An overview of Data Based Predictive Modeling Techniques used in Analysis of Vehicle Crash Severity*

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Abstract. Accident injury prediction is a crucial constituent to reducing fatalities linked to vehicle crashes. The vehicle development process and road safety planning includes also the injury prediction for occupants and Vulnerable Road Users (VRUs) in a vehicle crash and the identification of the factors responsible for increased traffic collision injuries. This paper reviews the different data-based prediction techniques to modeling a vehicle crash event, crash frequency and crash severity. Machine learning (ML) is a research field which has gained impetus in the recent years and is widely used in different engineering applications; including injury prediction in vehicle collisions. The paper is divided into two major sections; the first section presents an overview of the existing predictive models for estimating injury severity in a crash event to occupants and VRUs and the second section describes the applications of data-based modeling techniques to predict crash frequency in different traffic scenarios. We also discuss possible future applications of data-based modeling techniques in this domain.

Keywords: data-based prediction models · machine learning · vehicle crash · modeling and simulation · injury prediction · crashworthiness.

1 Introduction

Road accidents have been one of the major causes of injuries and fatalities in the world. The 2015 European Commission report identifies frontal impact as the most common crash scenario leading to serious injuries, followed by side impact. This might be due to the different forces acting in impact scenarios along with the cage protecting the occupants in a collision [50], [38].(this sentence should be reformulated) The report also suggests further study of mechanisms

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and measures to reduce injury severity in a crash. Researchers have developed and implemented several virtual modeling techniques to reduce impact severity in a vehicle crash. These virtual models reduce the dependence of vehicle safety on physical testing, also allowing to conduct multiple iterations to improve vehicle safety performance. Analytical modeling of crash events has replaced physical testing in the past; this applies both in the fields of vehicle design to mitigate crash injuries and in road safety planning. The vehicle development for crashworthiness has seen the emergence of analytical models like FEM (finite Element Models), LPM (Lumped Parameter Model) and MBM (Multi Body Models) [14]. These models replicate the geometrical and material details of the structure to a good extent and can be highly reliable in terms of correlation with real time crash tests. Researchers have used these models extensively to capture the vehicle crash dynamics and occupant injury characteristics in modern cars. Noorsumar et al. [39] have provided a comprehensive review of mathematical modeling techniques used to replicate vehicle crashes along with the advantages and drawbacks of each of the strategies. One of the drawbacks of these techniques is the high computational powers and the development time used in these highly complex mathematical models [29]. It is important to note that the data generated during these simulations can be used with prediction algorithms to determine crash injury severity. In the road safety prediction traditionally statistical models were widely used. Researchers in the early 2000s used regression based statistical models to describe relationship between road accidents and driver behaviour, road conditions etc. In the past decade these models have been replaced by ML based techniques which have higher accuracy in prediction of road accidents. Figure 1 shows the flowchart of crash injury prediction in vehicle development and road safety planning,

Predictive analytics is a term used in statistical and analytics techniques, to predict future events [25]. This powerful tool is widely used in engineering to analyze current and historical data by utilizing techniques from statistics, data mining, ML and artificial intelligence. Accident crash frequency refers to the number of crashes that would occur on that segment of the road in a time period; however crash severity models explains the relationship between crash severity and contributing factors to vehicle crash such as vehicle geometry, driver behaviour and road conditions. [1]. Data based modeling is an alternative to traditional modeling techniques and has proved to be successful in road planning and vehicle development.

This paper provides an overview of the applications of data-based modeling techniques in vehicle crash prediction and accident injury severity. We look at the different statistical and ML techniques and also highlight the advantages and limitations of these methodologies in crash prediction. The paper is divided into two sections; the first section deals with the data-based modeling techniques used in crashworthiness design and the second section looks at the recent techniques used in road collision prediction modeling. This paper does not review all the articles/studies in this area of research but focuses more on the existing method-

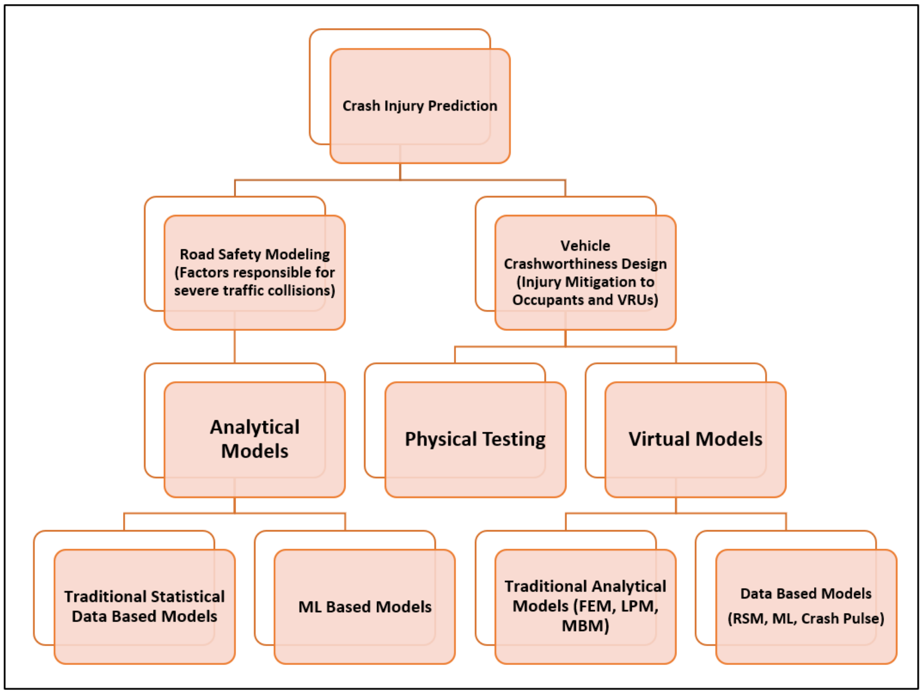

Fig. 1. Flowchart of Crash Injury Prediction in Vehicles

ologies employed by researchers and automotive companies and highlights the knowledge gaps in this area.

2 Applications of Data-Based Models in Vehicle Development to Predict Crash Severity

Parameter identification These problems deal with the reconstruction of unknown functions or geometric objects appearing as parameters (coefficients, right-hand sides, boundary values) in systems of differential equations [40]. Identification of parameters for mathematical models has been used in research for developing predictive models for crash loadcases. One of the earliest prediction models for vehicle front impact with LPM was [22] in 1976. A parameter study on the elastic passenger compartment indicates that the structure's capability to withstand crash increases with increasing metal thickness. This observation is in line with the basic properties of bending forces: the thickness of the structure contributes to the crashworthiness of the body. The spring and damper coefficients in LPMs and MBMs rely on robust parameter identification methodologies which support the prediction of the behaviour of a vehicle in real time crash event. Data-based methods are employed to determine the spring and damper coefficients by a number of researchers; [44] uses the National Highway Transport Safety Administration (NHTSA) database to define an algorithm to predict collisions. The studies in [16] and [26] use optimization strategies to estimate crash parameters, the algorithm developed in [16] uses the force deformation data for a full frontal impact to optimize the parameters. The parameter optimization approaches are further applied in [5], [35], [34], [30] and [7].

The paper by Joseph et al. [13] illustrates a parameter identification method for a thoracic impact model predicting the chest injuries. The method employs minimizing the error data between results from the mathematical model and experimental data using an optimization algorithm. It demonstrates a reasonable correlation between the curves and uses chest injury metrics to validate the mathematical model instead of real time acceleration data thereby highlighting the fact that these math based models could also support occupant protection loadcases. LPMs have been used in several studies to model occupants and pedestrians in a crash event [47], parameter identification for spring and damper models has been an area of research for these occupant/pedestrian models and researchers have successfully employed optimization algorithms to predict the spring and damper values.(Not clear what you wanted to say) The study in [33] uses Genetic Algorithm (GA) to determine the spring and damper parameters for a front end of the vehicle along with the occupant restraint system. This model was validated against crash test data and showed good correlation.

Optimization Techniques Researchers have also used optimization techniques to design and develop crashworthy vehicles, however the development of optimized vehicle energy absorption vehicles requires a synergy between multiple contradicting loadcases. These loadcases often have contradicting requirements; for example pedestrian protection loadcases require a stiff front end to resist against deformation and a softer front end to absorb crash energy in case of a pedestrian impact. This has led researchers and vehicle safety design teams to use Multidisciplinary Design Optimization (MDO) techniques to improve the vehicle crashworthiness performance Sobiesca et al. [48] and Yang et al. [53] have developed an MDO model of a full vehicle using high performance computing (HPC) to define the design process and identify variables contributing to improved safety performance while reducing the vehicle weight, ensuring higher fuel economy for vehicles. This methodology has been used by several researchers to perform component level optimization for meeting performance. [23], [31], [24]. Swamy et al. [49] used an MDO model to optimize the mass of a hood for a passenger car. This model compares the pedestrian protection performance of a hood against durability/stiffness requirements on the component level and reduces the time/effort in running multiple iterations to meet performance targets. One common aspect in all these studies is the application of simulation models primarily LS Dyna FE models to generate data for the optimization model.

Energy absorption of the front end in a full frontal/offset impact is a critical area in accident injury research in which the optimization packages are used to optimize the crush members in a vehicle to achieve maximum crush and absorb energy. One of the earliest studies using response surface optimization algorithm to optimize tubular structures was presented in [52] in 2000, this study paved the way to several papers ([20], [55],[28]) utilizing this technique. Mirzae et al. [32] in 2010 used the back propagation model to map the design objectives to the variables, and Non-dominated Sorting Genetic Algorithm –II (NSGAII) [9] was applied to generate the Pareto optimal solutions. The training dataset was created using explicit ABAQUS simulation models. The results validated against FEM data and show good correlation. Component level optimization was applied not only in passenger cars but also in ship designs to develop crashworthy structures. Jiang and Gu [21] presented a fender structure design model using FE simulation data on 196 samples to conduct parameter studies. The model uses a back propagation neural network constructed on a surrogate model to map the variables and the objective function. This is appended with a multi-objective genetic algorithm to obtain Pareto optimal solutions. The major objectives of the problem are the maximum crushing force and the specific energy absorption.

Machine Learning (ML) ML algorithms have also been employed to predict injury severity in vehicle crashes. Omar et al. [41] introduced Recurring Neural Networks to model vehicle crash event in 1998. It was one of the first applications of Artificial Neural Network (ANN) to predict impact dynamics. The ANN was trained to correlate to FE simulations for a simple spring mass system, a simple box beam system representing the crash box in a vehicle and a Ford Taurus front impact model. In all these cases the acceleration and displacement curves showed good correlation with the FE data. This work led to future applications of ANN in the field of accident research.

This study highlights the varied applications of data-based models in the field of vehicle crashworthiness design.

3 Applications of Data-Based Models to Predict Vehicle Traffic Collisions

This section focuses on the application of data-based models used in predicting crash frequency and injury severity in traffic accidents. Crash prediction models focusing on factors influencing the increased injury severity in a crash have been of significance in the past two decades, this is primarily to reduce the increasing trend of road accidents globally. The road traffic data, social media information and injury data collected over several years has given researchers an opportunity to derive a relationship between crash severity and other factors influencing these collisions. Many of the previous studies have focused on linear regression models where the functional relationships between crash severity and related factors have been assumed linear [11]. Mussone et al. [36] have pointed that linear models suffer from use of variables with non-homogeneous distribution, the correlation among the independent variables may be greater than the acceptable levels leading to greater errors which may not be acceptable to this field.

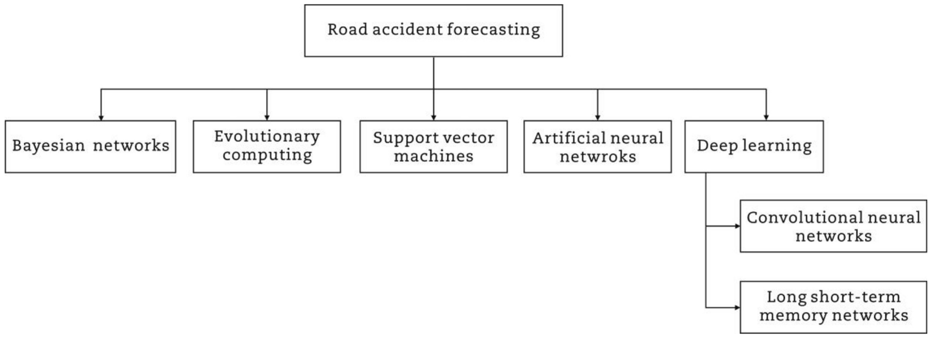

Fig. 2. Representative algorithms and methods used on road accident prediction [17]

Artificial Neural Networks (ANNs) First used in 1960, ANNs can solve many complex analytical problems. The algorithm works by mimicking the neurological functions in the human brain, just as neurons stimulate to a real life situation. The model is trained to predict outcomes based on patterns generated by historical data. ANNs are processed in 2 steps; a linear combination of input values and then the obtained results are used as an argument for non-linear activation function [19], [12], [3].

ANNs are non-parametric models frequently applied to analyse road safety problems. One of the earliest studies in crash prediction using ANNs, [37], [36] analyses collisions in urban roads. The study focuses only on accidents occurring at intersections and identifies factors responsible for an accident. The paper is also very specific because it uses data only from the city of Milan. The study concluded that ANNs can be implemented to model the accident data. A recent work using ANNs in this field, by Rezaie et al. used ANN to predict variables affecting the accident severity in urban highways. They conclude that the variables such as highway width, head-on-collision, type of vehicle at fault, ignoring lateral clearance, following distance, inability to control the vehicle, violating the permissible velocity and deviation to left by drivers are the most significant factors that increase crash severity in highways [46]. The study also highlights that feed forward back propagation (FFBP) networks yield the best results, also pointing that any single parameter is not necessarily responsible to increase crash severity; a combination of factors might work to lead to higher crashes. Codur and Tortum [54] developed a model for highway accident prediction based on ANN, taking this as an input to the model, they included not only the basic data like driver, vehicle, time but also detailed information about the road geometry and statistics around road traffic and volume. The authors concluded that the variable degree of road curvature was a significant contributor to increasing number of accidents on the highways. More recently [56] and [2] have proposed models using ANNs which improve the system accuracy more than few of the existing models.

Bayesian Networks Bayesian networks are a compact representation of a probability distribution over a set of discrete variables [43]. They are widely used models of uncertain knowledge. These networks have been used to predict vehicle crash severity, the study by Castro et al. [6] in 2016 uses bayesian networks along with J28 decision tree and ANN to determine the variables responsible for road accident severity.

Support Vector Machine (SVM) SVM is an extensively used ML technique. It works under the principle of Supervised Learning that uses labeled training data to deliver input and output functions.The input and output functions are related by regression or classification functions. The data is labeled and presented in the original formulation, the data is segregated into discrete sets consistent with the training examples. The SVM is a relatively strong ML technique due to its theoretical framework. The primary intent of SVM is to minimize the error and maximize the margin by separating hyperplanes between two classes [58], [10], [4].

Li et al. [27] used SVMs in 2008 to predict motor vehicle crashes and compare their performance to traditional Negative Binomial regression, SVMs were concluded to be performing better and also offering an advantage of not over-fitting the data. [51] used SVMs to predict traffic collisions, this framework is based on identifying if the driver is remaining in lane or leaving lane. This framework has an accuracy of 0.8730 which is a relatively high performance from a model. Pandhare and Shah [42] used SVM classification and logistic regression classification to classify and detect road accidents and events based on events in social media- Twitter. SVMs and Bayesian inference are combined together to predict road accidents in [15].

Evolutionary Computing and Genetic algorithms Genetic Algorithms (GAs) tend to converge on the optimal solution and not fall in the local optimal values. GAs present their solution as a chromosome, and in medical terminology a chromosome is composed as a set of genes, each gene is understood to be representing a particular value of a variable in a particular set of genes in a population. The solution is obtained by conducting iterative evolutionary process; the initiation is a random set of values from the population. Like in any evolutionary process, there is crossover and mutation between each set of iterations. This process is repeated until the criteria is met or the number of iterations is completed [17]. There are several applications of this methodology in the literature, [18] conducted a study using GAs and decision trees to define a prediction model based on the accidents occuring in urban and rural roads.

Deep Learning This is a subfield of ML concerned with algorithms inspired by the structure and function of the brain called ANN. DL architectures such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) and a combination of both are used to discover hidden relationships and structures in high dimensional data. Ren et al. [45] used the deep learning method to analyse spatial and temporal data of traffic accidents in Beijing and presented a spatio temporal correlation of the data. The authors presented a highly accurate deep learning model of accident prediction, this model can be applied to traffic accident warning system along with other potential applications. There have been several research studies conducted in this field of research using Deep learning in the past decade, [57], [59]. In [8] the authors combined CNN with long short-term memory (LSTM) to detect traffic events, the data was extracted from Twitter information, the study concluded to have outperform previous studies with an accuracy of 0.986 and F-measure of 0.986.

4 Conclusion and Next Steps

This paper reviews the data-based models applied to develop crash and injury severity prediction models. The modeling strategies used to predict crashworthiness of the vehicle indicate higher preference of researchers to use optimization strategies, response surface methods and ANNs to develop injury mitigation models. It is also observed that the use of ML techniques like Reinforcement Learning (RL), Unsupervised Learning have very few applications in this area of research. This indicates that there is scope for researchers to employ these strategies to create prediction models. One of the reasons that we can attribute to this gap in application is the highly non-linear complex dynamic event that most high speed crashes are associated with. It is also tough to replicate the non-linear behaviour of materials used in a vehicle and the presence of multiple components in the vehicle. This review highlights the widespread application of optimization algorithms in parameter identification problems; these focus more on the vehicle crush and energy absorption prediction models compared to the vehicle rotations leading to pitching/yawing/rolling. There is an opportunity to use data-based models to establish a relation between vehicle acceleration and vehicle rotations along with the factors contributing to the increase of vehicle rotation about its axes in case of a crash. Most of the data sets generated in these modeling strategies have used simulation based models, for example LS Dyna or Pamcrash based models for non-linear dynamic impacts. This is an encouraging trend because researchers are relying more on virtual simulation methods compared to physical test data.

We also observe that data-based modeling has been applied extensively to component based modeling in passenger cars, MDO is also used to meet contradictory requirements in the vehicle like mass of the vehicle and vehicle structural integrity. There is again scope to further use ML algorithms in this domain.

The second section of this paper reviews the prediction models used for estimating crash frequency, in other words these models predict road traffic collisions and crash severity. It was observed that the several ML based analytical techniques were employed in this domain. The use of ANNs, SVMs and GA based models has been predominant in the past decade to more accurately model vehicle crash severity. This trend aligns with the emergence of ML based algorithms since the year 2000; the developments in the field of computational powers has also supported this trend. We also realize that there are few models based on RL techniques and this can be a scope for future research. One of the drawbacks of these models is the dependence on data which may change over different parts of the world. It is important to create datasets which represent all types of traffic and road conditions; and validate these models against different road conditions. This would provide more robust prediction models.

It will be interesting to combine crash frequency and structural integrity/occupant injury models to improve prediction.

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