fit using the data. Speed limit data can be used to estimate the range of speeds at which vehicles would operate. Geo-spatial data could even be incorporated to model accelerations and decelerations due to changes in the physical shape of the road. For instance, severe curves in a road would necessitate decelerations. (Wilkie, Sewall, and Lin 2012) use GIS data to create three dimensional models for used in traffic simulations. (Wang 2005) discussed the integration of GIS methods and data with simulation models and visualization techniques.

The most conventional way to collect traffic data is through inductive loop detectors that are already deployed on many roads (Leduc 2008). Magnetic fields are generated by the loop detectors in order to detect vehicles, which are mostly made of metals. When vehicles pass through loop detectors, traffic count data can be recorded. If two loop detectors are very close to each other, they can also calculate the speeds of the vehicles that pass by.

Traffic data may also be collected by probe vehicles, which can be vehicles specifically deployed on the roads for the purpose of real-time traffic data collection or commercial vehicles like taxi equipped with GPS chips (Leduc 2008). Typically satellites and cellular networks can be used to transmit information such as locations and speeds of probe vehicles. The CarWeb system proposed by (Lo, Peng, Chen, Lin, and Lin 2008) utilizes GPS and Mobile networks to obtain position and speed data on non-freeway roads, which are less likely to have a comprehensive system of in-road sensors. With the relatively recent drastic increase in the number of smartphones, the amount of data that can potentially be collected has also sharply increased. Popular traffic apps such as Waze, Google Traffic and INRIX may collect anonymous data from users who are using the apps while driving.

Other ways to collect traffic data may include using automated toll collection stations to collect travel times data (El Faouzi, Klein, and De Mouzon 2009); (Hoogendoorn, Van Zuylen, Schreuder, Gorte, and Vosselman 2003) discussed using aerial images to extract more detailed data from road systems, specifically for use with microscopic traffic simulations; recently, in (Bhaskar and Chung 2013), the use of Bluetooth scanners to collect traffic data was suggested.

4 TYPES OF FORECASTING MODELS

Many forecasting models have been developed for forecasting time course data. These models may include statistical time series models and machine learning models. The applications of forecasting traffic variables or metrics using different models have been an area of growing research interests. Our interest in the field results from the idea that traffic forecast models can be used to drive elements of traffic simulations. For example, an accurate forecast of traffic volume can be used to simulate vehicle arrivals to the network.

4.1 ARIMA Family of Models

One of the most intuitive approaches to forecast traffic variables or metrics of interest such as traffic volume or travel time is to use the data from the recent past to predict the value of the variable in the immediate future. It would be reasonable to assume that the traffic volume on a particular road fifteen minutes later would be highly correlated to the current traffic volume. The univariate autoregressive integrated moving average (ARIMA) family of models (Box and Jenkins 1970) commonly used in time series analysis can be a good candidate for such a task.

The autoregressive (AR) portion relates the current variable of interest (e.g., travel time) to the same variable at the last p time points. Let Z_t represent the travel time at time t between two Traffic Control Sites, define $Y_t = Z_t - \mu_Z$, where μ_Z is the mean of the Z time series. In particular, the pth order autoregressive model for Y_t, AR(p), may be expressed as

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t$$

where ϕ_i is the parameter/coefficient associated with the ith lag Y_{t-i} and ε_t is the white noise process.

As an example, the SCALATION project may be download from http://www.cs.uga.edu/~jam/scalation_1.3/README.html. The dataset used contains minute-by-minute travel time data from midnight to 1:00pm from Traffic Control Site 2127 to 175 in Dublin, Ireland (Council 2016). This simple test creates an AR(1) model to forecast travel times 15 minutes into the future. By using the "rolling forecast orgin" technique (Hyndman and Athanasopoulos 2014) commonly used to validate time series models, only the most recent n (in our case n = 60) instances are used as training data to produce 15-step ahead forecast on the $n+15$-th time point. To run this test, simply type "run-main apps.analytics.Traffic_AR" in the sbt console. An R^2 value of 54.2% can be obtained. The forecasted (red) and actual (black) travels times are shown in Figure 3.

The ARIMA family of models has been used for short term traffic forecasting for almost four decades (Ahmed and Cook 1979), (Levin and Tsao 1980). However, a major shortcoming of the ARIMA family of models is its inability to quickly respond to sudden changes in the traffic condition such as congestion caused by an accident or sharp increase and decrease in traffic volumes (Vlahogianni, Golias, and Karlaftis 2004). In recent years, the ARIMA family of models has mostly either been used as a baseline comparison or a component of a hybrid or more generalized model.

An extension to ARIMA with seasonal components is called the SARIMA model. Seasonality typically denotes similar or repeated patterns in the univariate time series for every fixed period of time, such as

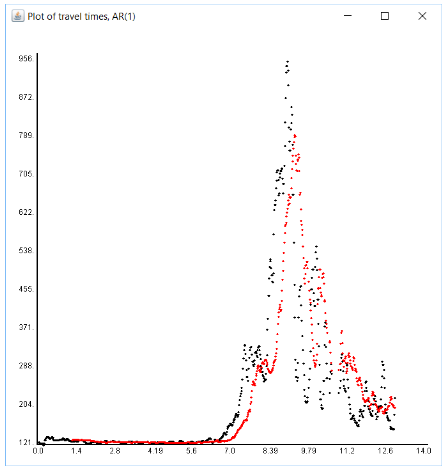

Figure 3: Travel Times: Forecasted (red) vs. Actual (black)

the daily traffic volume patterns on workdays. SARIMA was first used to forecast traffic flow of urban freeways in (Williams, Durvasula, and Brown 1998). A recent study in (Kumar and Vanajakshi 2015) demonstrated the potentials of SARIMA models fitted with only a limited amount of input data for traffic flow forecasting when comparing with non-seasonal ARIMA models.

4.2 State-Space Models and Kalman Filter

Suppose one desires to study the relationship between a traffic metric or variable of interest and other relevant traffic variables, the univariate ARIMA family of models may not be sufficient for such a task. For example, information on departure times and past travel times can give valuable insights on forecasting future travel times, but the univariate ARIMA family models are not able to take advantage of the extra information for prediction. One solution would be to use multivariate generalizations of the ARIMA models, such as in (Schimbinschi, Moreira-Matias, Nguyen, and Bailey 2017), which showed that a vector autoregressive (VAR) based model can outperform baseline ARIMA models in traffic flow predictions. Another solution would be to use the Kalman Filter (Kalman et al. 1960), a widely applied algorithm in multivariate time series analysis.

In essence, the Kalman Filter (Kalman et al. 1960) attempts to use the estimate of the state of a system (e.g., state may consist of traffic volume and velocity) and the degree of uncertainty of the estimate of the state (to account for noise and measurement errors) at time t, and produces an estimate or forecast of the state and its degree of uncertainty at time $t+1$. Any relevant measurements of some external influences on the state (e.g., weather condition) at time $t+1$ (with its own degree of uncertainty) can also be used to adjust the estimate of the state of the system at time $t+1$. A model that utilizes the Kalman filter algorithm falls into a more general category of state-space models.

The Kalman Filter was first used to forecast traffic volume in (Okutani and Stephanedes 1984). Application of travel time forecasting using the Kalman Filter was done in (Chien and Kuchipudi 2003). In (Stathopoulos and Karlaftis 2003), the state-space models using the Kalman Filter outperforms simple ARIMA model in traffic volumne forecasting. The difference in performance, in terms of the mean absolute percent error (MAPE) is as high as 8%. A more recent study in (Guo, Huang, and Williams 2014) combined Kalman filter with univariate time series models in order to produce better forecasts of traffic flow rate than the individual models.

4.3 Regression

Aside from multivariate time series analysis, another way to forecast a traffic variable using other traffic or traffic-related variables is regression, a very common technique in predictive analytics. The goal of regression is to find a function that best describes a given dataset. In other words, the differences between the observed values of the traffic variable of interest and the fitted values (the predicted values of the traffic parameter of interest given by the function) must be minimized. Typically, the function maps multiple predictors (traffic-related variables) to a single response (the traffic variable of interest). A major class of regression techniques is known as parametric regression, in which the forms of the function (e.g., linear, quadratic, higher-order polynomials, generalized linear models, etc.) is pre-determined and therefore the goal is to find the coefficients (parameters) on the predictors so that the function may best describe the dataset. A widely used yet simple parametric regression model is the linear regression model

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \cdots + b_n X_n + \varepsilon$$

where Y is the response variable; X_j is the jth predictor, $j = 1, 2, \ldots n$, where n is the total number of predictors; $b_0, b_1, \ldots b_n$ are the coefficients/parameters that need to be fit; and the ε random variable is used to represent residuals or errors. This model may also be generalized to polynomial regression models by including non-linear predictors (e.g., squared values of predictors).

In (Nikovski, Nishiuma, Goto, and Kumazawa 2005), linear regression was shown to be competitive with some non-linear techniques such as neural networks and k-nearest neighbors when performing univariate forecasting of short term travel times. The resolution of the data is 5 minutes and only data from the past two time points (5 and 10 minutes prior) are used as predictors in linear regression. In (Zhang and Rice 2003), a linear regression based model in which the coefficients/parameters vary according to departure time (as opposed to being constant in standard linear regression) was proposed, outperforming baseline predictors that rely solely on current traffic information or historical averages.

4.4 Neural Networks

The regression techniques can provide simplicity with the pre-defined form of the function to be fitted, but this may also be a disadvantage because traffic situations are often complex, involving sudden extremes due to accident, bad weather, etc, which can be difficult to capture by using a fixed form of function. Neural Networks, which can be understood as a form of multi-layer nonlinear regression, could be an alternative for such a task. In recent years, Neural Networks have captured the attention of many researchers in the field of traffic forecasting (Karlaftis and Vlahogianni 2011).

A Feedforward Neural Network is made up of interconnected layers of artificial neurons, inspired by the structure of a brain. The incoming signals of a neuron are first aggregated, then the aggregated signal is passed through a activation function to produce an output signal for the neuron to send forward to other connected neurons. The strength of the connections among the neurons are learned from the input data.

Much research has been devoted to using Neural Networks for traffic forecasting since the early 90's (Dougherty 1995). Recently, in (Schimbinschi, Nguyen, Bailey, Leckie, Vu, and Kotagiri 2015), a comparative study of different techniques was done on short-term traffic volume forecasting techniques. The forecasting problem was formulated as a classification problem (high traffic, low traffic). Neural Networks were found to generally have superior performances in both forecasting accuracies and efficiencies than RUSBoost (Seiffert, Khoshgoftaar, Van Hulse, and Napolitano 2010), Linear Discriminant Analysis (LDA), classification trees, Support Vector Machines (SVM) using Radio Basis Functions (RBF) kernel, Naive Bayes and k-Nearest Neighbors (kNN).

4.5 Other Forecasting Techniques

Other traffic forecasting techniques include Bayesian Networks (Sun, Zhang, and Yu 2006), functional regression and classification (Chiou et al. 2012), among others. More comprehensive reviews on traffic forecasting may be found in (Vlahogianni, Golias, and Karlaftis 2004), (Vlahogianni, Karlaftis, and Golias 2014) and (Mori, Mendiburu, Álvarez, and Lozano 2015).

4.6 Traffic Apps

Some of the most popular traffic apps include Waze, Google Traffic and INRIX. Typically, those apps rely on drivers using the apps while driving to collect real-time anonymous data through their mobile devices that are present in vehicles. Information such as the speed of mobile devices reflecting the speed of vehicles and the number of mobile devices moving around on different roads can be used to provide the current traffic condition (Herring, Hofleitner, Amin, Nasr, Khalek, Abbeel, and Bayen 2010).

5 CHALLENGES AND FUTURE WORK

Problems with traffic conditions continue to plague humanity every day around the world, and the field of traffic modeling and simulation still has much work to do to find solutions to these problems. Below are some specific challenges that we feel need to be addressed in the future.

5.1 Discrete-Event Simulation

Many microscopic traffic simulation models use a DTS approach. (Florian, Mahut, and Tremblay 2008) proposed that DES is more efficient, where the system would only update vehicles when it needs to. They mention that DES will also allow for times in a continuous space instead of a discrete space, which should improve results and reflect reality to a higher degree. They present a discrete-event system using a simplified car-following model based only on the positions of the lead and following cars, the response time of the driver in the following car, and the effective vehicle length of the following car. (Sumaryo, Halim, and Ramli 2013) and (Salimifard and Ansari 2013) both considered the problem of using discrete-event modeling in traffic light simulation. (Burghout, Koutsopoulos, and Andreasson 2006) developed a mesoscopic traffic simulation model for use with a discrete-event, hybrid mesoscopic-microscopic simulation. (Thulasidasan, Kasiviswanathan, Eidenbenz, Galli, Mniszewski, and Romero 2009) used a parallel DES system for large-scale microscopic traffic simulation.

5.2 Calibration And Validation

Calibration and validation are difficult to carry out for several reasons. For instance, collecting enough data is difficult, and there may not be enough for calibration or validation. Also, geography is important and models are highly dependent on the location under analysis. It can also be difficult to account for the variablitly found among drivers. It is best to use real road data to validate traffic models, but closed courses with a controlled collection of drivers have also been used. (Henclewood, Suh, Rodgers, Hunter, and Fujimoto 2012) argued for using real-time calibration for online traffic simulation systems. They point out that even in the same geographic area, parameters found under through calibration can be inappropriate at other times of the day.

5.3 Scaling

Traffic simulations are difficult to scale up as the number of vehicles and the complexity of their interactions can explode in even a fairly small geographic area. Recently, with growth in the areas of parallel and distributed computation, efforts have been made at improving the scale of traffic simulations. (Fujimoto 2015) presented an overview of the current state of parallel and distributed simulation, and includes traffic simulation as a major motivator for the field. (Thulasidasan and Eidenbenz 2009) proposed FastTrans, a parallel simulator using distributed memory techniques for traffic simulation. They also show how the choice of search algorithm for routing can affect the overall performance of the system. (Hanai, Suzumura, Theodoropoulos, and Perumalla 2015) discussed the problem of multiple runs of what-if scenarios for large-scale traffic simulations, and proposed a filtering technique to reduce the number of scenarios (Suzumura and Kanezashi 2013), (Kanezashi and Suzumura 2015). (Zehe, Cai, Knoll, and Aydt 2015) presented a tutorial on a cloud-based simulation service, with a specific implementation example being simulation of urban traffic.

5.4 Autonomous Vehicles

Autonomous vehicles will open up many new avenues of research into traffic systems, and will bring about new opportunities for traffic management. A solution could be to have inter-vehicle communication. (Sichitiu and Kihl 2008) gave an overview of various inter-vehicle communication methods. (Suh, Henclewood, Guin, Guensler, Hunter, and Fujimoto 2017) discussed data-driven transportation systems.

(Ishikawa and Arai 2015) considered the impact of intelligent vehicles that can relay important information to other vehicles to prevent traffic jams. (Fernandes and Nunes 2010) discussed implementing vehicle-to-vehicle communication within the SUMO (Simulation of Urban MObility) simulation system (Krajzewicz, Erdmann, Behrisch, and Bieker 2012). (Pereira and Rossetti 2012) proposed microscopic traffic simulation as a testbed for theoretical aspects of autonomous vehicles. (Hasebe, Nakayama, and Sugiyama 2003) formulated an extension to the Optimal Velocity Model in which a vehicle can look ahead or behind some number of cars to calculate its new acceleration.

5.5 Intelligent Traffic Lights

Intelligent traffic light systems would be highly adaptive and also cooperative with other traffic lights. Traffic data sensors can send information to the lights and the timings can be adjusted to meet the current demand of the intersection. If the problem cannot be solved by a single traffic light, then other traffic lights are adjusted within a specified radius (perhaps adjustable as well), to attempt to reach a solution.

(Zozaya-Gorostiza and Hendrickson 1987) and (Radwan, Elahi, and Goul 1990) both designed knowledge-based expert systems to adjust the parameters of traffic lights at single intersections. (Hunt, Robertson, Bretherton, and Royle 1982) created the SCOOT (Split Cycle Offset Optimisation Technique) system which has been used extensively in England, as well as other parts of the world, for adaptive control of traffic lights. (Semarak 1996) proposed a fuzzy-logic approach to controlling traffic lights.

6 CONCLUSIONS

There has been a tremendous amount of work in the past decades to accurately model and simulate traffic networks, though there are still many questions and avenues of research to be worked on. In this paper we have presented many of the most important results from the past, and given an indication of the important issues still left to be resolved. There is a discussion on autonomous vehicles, which have attracted increasing attention from both researchers and consumers. We have also briefly reviewed some techniques commonly found in the field of traffic forecasting, which is an important goal of traffic simulation. It is important to pursue research in both forecasting and simulation in order to build more reliable traffic prediction systems. More reliable prediction and simulation systems will allow us to solve many of the problems still plaguing our roads, such as traffic congestion and safety. They will allow, as an example, for more efficient programming of traffic lights, which could have an immediate impact on traffic congestion. Forecasting, modeling, and simulation will also certainly play a large role in the continued development of autonomous vehicles, which hold the hopes of having much safer roads to travel.

REFERENCES

Ahmed, M. S., and A. R. Cook. 1979. *Analysis of freeway traffic time-series data by using Box-Jenkins techniques*. Number 722. Transportation Research Board.

Bando, M., K. Hasebe, K. Nakanishi, and A. Nakayama. 1998. "Analysis of optimal velocity model with explicit delay". *Physical Review E* 58 (5): 5429.

Bando, M., K. Hasebe, A. Nakayama, A. Shibata, and Y. Sugiyama. 1995. "Dynamical model of traffic congestion and numerical simulation". *Physical review E* 51 (2): 1035.

Bhaskar, A., and E. Chung. 2013. "Fundamental understanding on the use of Bluetooth scanner as a complementary transport data". *Transportation Research Part C: Emerging Technologies* 37:42–72.

Box, G. E., and G. M. Jenkins. 1970. "Time Series Analysis Forecasting and Control". Technical report, DTIC Document.

Brackstone, M., and M. McDonald. 1999. "Car-following: a historical review". *Transportation Research Part F: Traffic Psychology and Behaviour* 2 (4): 181–196.

Branston, D. 1976. "Models of single lane time headway distributions". *Transportation Science* 10 (2): 125–148.

Buckley, D. 1968. "A semi-Poisson model of traffic flow". *Transportation Science* 2 (2): 107–133.

Burghout, W., H. N. Koutsopoulos, and I. Andreasson. 2006. "A discrete-event mesoscopic traffic simulation model for hybrid traffic simulation". In *Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE*, 1102–1107. IEEE.

Buss, A., and A. Al Rowaei. 2010. "A comparison of the accuracy of discrete event and discrete time". In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, , and E. Ycesan, 1468–1477. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chien, S. I.-J., and C. M. Kuchipudi. 2003. "Dynamic travel time prediction with real-time and historic data". *Journal of transportation engineering* 129 (6): 608–616.

Chiou, J.-M. et al. 2012. "Dynamical functional prediction and classification, with application to traffic flow prediction". *The Annals of Applied Statistics* 6 (4): 1588–1614.

Ciuffo, B., V. Punzo, and M. Montanino. 2012. "Thirty Years of Gipps' Car-Following Model: Applications, Developments, and New Features". *Transportation Research Record: Journal of the Transportation Research Board* 2315:89–99.

Dublin City Council 2016. "Journey times across Dublin City, from Dublin City Council Traffic Department's TRIPS system".

Daganzo, C. F. 1994. "The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory". *Transportation Research Part B: Methodological* 28 (4): 269–287.

Daganzo, C. F. 1995. "Requiem for second-order fluid approximations of traffic flow". *Transportation Research Part B: Methodological* 29 (4): 277–286.

Daganzo, C. F. 1997. "A continuum theory of traffic dynamics for freeways with special lanes". *Transportation Research Part B: Methodological* 31 (2): 83–102.

Daganzo, C. F. 2002. "A behavioral theory of multi-lane traffic flow. Part I: Long homogeneous freeway sections". *Transportation Research Part B: Methodological* 36 (2): 131–158.

Dougherty, M. 1995. "A review of neural networks applied to transport". *Transportation Research Part C: Emerging Technologies* 3 (4): 247–260.

El Faouzi, N.-E., L. Klein, and O. De Mouzon. 2009. "Improving travel time estimates from inductive loop and toll collection data with dempster-shafer data fusion". *Transportation Research Record: Journal of the Transportation Research Board* 2129:73–80.

Fernandes, P., and U. Nunes. 2010. "Platooning of autonomous vehicles with intervehicle communications in SUMO traffic simulator". In *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, 1313–1318. IEEE.

Florian, M., M. Mahut, and N. Tremblay. 2008. "Application of a simulation-based dynamic traffic assignment model". *European Journal of Operational Research* 189 (3): 1381–1392.

Fujimoto, R. 2015. "Parallel and distributed simulation". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 45–59. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Gazis, D. C., R. Herman, and R. W. Rothery. 1961. "Nonlinear follow-the-leader models of traffic flow". *Operations research* 9 (4): 545–567.

Gipps, P. G. 1981. "A behavioural car-following model for computer simulation". *Transportation Research Part B: Methodological* 15 (2): 105–111.

Guo, J., W. Huang, and B. M. Williams. 2014. "Adaptive Kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification". *Transportation Research Part C: Emerging Technologies* 43:50–64.

Hanai, M., T. Suzumura, G. Theodoropoulos, and K. S. Perumalla. 2015. "Towards large-scale what-if traffic simulation with exact-differential simulation". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 748–756. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Hasebe, K., A. Nakayama, and Y. Sugiyama. 2003. "Dynamical model of a cooperative driving system for freeway traffic". *Physical review E* 68 (2): 026102.

Helbing, D. 1997. "Modeling multi-lane traffic flow with queuing effects". *Physica A: Statistical Mechanics and its Applications* 242 (1-2): 175–194.

Helbing, D., and M. Schreckenberg. 1999. "Cellular automata simulating experimental properties of traffic flow". *Physical review E* 59 (3): R2505.

Hellinga, B. R. 1998. "Requirements for the calibration of traffic simulation models". *Proceedings of the Canadian Society for Civil Engineering* 4:211–222.

Henclewood, D., W. Suh, M. Rodgers, M. Hunter, and R. Fujimoto. 2012. "A case for real-time calibration of data-driven microscopic traffic simulation tools". In *Proceedings of the 2012 Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 1670–1681. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Herrera, J. C., D. B. Work, R. Herring, X. J. Ban, Q. Jacobson, and A. M. Bayen. 2010. "Evaluation of traffic data obtained via GPS-enabled mobile phones: The Mobile Century field experiment". *Transportation Research Part C: Emerging Technologies* 18 (4): 568–583.

Herring, R., A. Hofleitner, S. Amin, T. Nasr, A. Khalek, P. Abbeel, and A. Bayen. 2010. "Using mobile phones to forecast arterial traffic through statistical learning". In *89th Transportation Research Board Annual Meeting*, 10–2493.

Hoogendoorn, S., H. Van Zuylen, M. Schreuder, B. Gorte, and G. Vosselman. 2003. "Microscopic traffic data collection by remote sensing". *Transportation Research Record: Journal of the Transportation Research Board* 1855:121–128.

Hoogendoorn, S. P., and P. H. Bovy. 2001. "Generic gas-kinetic traffic systems modeling with applications to vehicular traffic flow". *Transportation Research Part B: Methodological* 35 (4): 317–336.

Hunt, P., D. Robertson, R. Bretherton, and M. C. Royle. 1982. "The SCOOT on-line traffic signal optimisation technique". *Traffic Engineering & Control* 23 (4): 190–192.

Hyndman, R. J., and G. Athanasopoulos. 2014. *Forecasting: principles and practice*. OTexts.

Ishikawa, S., and S. Arai. 2015. "Evaluating advantage of sharing information among vehicles toward avoiding phantom traffic jam". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 300–311. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Kalman, R. E. et al. 1960. "A new approach to linear filtering and prediction problems". *Journal of basic Engineering* 82 (1): 35–45.

Kanezashi, H., and T. Suzumura. 2015. "Performance optimization for agent-based traffic simulation by dynamic agent assignment". In *Proceedings of the 2015 Winter Simulation Conference*, edited by

L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 757–766. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Karlaftis, M. G., and E. I. Vlahogianni. 2011. "Statistical methods versus neural networks in transportation research: Differences, similarities and some insights". *Transportation Research Part C: Emerging Technologies* 19 (3): 387–399.

Kesting, A., M. Treiber, and D. Helbing. 2010. "Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity". *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences* 368 (1928): 4585–4605.

Kometani, E., and T. Sasaki. 1961. "Dynamic behaviour of traffic with a nonlinear spacingspeed relationship". In *Proceedings of Symposium on Theory of Traffic Flow*, 105–119. Elsevier.

Krajzewicz, D., J. Erdmann, M. Behrisch, and L. Bieker. 2012, December. "Recent Development and Applications of SUMO - Simulation of Urban MObility". *International Journal On Advances in Systems and Measurements* 5 (3&4): 128–138.

Kumar, S. V., and L. Vanajakshi. 2015. "Short-term traffic flow prediction using seasonal ARIMA model with limited input data". *European Transport Research Review* 7 (3): 1–9.

Leclercq, L. 2007. "Hybrid approaches to the solutions of the Lighthill–Whitham–Richards model". *Transportation Research Part B: Methodological* 41 (7): 701–709.

Leduc, G. 2008. "Road traffic data: Collection methods and applications". *Working Papers on Energy, Transport and Climate Change* 1 (55).

Levin, M., and Y.-D. Tsao. 1980. "On forecasting freeway occupancies and volumes (abridgment)". *Transportation Research Record* (773).

Lieberman, E., and A. K. Rathi. 1997. "Traffic simulation". *Traffic flow theory*.

Lighthill, M. J., and G. B. Whitham. 1955. "On kinematic waves. II. A theory of traffic flow on long crowded roads". In *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, Volume 229, 317–345. The Royal Society.

Lo, C.-H., W.-C. Peng, C.-W. Chen, T.-Y. Lin, and C.-S. Lin. 2008. "Carweb: A traffic data collection platform". In *Mobile Data Management, 2008. MDM'08. 9th International Conference on*, 221–222. IEEE.

Mahnke, R., and R. Kühne. 2007. "Probabilistic description of traffic breakdown". *Traffic and Granular Flow05*:527–536.

Mori, U., A. Mendiburu, M. Álvarez, and J. A. Lozano. 2015. "A review of travel time estimation and forecasting for Advanced Traveller Information Systems". *Transportmetrica A: Transport Science* 11 (2): 119–157.

Nagel, K., and M. Schreckenberg. 1992. "A cellular automaton model for freeway traffic". *Journal de physique I* 2 (12): 2221–2229.

Newell, G. F. 1961. "Nonlinear effects in the dynamics of car following". *Operations research* 9 (2): 209–229.

Nikovski, D., N. Nishiuma, Y. Goto, and H. Kumazawa. 2005. "Univariate short-term prediction of road travel times". In *Intelligent Transportation Systems, 2005. Proceedings. 2005 IEEE*, 1074–1079. IEEE.

Okutani, I., and Y. J. Stephanedes. 1984. "Dynamic prediction of traffic volume through Kalman filtering theory". *Transportation Research Part B: Methodological* 18 (1): 1–11.

Paveri-Fontana, S. 1975. "On Boltzmann-like treatments for traffic flow: a critical review of the basic model and an alternative proposal for dilute traffic analysis". *Transportation research* 9 (4): 225–235.

Pereira, J. L., and R. J. Rossetti. 2012. "An integrated architecture for autonomous vehicles simulation". In *Proceedings of the 27th annual ACM symposium on applied computing*, 286–292. ACM.

Pipes, L. A. 1953. "An operational analysis of traffic dynamics". *Journal of applied physics* 24 (3): 274–281.

Prigogine, I., and F. C. Andrews. 1960. "A Boltzmann-like approach for traffic flow". *Operations Research* 8 (6): 789–797.

Radwan, E., M. Elahi, and M. Goul. 1990. "Knowledge based systems applications for traffic signal control". In *OECD Workshop on Knowledge-Based Expert Systems in Transportation Part 1 (of 2)*. Publ by Technical Research Cent of Finland.

Richards, P. I. 1956. "Shock waves on the highway". *Operations research* 4 (1): 42–51.

Salimifard, K., and M. Ansari. 2013. "Modeling and simulation of urban traffic signals". *International Journal of Modeling and Optimization* 3 (2): 172.

Schimbinschi, F., L. Moreira-Matias, V. X. Nguyen, and J. Bailey. 2017. "Topology-regularized universal vector autoregression for traffic forecasting in large urban areas". *Expert Systems with Applications*.

Schimbinschi, F., X. V. Nguyen, J. Bailey, C. Leckie, H. Vu, and R. Kotagiri. 2015. "Traffic forecasting in complex urban networks: Leveraging big data and machine learning". In *Big Data (Big Data), 2015 IEEE International Conference on*, 1019–1024. IEEE.

Seiffert, C., T. M. Khoshgoftaar, J. Van Hulse, and A. Napolitano. 2010. "RUSBoost: A hybrid approach to alleviating class imbalance". *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 40 (1): 185–197.

Semarak, J. 1996. "Intelligent traffic lights control by fuzzy logic". *Malaysian Journal of Computer Science* 9 (2): 29–35.

Sichitiu, M. L., and M. Kihl. 2008. "Inter-vehicle communication systems: a survey". *IEEE Communications Surveys & Tutorials* 10 (2).

Stathopoulos, A., and M. G. Karlaftis. 2003. "A multivariate state space approach for urban traffic flow modeling and prediction". *Transportation Research Part C: Emerging Technologies* 11 (2): 121–135.

Suh, W., D. Henclewood, A. Guin, R. Guensler, M. Hunter, and R. Fujimoto. 2017. "Dynamic data driven transportation systems". *Multimedia Tools and Applications*:1–17.

Sumaryo, S., A. Halim, and K. Ramli. 2013. "Improved discrete event simulation model of traffic light control on a single intersection". In *QiR (Quality in Research), 2013 International Conference on*, 116–120. IEEE.

Sun, S., C. Zhang, and G. Yu. 2006. "A Bayesian network approach to traffic flow forecasting". *IEEE Transactions on intelligent transportation systems* 7 (1): 124–132.

Suzumura, T., and H. Kanezashi. 2013. "A holistic architecture for super real-time multiagent simulation platforms". In *Proceedings of the 2013 Winter Simulation Conference*, edited by R. P. S.-H. K. A. T. R. Hill and M. E. Kuhl, 1604–1612. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Thulasidasan, S., and S. Eidenbenz. 2009. "Accelerating traffic microsimulations: A parallel discrete-event queue-based approach for speed and scale". In *Proceedings of the 2009 Winter Simulation Conference*, edited by M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 2457–2466. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Thulasidasan, S., S. Kasiviswanathan, S. Eidenbenz, E. Galli, S. Mniszewski, and P. Romero. 2009. "Designing systems for large-scale, discrete-event simulations: Experiences with the FastTrans parallel microsimulator". In *High Performance Computing (HiPC), 2009 International Conference on*, 428–437. IEEE.

Treiber, M., A. Hennecke, and D. Helbing. 2000. "Congested traffic states in empirical observations and microscopic simulations". *Physical review E* 62 (2): 1805.

Van Aerde, M., B. Hellinga, M. Baker, and H. Rakha. 1996. "INTEGRATION: An overview of traffic simulation features". *Transportation Research Records*.

Van Aerde, M., and S. Yagar. 1988. "Dynamic integrated freeway/traffic signal networks: A routing-based modelling approach". *Transportation Research Part A: General* 22 (6): 445–453.

van Wageningen-Kessels, F., H. Van Lint, K. Vuik, and S. Hoogendoorn. 2015. "Genealogy of traffic flow models". *EURO Journal on Transportation and Logistics* 4 (4): 445–473.

Vlahogianni, E. I., J. C. Golias, and M. G. Karlaftis. 2004. "Short-term traffic forecasting: Overview of objectives and methods". *Transport reviews* 24 (5): 533–557.

Vlahogianni, E. I., M. G. Karlaftis, and J. C. Golias. 2014. "Short-term traffic forecasting: Where we are and where were going". *Transportation Research Part C: Emerging Technologies* 43:3–19.

Wang, X. 2005. "Integrating GIS, simulation models, and visualization in traffic impact analysis". *Computers, Environment and Urban Systems* 29 (4): 471–496.

Wiedemann, R. 1974. "Simulation des Strassenverkehrsflusses". *Schriftenreihe des Instituts fuer Verkehrswesen der Universitaet Karlsruhe (* (8).

Wilkie, D., J. Sewall, and M. C. Lin. 2012. "Transforming GIS data into functional road models for large-scale traffic simulation". *IEEE transactions on visualization and computer graphics* 18 (6): 890–901.

Williams, B., P. Durvasula, and D. Brown. 1998. "Urban freeway traffic flow prediction: application of seasonal autoregressive integrated moving average and exponential smoothing models". *Transportation Research Record: Journal of the Transportation Research Board* (1644): 132–141.

Wong, G., and S. Wong. 2002. "A multi-class traffic flow model–an extension of LWR model with heterogeneous drivers". *Transportation Research Part A: Policy and Practice* 36 (9): 827–841.

Zehe, D., W. Cai, A. Knoll, and H. Aydt. 2015. "Tutorial on a modeling and simulation cloud service". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 103–114. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Zhang, X., and J. A. Rice. 2003. "Short-term travel time prediction". *Transportation Research Part C: Emerging Technologies* 11 (3): 187–210.

Zhou, X., and J. Taylor. 2014. "DTALite: A queue-based mesoscopic traffic simulator for fast model evaluation and calibration". *Cogent Engineering* 1 (1): 961345.

Zozaya-Gorostiza, C., and C. Hendrickson. 1987. "Expert system for traffic signal setting assistance". *Journal of Transportation Engineering* 113 (2): 108–126.

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