

# Autonomous Prediction of Performance-based Standards for Heavy Vehicles

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**Abstract**—In most countries throughout the world, heavy vehicle use on public roads are governed by prescriptive rules, typically by imposing stringent mass and dimension limits in an attempt to control vehicle safety. A recent alternative framework is a performance-based standards approach which specifies on-road vehicle performance measures. One such standard is the low-speed swept path, which is a measure of road width required by a vehicle to complete a prescribed turning manoeuvre. This is typically determined by physical testing or detailed vehicle simulations, both of which are costly and time consuming processes. This paper presents a data driven, detailed model to predict the low-speed performance of an articulated vehicle, given only the vehicle geometry. The development of a lightweight tool to predict the swept path of an articulated heavy vehicle, without the need for detailed simulation or testing, is discussed.

**Keywords**— *Performance-based standards; Vehicle safety; Heavy vehicle performance; Regression; Support vector machines*

## I. INTRODUCTION

In most countries throughout the world, heavy vehicle use on public roads is governed by prescriptive rules. In South Africa, the National Road Traffic Act (NRTA) specifies legal mass and dimension limits for all vehicles that operate on public roads. Two of the main constraints placed on heavy vehicles are overall length and mass limits, specified as a maximum of 22 m and 56 000 kg, respectively. These prescriptive limits are both easy to understand as well as enforce, however they do not inherently regulate vehicle safety as factors that influence the actual on-road performance of the vehicle are largely not governed.

A recent alternative framework is the performance-based standards (PBS) approach which specifies actual on-road vehicle performance measures, as opposed to merely limiting what the vehicle looks like. The South African PBS pilot project has been operational since 2007 (CSIR Built Environment, July 2015) and currently boasts 160 so-called Smart Trucks operating on designated routes across the country. A typical 9-axle, 73 tonne, 26 m Smart Truck, known as a B-double (due to the roll-coupled trailers, the towing mechanism and the two trailers in addition to the truck tractor) is shown in Figure 1.

For a PBS Smart Truck to be granted a permit to operate on the road, a detailed vehicle safety assessment of the vehicle is required, considering all aspects of the vehicle: engine,



Fig. 1. Representation of a PBS B-Double

suspension, springs, dampers, tyres, vehicle mass properties and payload mass properties. These safety assessments require input from the truck tractor original equipment manufacturer (OEM), the trailer OEM, as well as the vehicle operator, resulting in the PBS assessment being a costly and time consuming process due to many hours of costly physical and software testing. The vehicle safety assessment process is also highly iterative, with the OEMs creating a vehicle layout design, the assessment is then conducted and the results forwarded to the OEM to update the design if necessary. There are currently no simple, standalone tools available for the OEMs to calculate or predict the vehicle performance without conducting a formal assessment. Therefore, a simple model that is able to predict vehicle performance given simple geometric vehicle properties will provide great insight for the OEMs as well as reduce the time and financial costs of the formal vehicle safety assessment.

To date, vehicle safety assessments have been conducted using multi-body dynamic analysis software simulation packages, requiring a detailed and comprehensive understanding of the physics and dynamics of the entire vehicle system as well as its subsystems such as suspension and tyres. This paper presents a data driven approach to predict the low-speed performance of articulated heavy vehicles, requiring only simple geometric vehicle properties and no knowledge of the mechanics of the system. The model presented in this paper utilises commonly used supervised machine learning methods.

The remainder of this paper is structured as follows. In Section II we provide a detailed discussion of the performance standards against which these vehicles are measured. In Section III, a brief background to the learning techniques is given. The overall structure of the system is presented in Section IV, with Section V and Section VI covering the system performance and other related work respectively. Finally, we present a discussion of the data driven model and the conclusions of the research.

## II. THE PERFORMANCE STANDARDS

There are two main components of a PBS vehicle safety assessment, namely low-speed directional standards and high-speed stability standards. Each standard is given a performance level, either pass/fail or level 1 to level 4, with level 1 having the most stringent performance criteria. This paper focuses on the five low-speed standards, which, for a specific vehicle, are measured from a prescribed 12.5 m radius, 90° degree turn. The five low-speed standards are defined as (NTC, 2008):

**Low-Speed Swept Path (LSSP)** is the amount of road width required by the vehicle when executing the prescribed low-speed 90° turn, as the trailing units track inside of the path followed by the hauling unit. LSSP is given a performance rating of level 1, level 2, level 3, level 4 or fail.

**Frontal Swing (FS)** is the amount that the front outside corner of the hauling unit swings beyond of the exit tangent of the widest section of the vehicle at the completion of the low-speed 90° turn. FS has a pass/fail performance level.

**Difference of Maxima (DoM)** and **Maximum of Difference (MoD)** pertain to the amount by which the front outside corner of a semitrailer swings out beyond that of the path of the hauling unit or preceding semitrailer. DoM and MoD both have pass/fail performance levels.

**Tail Swing (TS)** is the amount which the rear outside corner of a vehicle unit swings out at the commencement of the prescribed low-speed 90° turn. This may cause collisions with objects in adjacent lanes or on the roadside. TS is given a performance rating of level 1, level 2, level 4 or fail.

Figure 2 shows the critical points of a vehicle during the prescribed turn for a) LSSP and b) MoD and DoM.

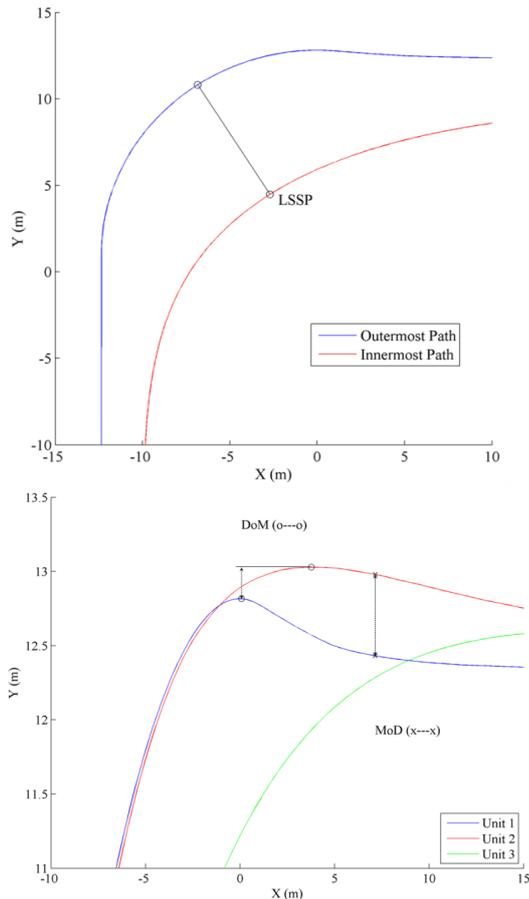


Fig. 2. a) LSSP, b) FS, MoD and DoM

## III. BACKGROUND TO LEARNING TECHNIQUES

The model presented in this paper uses commonly implemented machine learning techniques and methods to predict the low-speed performance of heavy vehicles.

Due to the availability of vehicle geometrical data as well as ground truth outputs, supervised learning techniques utilised for this study. The requirement for an appropriate technique was to accurately map the vehicle geometric parameters to low-speed performance.

The first supervised machine learning technique used in the model is a multilayer perceptron (MLP). MLP networks have been in use for many years, but have made a recent resurgence in deep learning, as evidenced by (Raiko, Valpola, & LeCun., 2012). They note that this rise has followed the invention of unsupervised pretraining, however there has also been a modern trend to utilise traditional back-propagation as this method is able of giving sufficient accuracy.

The second supervised machine learning technique used in the prediction model is support-vector machines (SVM). SVMs have been used for a wide variety of learning problem for classification, regression as well as other learning tasks. The LIBSVM library has been used extensively and is widely cited in the literature (Chang & Lin, 2011). SVMs represent a powerful technique for general non-linear classification (Meyer & Wien, 2014), and are used for such in this study.

## IV. SYSTEM ARCHITECTURE

The mechanics of articulated vehicles executing turning manoeuvres are such that the geometric input parameters for the low-speed model are not uncoupled, and cannot be considered to be independent (Winkler & Aurell, 1998). Winkler and Aurell also show that the mechanics of articulated vehicle turning are non-linear and non-elementary.

In the next section, a model comparing the geometric inputs directly to the overall vehicle level is presented, however this overly naïve model is not able to capture any of the dependencies of these variables, nor is it able to give any insight into the relative performance of the vehicle in each standard. In order to capture the input parameter dependencies, as well as the system non-linearity, a complex data driven model was created to predict the level of each low-speed standard.

In practice, the exact LSSP value of an articulated vehicle directly affects its ability to navigate a given intersection. The magnitude of the LSSP provides the OEM with a greater insight into the vehicle performance than that of the LSSP level, and as such, a regression model was selected for this standard. The output of the numeric regression is fed through a thresholding operation to give the LSSP level.

The remainder of the standards relate more to overall vehicle safety whilst the vehicle navigates the turn than they do to its ability to navigate the turn. Thus, for these standards, the level is of greater interest than the magnitude of the output, and as such, classification models were implemented to directly output the level. The model for each standard is presented as a system with the output from each sub-system combined in a final layer due to prior knowledge of the definition of each

standard, as such, it would be redundant to learn these. This is represented schematically in Figure 3.

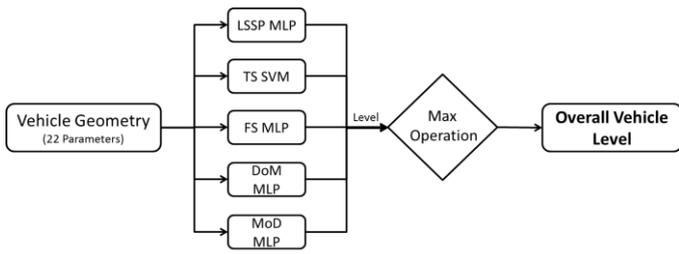


Fig. 3. System Block Diagram

A diagram showing the detailed system architecture, illustrating the relationship of all the low-speed standard models to the overall output level, O, is given in Figure 4.

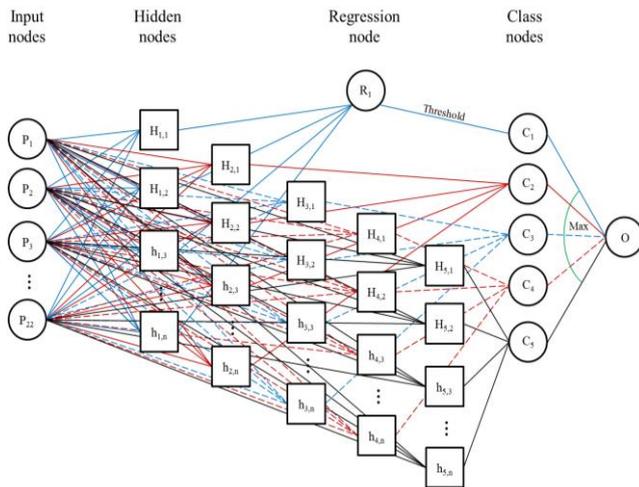


Fig. 4. System Diagram

In addition to capturing the nuances of each standard, the system presented here provides greater transparency with the level of each standard, which will aid the justification to the external legislative bodies for implementing such a system. This system will also provide additional benefits to the OEMs during the design of articulated vehicles, as mentioned above.

A simplified system model was also created, relating the 22 input parameters directly to the overall low-speed level. This simple model gives insight into the overall performance of the vehicle combination, but is not able to give any insight into the relative performance across each standard. This simple model will provide a useful check to OEMs to confirm whether or not their design meets the required level. The detailed model however, will be a more valuable tool, as it can be integrated into the design process to not only confirm a design's performance, but also to optimise vehicle designs.

The complex system presented here will also form the basis of a model that also includes the high-speed standards. This modular model easily allows for the addition of individual standards, ensuring that the detailed insights into the performance for each standard are retained, without the need to recreate the entire model.

## V. DATA ANALYSIS

A set of 10 000 simulations, with randomly selected vehicle geometrical parameters for a B-double were run to obtain the ground truth values for all five low-speed standards. In total, 22 parameters were selected as inputs, seven for each of the first two units and eight for last unit. These data were then used to create a regression model for LSSP and classification models for each remaining of the four standards. These models were then combined into a single system, given above, to predict the level for each standard, as well as the overall low-speed level for the combination. The regression and classification models were created in Weka 3.6, using default parameters, unless otherwise stated.

The MLP's used in this study all utilised sigmoid activation functions. The number of hidden units and nodes were selected according to the combination that yielded the greatest accuracy, starting with a single hidden layer and the number of nodes equal to half the sum of the number of inputs and outputs.

The regression model for LSSP utilised a MLP comprising two hidden layers, with six and three nodes respectively. The hierarchical structure of the simple MLP was capable of capturing the complexity of the LSSP mechanics without being overly complex itself. The number of basis functions was selected in advance, ensuring the simplicity of the model, as well as ensuring a compact model that is able to quickly process new data (Bishop, 2006). The classification models for FS, DoM and MoD also utilised MLP for the same reasons. It was found that for these standards, the MLPs were able to achieve good accuracy for classification, whilst limiting the number of false positives, which are highly undesirable.

The MLP classification of the FS standard comprised three hidden layers with twelve, ten and five nodes, respectively. The MLP for DoM contained only a single hidden layer with three nodes, while that of the MoD standard comprised four hidden layers with 21, fifteen, ten and five nodes respectively.

The classification model for TS utilised SVM for the four class classification. Multiclass SVM models have undergone a number of development iterations to improve their capability of fundamentally being a two-class classifier (Bishop, 2006). The LibSVM library in Weka, with a radial basis function (RBF) kernel, was selected to capture any non-linearity in the TS data (Witten & Frank, 2005). A cross-validation and grid-search, was conducted to select the two RBF kernel parameters,  $(C, \gamma)$ . The parameters which gave the greatest accuracy were a gamma of 0.017 and a cost of 48.

The accuracy and performance of all the low-speed models are given in Table 1, with the confusion matrices for the four classification models given in Table 2 to Table 5.

## VI. RELATED WORK

TABLE I. PERFORMANCE OF LOW-SPEED PREDICTION MODELS

Std	Alg	Corr. Coeff.	Relative Absolute Error (%)	Relative Squared Error (%)	Classified Correctly (%)	False Positive (%)
LSSP	MLP <sub>r</sub>	0.9995	2.8615	3.0176		
TS	SVM <sub>c</sub>				96.31	
FS	MLP <sup>c</sup>				95.72	7.83
DoM	MLP <sub>c</sub>				91.14	6.12
MoD	MLP <sub>c</sub>				98.3	0.84
<b>Combined</b>					<b>95.36</b>	<b>3.29</b>
Direct	MLP <sub>c</sub>				94.67	1.76

The majority of simplified models for predicting PBS performance of heavy vehicles comprise simplified models of the system mechanics and physics, notably the static rollover threshold (SRT) calculator, that has been written into legislation in New Zealand (de Pont, Baas, Hutchinson, & Kalasih, 2002). This tool takes simplified overall vehicle parameters as inputs and calculates SRT from first principles.

A similar first principle approach is the complex vehicle model for turning that uses the physics and mechanics of the vehicle to calculate the trajectory of a vehicle in a turn (Winkler & Aurell, 1998). This model utilises a comprehensive system of equations to model the physics of the vehicle and the manoeuvre. It gives highly accurate results, yet requires a full understanding of the physics of the system in order to use and successfully implement.

Dessein et al. presented a simplified, third order polynomial, regression model to estimate LSSP (Dessein, Kienhofer, & Nordengen, 2012). This model gives good accuracy for a generic articulated vehicle, but is unable to give any insight into the other four low-speed PBS standards.

De Pont presented a pro-active approach to ensure LSSP compliance through a so called pro-forma approach (De Pont, 2010). The pro-forma design specifies limits on the geometric properties of an articulated heavy vehicle such that the required LSSP level is met. Benade et al. expanded on this approach with a pro-forma design to additionally include the FS and TS standards (Benade, Berman, Kienhofer, & Mordengen, 2015). This adapted pro-forma design is limited by the allowed range for each input parameter and thus is only applicable to a narrow spectrum of vehicles.

## VII. DISCUSSION AND CONCLUSION

The existing tools that are used to calculate the low-speed performance of articulated heavy vehicle have been shown to give good accuracy, however require a detailed understanding of vehicle dynamics to successfully implement. The development of pro-forma designs has sought to introduce a data driven approach to vehicle design, but to date have been only partially successful, and have been limited to stringent constraints for a specific vehicle combination.

The data driven model presented in this paper provides an accurate tool that is naïve towards the physics of the system, yet is able to capture the nuances of the physics. The system gives insights into the individual low-speed standards as well as overall vehicle performance based on basic geometric vehicle properties.

This model is not limited by vehicle layout and is able to generalise to any B-double combination. Current work includes an extension of the low-speed prediction model to include a wider variety of vehicle configurations, with differencing numbers of trailers to improve the applicability of this model to heavy vehicle industry in South Africa. Future work will include further expanding the data driven model to predict vehicle performance in the high-speed stability standards.

TABLE II. TS CONFUSION MATRIX

Level 1	Level 2	Level 4	Fail	
<b>9043</b>	26	41	1	Level 1
65	<b>6</b>	45	6	Level 2
56	22	<b>158</b>	22	Level 4
3	3	47	<b>3</b>	Fail

TABLE III. FS CONFUSION MATRIX

Level 1	Fail	
<b>5968</b>	173	Level 1
198	<b>2330</b>	Fail

TABLE IV. DoM CONFUSION MATRIX

Level 1	Fail	
<b>1366</b>	259	Level 1
257	<b>3944</b>	Fail

TABLE V. MoD CONFUSION MATRIX

Level 1	Fail	
<b>2125</b>	80	Level 1
48	<b>5651</b>	Fail

The performance of the simple overall model relating inputs to overall vehicle level is given in Table 6.

TABLE VI. SIMPLE OVERALL LEVEL CONFUSION MATRIX

Level 1	Level 2	Level 3	Level 4	Fail	
<b>1055</b>	6	0	0	184	Level 1
11	<b>463</b>	6	1	76	Level 2
0	5	<b>341</b>	0	34	Level 3
17	0	2	<b>5</b>	55	Level 4
87	33	16	0	<b>7603</b>	Fail

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