# Intelligent Mobility for minimizing the traffic incidents' impact on transportation network

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**Abstract**

Due to the major development in urbanization and the expanding population, traffic congestion has become a critical problem in metropolitan cities. Traffic congestion happens whenever the demand exceeds the maximum capacity of a road. Therefore, to make optimum use of the road network capacity, Intelligent Transport Systems (ITS) are often employed to cope up with this situation efficiently. Using advanced sensor technologies, the real-time traffic information is collected from large transportation networks and utilized in various applications such as route guidance, congestion avoidance, traffic control and management, etc. Apart from the regular peak hour congestion, the unexpected occurrence of non-recurrent traffic events such as accidents, vehicle breakdowns, road crashes, etc. causes about 25% of traffic congestion on the arterial roads and even a higher proportion for urban highways and expressways. Every year 1.35 million people die on an average as a result of road traffic crashes. Besides, 20-50 million people suffer from non-fatal injuries, sometimes leading to short-term or long-term disability. Moreover, the non-recurring incidents lead to significant economic losses because of their unpredictable nature. The road accidents can cost upto 3% of the countries' gross domestic product. Therefore, anticipating such events in advance can be highly useful in mitigating the resultant congestion and therefore benefiting the national economy as a whole. However, since these types of incidents are non-recurrent and unplanned, the probability of occurrence of these incidents is hard to forecast. Therefore, Intelligent transport systems (ITS) are more concerned about minimizing the severity of congestion after the incidents have already happened. The

two integral systems of ITS are Traffic Information Management System (TIMS) and Dynamic Routing Guidance System (DRGS). Both of these systems play a vital role because TIMS is responsible for real-time data acquisition of traffic parameters like speed, the number of vehicles passing by, weather condition of the roadway, etc., and DRGS helps the commuters to dynamically choose the routes by providing information on network traffic and other possible routes to be taken. The two techniques used for traffic prediction are either simulation-based or data-driven. In a simulation-based approach, traffic prediction models which predict the future state are designed based on some theoretical models. This approach needs some expertise to build the network traffic simulation. On the other hand, data-driven models can be built for prediction with the usage of historical or real-time data-sets.

Apart from the predictive solutions, there are several other new technologies to assist the drivers in the occurrence of an incident. For example, the traffic management authorities have installed the new age Variable Message Signs (VMS displays) with modern technologies (such as graphics and more colours) on the roads of the cities. These LED road traffic signs notify the drivers about any kind of disruption in traffic, such as accidents, obstacles, roadworks, etc., and therefore help in rerouting the vehicles. Nowadays, VMS system is an integral part of Dynamic Routing Guidance System. Therefore, traffic management authorities from several smart cities have been investing a significant amount of resources to install the VMS displays in different places. Thus, ITS are often being employed in different aspects of transportation to provide better mobility solutions for commuters and drivers. Moreover, advancements in sensor technologies have helped ITS to improve the efficiency of existing transportation infrastructure. In this chapter, we address the applications of ITS for incident management and congestion avoidance in real-time.

Keywords: Traffic incidents, intelligent mobility, traffic congestion, incident duration and impact prediction

## 10.1 Introduction

Non-recurrent traffic incidents such as accidents, vehicle breakdowns, crashes, obstacles, etc. lead to severe congestion in the metropolitan cities, and therefore, have a major impact on the roadway traffic. These incidents affect the daily life of the commuters directly or indirectly. Moreover, due to the ever-growing population the need for an intelligent and proper traffic management systems arises that would provide better traffic congestion control during the incidents [1]. Of late, intelligent transportation systems are being employed to study the traffic incidents systematically and identify their root causes [2]. Apart from adverse geographical or environmental conditions, human errors are also responsible for a large percentage of traffic incidents across the world [3] [4].

Since these incidents are non-recurrent and unplanned, many a times these incidents cannot be predicted in advance and as such, there are many false negative cases. Therefore, recent studies focus on building the predictive models for minimizing their impact after the incidents have already happened. Moreover, smart technologies such as Variable Message Signs (VMS) or Variable Speed Limit (VSL) are also in operation to assist the drivers during the incidents in major cities [5] [6]. Thus, intelligent mobility has come into play for minimizing the overall traffic disruption caused by the incidents, and thereby facilitating better travel for commuters and transport management.

## 10.2 Different Types of Incidents

Based on the geographical locations of the cities or countries, several types of incidents can be found in the literature. For example, Araghi *et al.* [7] identified ten types of incidents in Greater London Area, viz. broken-down vehicle, broken-down lorry, accident, flood, fuel spillage, gas leak, fire, police incident, collapsed manhole, and traffic light failure. On the other hand, each of these types may have several sub-categories. For example, accidents can be of different kinds: rear-end collision, side-impact collision, head on collision, rollover, single car accident, multiple vehicle pile-up, etc. [4]. The annual number of deaths per 100K people due to road accidents in 2017 is shown in Fig. 10.1 for different countries all over the world. In general, the types of incidents vary with the traffic condition (speed limit, traffic flow),

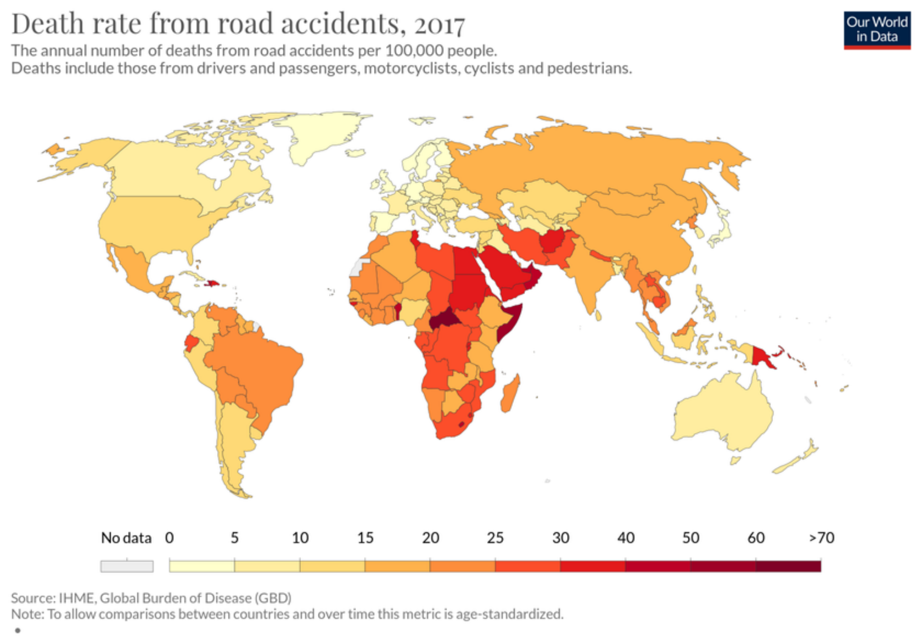


Figure 10.1: Annual death rate from road accidents in 2017 [8].

geographical attributes (width of the roads, capacity), as well as weather (rainfall, fog, snow). Moreover, the types of incidents recorded from highways or freeways can be significantly different from the incident types that are recorded from arterial roads. Considering all these variations, we can broadly classify the traffic incidents into six categories: vehicle breakdown (disabled vehicles), accident (crashes and collisions), obstacle on road (stationary and abandoned vehicles), road block or diversion, car on fire, and miscellaneous (which includes other types of incidents such as fuel spillage, traffic light failure, etc.). These types of incidents are mostly common for all cities, as mentioned in past studies [1] [9].

## 10.3 Causes of Incidents

Traffic incidents can be caused due to several reasons. Although adverse environment or poor vehicle condition may lead to traffic incidents, however human beings can also be responsible for a large percentage of traffic incidents [3]. Below are the most common causes of traffic incidents:

1. **Drivers:** There are many laws and rules concerning driving in every country, since many a times drivers are solely responsible for road accidents and crashes. Distracted driving brings about 25% of the incidents all over the world which includes texting, eating, talking or doing other works while driving. Besides, drunk and sleepy driving is more dangerous which pose a great threat to all road users. Apart from that, reckless or rash driving, speeding beyond the speed limit, violation of traffic rules and traffic lights, all these can lead to mishaps on the roads.
2. **Defects in the Vehicle:** Vehicle breakdowns are mostly caused by the flaws in the vehicles, such as brake failure, failure of steering system or lighting system, tire burst, etc. Therefore, the owners of the cars should take their cars for regular maintenance to avoid such incidents on roads.
3. **Poor Environment:** Poor environmental condition, such as rainfall, snowfall, fog, etc. cause hindrance in smooth driving, and therefore may lead to traffic incidents. Due to rainfall and snowfall, the roads become slippery. As such, vehicles tend to skid more due to lower friction with the roads. Moreover, poor visibility due to heavy precipitation or fog, mist, smoke, etc. makes driving unsafe [10].
4. **Obstructions on the Road:** Sometimes, trees or the broken parts of the trees can block the roads partially or fully. Moreover, there can be stopped vehicles on the roads which may require the road users brake abruptly. Apart from that, cones placed on the roads due to roadworks, animals crossing the roads, etc. can also lead to accidents. Although there exist many other potential scenarios causing traffic hazard, these are the major causes of traffic incidents in different cities across the world.

## 10.4 What is Intelligent Mobility?

Intelligent mobility is a buzzword nowadays which encompasses the technological solutions for communication, control, and information processing in transportation [11]. With the growing population of vehicles on the road, traffic safety has become of utmost concern. Therefore, vehicles are coming with new technologies which can help avoid crashes, minimize the aftereffects and therefore, ensure road safety. Moreover, traffic management authorities are also being proactive to maintain the smooth operations of traffic. They are adopting new technologies to inform the road users about any roadwork going on or other obstructions existing on the roads [12]. Nevertheless, traffic incidents are inevitable mostly because of the human errors or faulty parts of the vehicles [4]. To circumvent such situations, the real-time traffic prediction models have been developed which can forecast the incident duration and spread of congestion in advance so that the road users can avoid getting stuck in the traffic jams [13]. Thus, the overall congestion caused by the incidents can also be minimized.

## 10.5 Incident Duration Prediction

To optimize and improve the incident management strategies, the duration of the incidents is an important parameter to be considered. Predicting the incidents' duration in real-time can be highly useful for the driver assistance systems. Based on the predictions, they can provide advisories to the drivers to avoid the incident-affected location for the remaining duration. Therefore, incident duration prediction has always been an active research problem in the area of transportation.

The total incident duration comprises four major stages: (1) reporting time: the time taken to detect, verify and report the incident after its occurrence, (2) response time: the time taken by the response team to arrive at the spot after reporting of the incident, (3) clearance time: the time required by the team to clear the affected area, and (4) recovery time: the time taken by the traffic condition to restore back to normal [14]. However, the standards and definitions vary from one country to another. Some studies defined incident duration as the sum of first three stages since the incidents get cleared by the end of the clearance time [15]. A few other studies considered the reporting time (i.e., when the incidents had been reported) as the starting time of the incidents. As per these studies, the span of the incidents includes the response time and the clearance time, i.e. the second and third stage [16]. Nevertheless, most of the studies took all the four stages into consideration since the impact of the incidents exist in the network from the beginning of the reporting time (first stage) to the end of the recovery time (fourth stage) [17].

The existing studies related to incidents' duration prediction are enlisted in Table 10.1.

Table 10.1: Summary of the previous studies on incident duration prediction.

| Type of model | Methodology used | Literature | Target variable | Error |
|---|---|---|---|---|
| Hazard-based model | log-logistic model | Chung *et al.* [18] | Accident duration | MAPE value 47% |
| | Gamma, Weibull and log-logistic models | Jiang *et al.* [19] | Incident duration | 40% of incident having $< 10$ min error |
| | Mixture model and AFT model | Ruimin *et al.* [20] | Incident duration | MAPE 45% for $> 15$ min |
| Traditional machine learning | Hybrid tree-based quantile regression | Qing *et al.* [14] | Incident duration | MAPE value 49.1% |
| | ANN, SVM/RVM, KNN | Valenti *et al.* [21] | Incident duration | MAPE in the range of $34 - 44\%$ |
| | Text analysis and ANN | Pereira *et al.* [22] | Incident duration | MAPE varies over time from 100% to 40% |
| | Support Vector Regression | Wu *et al.* [23] | Incident duration | Total accuracy 70% |
| | Bagging and Boosting, SVR, MLP | Banishree *et al.* [17] | Incident duration | MAPE varies over time from 61% to 27.58% |
| Combined model | Combined M5P tree and HDBM | Lin *et al.* [24] | Accident duration | 39.1% and 33.15% for two different data-sets |
| | Combination of ANN models | Lopes *et al.* [25] | Clearance time | mean error: $10 - 20$ min |

In earlier years, most of the studies applied simulation-based theoretical modeling for traffic prediction. For example, Golob *et al.* [26] developed log-normal models of incident duration, whereas Hojati *et al.* [9] built prediction models with Weibull and log-logistic distributions, as shown in Fig. 10.2. Later, a few studies found that incident duration can be better approximated if separate statistical models are fitted to different stages of the incidents. For example, Ruimin *et al.* applied separate statistical models for each stage, such as dispatch time, clearance time, etc. [27], and subsequently developed a mixture model combining generalized gamma, Weibull and log-logistic distribution for different incident clearance methods [20]. However, all these studies developed static models which did not incorporate real-time traffic information.

In recent years, various data-driven modeling algorithms, such as Support Vector Regression (SVR) [23], Artificial Neural Networks (ANN) [13], Bagging and Boosting [28] etc. have been applied for predicting the duration of traffic incidents. Moreover, adaptive network-based fuzzy inference system (ANFIS) has proved to be efficient because it combines the efficiency of the fuzzy model in handling the uncertainty with the prediction accuracy of

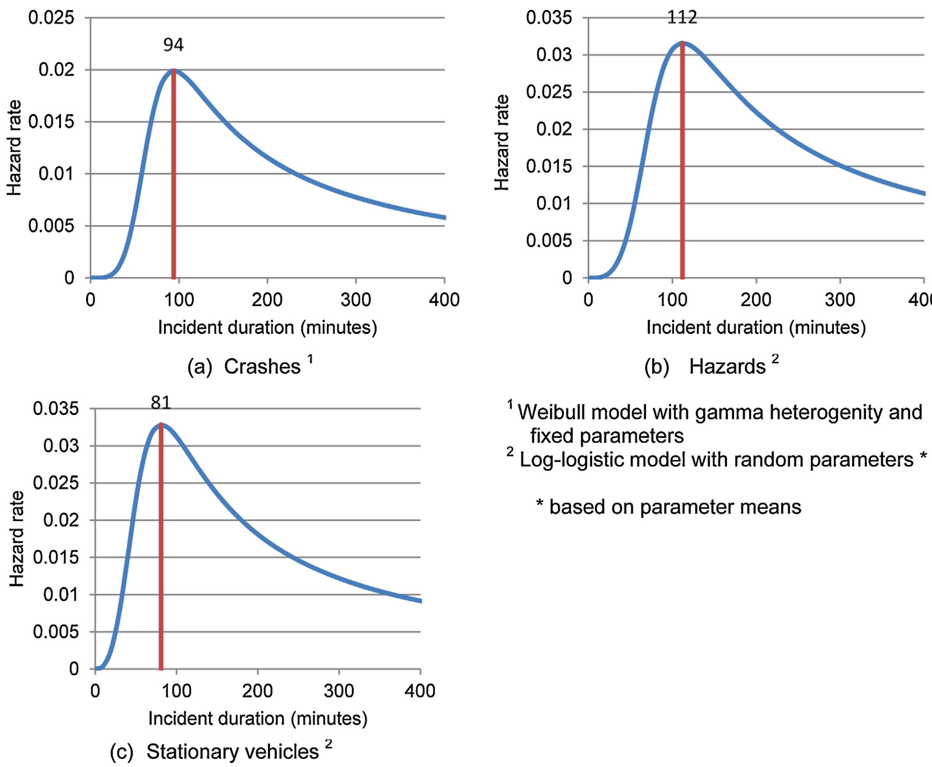


Figure 10.2: Hazard functions for different incident types [9].

artificial neural network method using back-propagation [29].

However, an important consideration in building the data-driven models is the comprehensiveness of the data-set. The incident duration depends on several external factors, such as spatio-temporal features, geographical features, incidents' information, stakeholders, traffic condition, etc. Examples of each category of features are mentioned in Table 10.2, although the list is not exhaustive [30].

Among these features, real-time traffic information is one of the most important features since the forecast should be updated every time the traffic condition changes. Therefore, most of the recent studies have analyzed the impact of incidents by incorporating real-time traffic data [13] [14]. In particular, it is essential to consider both important traffic variables, i.e. speed and flow, in the analysis which can be explained by the fundamental diagram of speed-flow as shown in Fig. 10.3.

The relationship between the variation of speed and flow can be described

Table 10.2: Features related to traffic incident duration.

| Categories | Features | Feature type |
|---|---|---|
| Temporal features | Weekday/weekend | Categorical |
| | Day of the week | Categorical |
| | Peak-hour/off-peak | Categorical |
| | Season of the year | Categorical |
| Spatial features | Type of the road | Categorical |
| | Street/Expressway | Categorical |
| | Direction of the road | Categorical |
| Geographical features | Intersection/bottleneck | Categorical |
| | Number of lanes | Numerical |
| | Number of affected lanes | Numerical |
| | Type of affected lanes | Categorical |
| | Status of shoulder lane | Categorical |
| Incidents' characteristics | Incident severity | Categorical |
| | Type of incidents | Categorical |
| | Number of casualties | Numerical |
| Stakeholders | Number of vehicles involved | Numerical |
| | Types of vehicles involved | Categorical |
| | Fatality/injured | Numerical |
| Traffic condition | Traffic flow | Numerical |
| | Traffic speed | Numerical |
| | Queue-length | Numerical |
| Others | Police response time | Numerical |
| | Arrival of emergency response service | Numerical |
| | Type of reporting | Categorical |

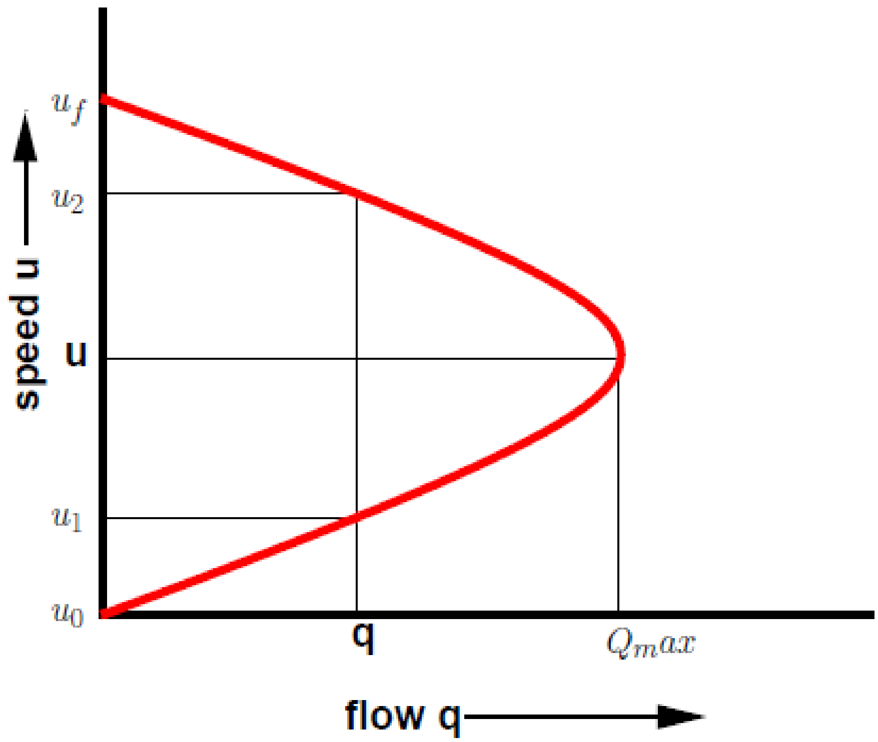


Figure 10.3: Speed-flow diagram [31].

as follows. The flow can be low because either there is not much traffic on the road or the vehicles cannot move because of the congestion. Now, when there is not much traffic, the vehicles can move at almost free flow speed. By contrast, if the flow is low due to congestion, the average speed of the vehicles will be low as well. Therefore, from the fundamental speed-flow relationship [31], we can deduce that if both the speed and flow is lower than usual, the road is clearly congested. Moreover, rules based on a single traffic variable do not generalize well to diverse city-scale networks. For example, the speed limit of the arterial roads is usually lower than that of expressways. Therefore, the speed will drop less during incidents at arterial roads compared to expressways. Hence, the change in flow is a better indicator of congestion for the incidents in arterial roads. Thus, considering both speed and flow helps to avoid false alarms raised due to sensor noise as well as allows us to design more robust decision rules for detecting congestion. Furthermore, the resolution of traffic data should be fine enough to understand the subtle changes in the impact of incidents accurately. For example, in Banishree *et al.*'s work, the spatial resolution of traffic data is 100 meter and the temporal resolution is 5 min [17] which can indicate the start and end of congestion with high precision.

Despite considering all potentially significant features in the model, the availability of partial information or ever-changing ground conditions makes the task of forecasting particularly challenging. Therefore, the predictive models need to be adaptive to flexibly incorporate features as incident and traffic data gradually become available. Moreover, the model should provide reasonable forecasts even when a limited amount of information is available which gets more refined with elapsing time [17]. A block diagram of such a dynamic adaptive prediction model is shown in Fig. 10.4. The entire feature-

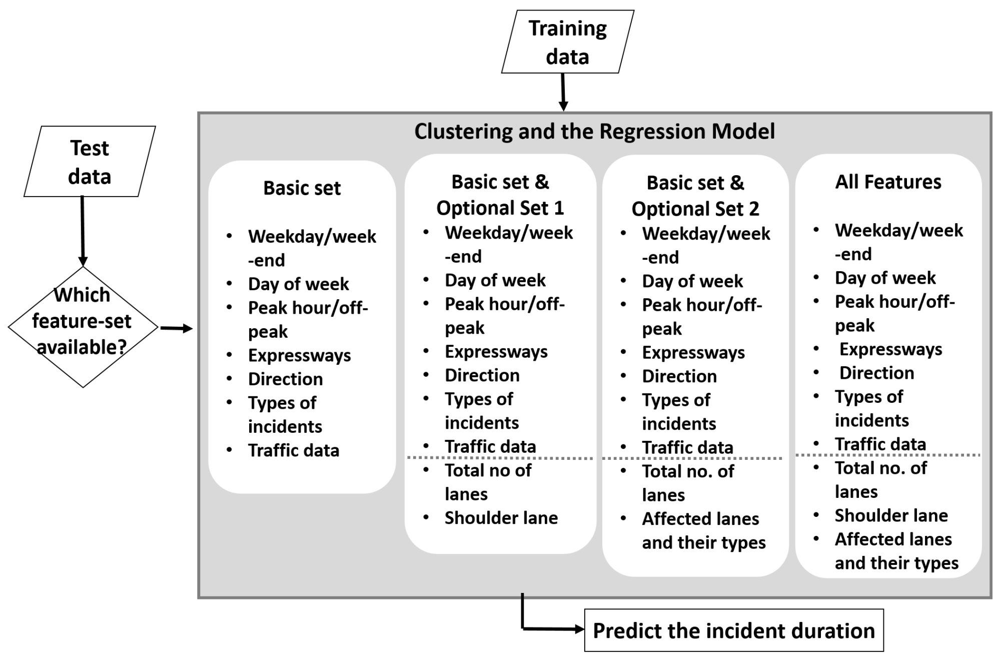


Figure 10.4: Block diagram of a dynamic adaptive predictive model.

set is divided into four subsets of features based on their order of availability. The first one is named basic set comprising the basic features which are available immediately after the incident happens. Second set contains the basic features and total number of lanes, shoulder lane. Similarly, the third set covers the basic set and few other additional features about the lanes. Finally, the fourth set includes all features together. The regression model is trained with each sub-set individually so that the model can perform the prediction when any of the sub-set is available. Therefore, when a new data-point comes, the model at first checks which feature set is available, and the prediction can be performed by the corresponding model. Any traditional machine learning method can be applied in this model. Moreover, prior to the prediction, clustering method can also be applied for dividing the incidents into different clusters based on their latent similarities. In that case, separate regression models are built for individual cluster [32]. Different clustering algorithms, such as K-means Clustering [33], Affinity Propagation [34], Gaussian Mixture Model [35], etc. can be employed in this model.

While the model performs prediction, the commuters and other users need to know the confidence in prediction so that they can decide whether it is reliable or not. It is quite obvious that the confidence of the model will increase with elapsed time. In this context, Bayesian methods can be applied for determining the confidence intervals associated with the predictions. In the past, Van *et al.* [36] built a Bayesian neural network model for prediction of travel-time. However, neural network algorithms may sometimes converge on local minima instead of global minima. To solve this issue, naive Bayesian classifier [37], Bayesian SVR [38] [39] etc. methods have been employed in other studies.

The following example in Fig. 10.5 demonstrates how a dynamic adaptive incident duration prediction model works in real-life. At first the traffic is normal at around 5:00 pm in a highway. At 5:05 pm, a vehicle breakdown occurs and blocks the road. Therefore, traffic starts to slow down. The model detects the change in the traffic data and speculates that an incident has happened. Although the incident reports are not available yet (since it takes some time to report the incidents to the management authority), the regression model performs the first prediction with the information it obtains from the traffic data. Meanwhile, the incident is reported approximately at 5:15 pm (10 minutes after the incident happened). The essential features are disseminated after the incident has been reported and therefore the database can be updated (i.e., the location etc.) according to the report. Consequently, the model performs the prediction again at 5:20 pm. Further, the details about the closure of the lanes are reported at 5:30 pm. Therefore, as all features are available by this time, the prediction gets more accurate. In the

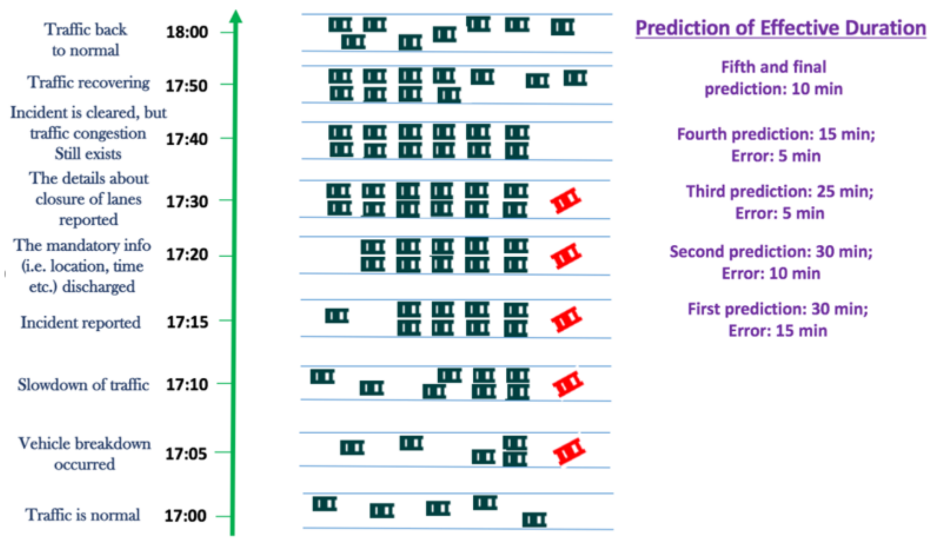


Figure 10.5: A real-life scenario demonstrating how the incident duration predictive model works [17].

mean time, the response team reaches the location and clears the damaged vehicle from the road at 5:40 pm. However, traffic usually takes some time to go back to normal after the incident has been cleared. At 5:50 pm, the traffic conditions are recovered although the queue of the cars still exists. Finally, at 6:00 pm, the model finds the traffic data to be back to normal again and hence, stops the prediction [17].

## 10.6 Incident Impact Prediction

Modeling and estimation of traffic congestion has been another most sought-after research areas in the field of urban transportation. Nowadays traffic data have become readily available in many government websites, since traffic management authorities regularly update the traffic information on their websites collected from a variety of sensors. However, analysis of traffic congestion is critical because it spreads both spatially and temporally. Moreover, the prediction has to be updated at every instant.

A large fraction of studies applied the cell transmission model [40] or shock wave model [41] for modeling the congestion propagation in the network. However, none of these studies dealt with the real-time traffic data.

Hence, the performance of these models may degrade when used in real-time applications. Moreover, the spatial transferability of these models may be compromised as well. Apart from that, several studies have employed the time-series approaches, such as Auto Regressive Moving Average (ARMA) and its variants. For example, Alghamdi *et al.* developed the widely-used ARIMA (Auto Regressive Integrated Moving Average) model for forecasting traffic congestion [42], whereas Kumar *et al.* built Seasonal ARIMA (SARIMA) model [43]. Nevertheless, SARIMA model is more suitable for modeling the recurring congestion because this model can capture the periodicity of the data better. Besides, Kamarianakis *et al.* proposed the multivariate approaches, Vector ARMA (VARMA) and Space-Time ARIMA (STARIMA) for forecasting traffic flow [44]. VARMA model captures the linear dependence between multiple time series, whereas STARIMA model requires less parameters which makes it more suitable for handling large-scale traffic prediction. Thus, time-series methods perform well in forecasting the spread of congestion for both long and short time horizons.

On the other hand, traditional machine learning methods such as ANN [45], SVR [46], Gaussian Process Regression [47], etc. are also extensively applied in the task of forecasting. In addition, the variants of Bagging and Boosting, such as XGBoost [48], Gradient Boosting [49] AdaBoost [50], Bagging [47], etc. have also been employed in several other studies. Most of these literature target for traffic flow prediction, which is an indicator of traffic congestion. On the other hand, some studies developed predictive model for forecasting traffic speed using SVR [51], Random Forest [52], Multi Layer Perceptron (MLP) [52], etc. Moreover, Leong *et al.* proposed that speed prediction can further be improved incorporating the rainfall data [53].

With the emergence of deep learning architectures, the deep neural networks are being explored a lot of late to capture the spatiotemporal dynamics of the road network. For example, Haiyang *et al.* [54] introduced the spatiotemporal recurrent convolutional networks combining convolutional neural networks (CNN) and long short-term memory (LSTM) neural networks in order to predict traffic speed for different horizons. Since LSTM model can handle the temporal dynamicity of the data efficiently, many studies opted for LSTM model for traffic related applications. For example, Min *et al.* [55] introduced a stacked LSTM neural network considering both spatial and temporal correlations to predict traffic speeds, whereas Honglei *et al.* [56] built an LSTM network for predicting the accident risk citywide.

In general, the process of development and dissipation of congestion follows a birth-death mechanism [57] as shown in Fig. 10.6. The prediction

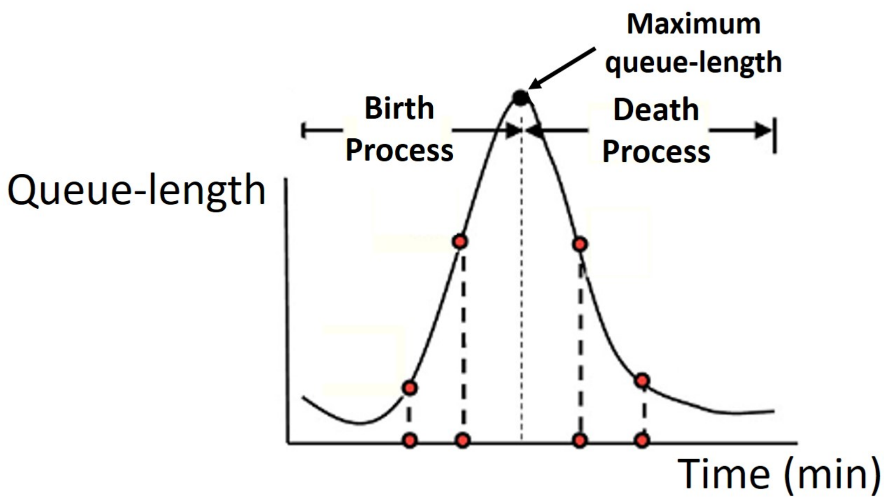


Figure 10.6: The birth and death process of congestion [58].

models have to capture the pattern of the entire birth-death process during the congestion. However, the dynamics of the birth process and death process are different. Therefore, the models need some time to learn the underlying patterns. For short duration incidents, the models do not get enough time, which leads to high prediction errors for most of the cases. For medium and long duration incidents, the models get sufficient time to learn the birth and death process individually. However, the errors may be higher during the switching from birth to death process. The sequence is as follows: the prediction error decreases at first during the birth process until the queue reaches its maximum length, followed by subsequent dissipation afterward while the error is a bit high. Once the model learns about the death process from the previous data, the prediction gets more refined in the later instants.

## 10.7 Other Technologies

For optimal utilization of the road network capacity and efficient traffic management during the incidents, several countries have adopted a new technology named Variable (or electronic) Message Signs, often abbreviated as VMS. These messages appear in electronic displays in the form of texts and

graphics to notify the drivers about any kind of disruption in traffic, such as accidents, obstacles, roadworks, etc. Moreover, the signs can display the warning and advisories about taking alternative routes or limiting travel speed, and disseminate the information about the duration and location of the incidents [59].
Variable speed limit is a part of VMS technology, where it indicates a flexible speed limit of the vehicles on the roads [5]. As opposed to the conventional speed limit signs which are fixed-valued, the variable speed limits are adjusted in accordance with the present environmental and traffic conditions. Therefore, during traffic incidents, bad weather or roadworks, the maximum speed limits are reduced compared to that of the optimal condition and the commuters should adhere to the limit accordingly.

It has been proven in several studies that the Variable Message Signs can potentially reduce the number of secondary crashes [12] [60]. Moreover, Dos *et al.* [6] reported that the combination of VMS and variable speed limit techniques can be a potential solution to reduce rear-end collisions. Therefore, apart from the predictive solutions, these technologies can also assist the drivers in the occurrence of the traffic incident. However, the technologies are still in the nascent stage. The awareness among drivers and thereby, the effectiveness of these messages as a traffic guidance tool turns out to be significantly less than optimal in many cities [61]. Therefore, with growing recognition for the efficacy of VMS technology, we hope to see a significant increase in the impact of VMS on overall traffic conditions in coming years.

## 10.8 Conclusion

For efficient traffic incidents management, it is important to adopt new technologies in the urban areas. Prediction of the parameters, such as incident duration or congestion length are proved to be highly effective in this regard. However, the incident management authorities need to ensure that the commuters and drivers install those applications in their systems and follow the guidance. Moreover, the prediction models should be robust, accurate and adaptive to the varying ground conditions. Apart from that, of late VMS system has been an integral part of the dynamic routing guidance system. Therefore, several smart cities across the world are investing a significant amount of resources to install the VMS displays in different locations.

Last but not the least, prevention is better than cure! Hence, the road users need to be careful and responsible enough while driving or walking along the roads and thus, take their part in minimizing the risks of incidents on the roads. Moreover, Advanced Driver-Assistance Systems, or abbreviated as ADAS, are being employed to assist the drivers while driving or parking. The safety features of ADAS are designed to alert the drivers or take over control of the vehicles in the occurrence of the incidents [62]. Therefore, ADAS have proved to be efficient in reducing the road accidents significantly. Besides, there are other technologies associated to ADAS as well, such as lane departure warning system, automatic lane centering, automated lighting, incorporating traffic warnings, etc. which can aid in minimizing human errors [63].

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