HYPERFORMANCE: PREDICTING HIGH-SPEED PERFORMANCE OF A B-DOUBLE

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Abstract

This paper presents a data driven approach to develop a prediction model for the PBS performance of heavy vehicles. A gap exists between trailer manufacturers who create PBS vehicle designs and the PBS assessors who evaluate the performance of the vehicles. The prediction model bridges that gap in the form of a light-weight methodology to predict the PBS performance of a new vehicle design given a set of vehicle input data. Such a model was developed for typical South African 9-axle B-double PBS combinations. The model considers vehicle geometry, suspension parameters and payload properties as variable inputs and is able to predict the high-speed PBS performance with an average error of less than 1% for four of the five standards and less than 5% for the fifth, yaw damping. The model we present can be used as a standalone application for vehicle designers to develop PBS designs, or by transport regulators to verify or validate the results of a proposed vehicle. In addition to this, the model can be used in an optimisation regime to determine the optimal set of vehicle parameters for a given goal, such as maximum payload mass or volume.

Keywords: Performance-based standards, B-Double, pro-forma designs, data driven, performance prediction, high-speed stability

1. Introduction

A performance-based standards (PBS) scheme has been running as a pilot project in South Africa (RSA) under the banner of the “Smart Truck” project, since the introduction of the first two PBS vehicles in 2007 (Nordengen, 2014). Since then, the project has grown to include 163 PBS vehicles operating across six industries, and grew by 45 vehicles in 2015 alone (Steenkamp & Nordengen, 2016). With only four certified PBS assessors in the country, of which only two assessors are currently available full-time, the local assessment capacity is limited.

The increase in the number of PBS vehicles has highlighted a number of challenges for the RSA PBS pilot project. Conducting PBS assessments in the South African context has proven to be a costly and time-consuming process. This is due to the limited knowledge and understanding of the effects of overall vehicle design on dynamic performance of vehicles; as well as on the performance standards.

These challenges are highlighted in the long, highly iterative design cycles of back-and-forth design iterations between trailer designers, truck tractor OEMs, and PBS assessors; to create new PBS vehicle designs that meet the operator’s requirements, as well as meeting the minimum required PBS limits. It is not uncommon for this process to span two or three years, which greatly increases the cost of developing and deploying PBS vehicles. This is contrary to the overarching goals of PBS, namely increasing the efficiencies, and reducing the costs, of road freight transportation.

In this paper, we propose a methodology for the development of a novel, lightweight tool for predicting the performance of PBS vehicles; as well as present a proof of concept for a 9-axle B-double. The model we present is similar to previous lightweight assessment tools, such as pro-forma designs and blueprint designs, by being able to predict compliance to the performance standards. Its novelty however, lies in the flexibility and range of input parameters it accepts.

2. Current PBS Process in RSA

Typically, a heavy vehicle operator wishing to implement a PBS vehicle will approach a trailer manufacturer for a concept design. This design will then be submitted for evaluation to one of the certified assessors utilising the PBS approach. The design will also be submitted for an infrastructure assessment that considers both pavement wear and bridge loading. Should the proposed vehicle perform adequately, in both the safety assessment and the infrastructure analysis, the operator may then apply for Concept Approval (CA) from each of the nine South African provincial Departments of Transport (DoT), in which the vehicles are intended to operate (CSIR, 2016).

If the operator is granted a CA, the safety assessment and infrastructure analysis reports are evaluated by the Smart Truck Review Panel (RP). The operator will only be permitted to apply to the DoT for operational permits to begin operating the vehicles once the analyses have been approved by the RP. Before the operational approval will be granted, each PBS vehicle is individually commissioned (or certified) to ensure that the combination is within specification of the approved design.

The development and assessment process is time consuming and costly, even in the rare case of a proposed vehicle passing both the safety assessment and infrastructure analysis without any design revisions being required.

The DoT and trailer manufacturers rely on the two full-time PBS certified assessors for the results of each iteration of every PBS concept design. This places a great demand on the current assessors and further increases the time and financial costs for the operator in question. In addition, the rate at which new combinations can be assessed is limited, which stifles the growth of the South African PBS project.

Trailer manufacturers and DoT authorities are fully reliant on the qualified PBS assessors for not only conducting PBS safety assessments, but also for verification, guidance, and advice, relating to the performance of concept vehicles.

Many of the current legal vehicle designs, complying with the South African National Road Traffic Act (NRTA), have evolved over many years on a trial and error basis. It has been discovered that many of the common so-called workhorse vehicles in RSA do not meet the minimum performance requirements of the PBS scheme. It is worth noting that local trailer manufacturers, through developing PBS vehicles, have begun incorporating the design elements to their baseline vehicles.

There is therefore a need for a tool to quickly determine the PBS performance of a new vehicle design, without submitting it through the formal PBS assessment process. Such a tool would also be able to provide insights into the performance of legal baseline vehicles, and would not be limited to proposed PBS vehicles.

3. Current Assessment Tools

De Pont presented a set of pro forma designs for various vehicle configurations, after having assessed a number of designs for each configuration: the designs that achieve satisfactory performance formed the basis for the pro forma designs (De Pont, 2010). De Pont focussed mainly on the low-speed performance of the vehicles, however once the low-speed pro-forma designs were established, high-speed performance was also cross-checked for the limiting cases.

Building on from the pro-forma designs of de Pont, Benade *et al.* presented a parameterised model for evaluating the low-speed performance of typical RSA truck-and-trailer car-carriers that was based solely on vehicle geometry (Benade, et al., 2015). This model considered the effects of varying vehicle geometry on the low-speed standards, giving the vehicle designer greater insight into the performance of their design as well as the vehicle parameters that would need to be adjusted to ensure low-speed PBS compliance.

de Saxe presented a generic model for determining the low-speed PBS performance. This approach is based solely on vehicle geometry, and as such, this model is very efficient at evaluating low-speed performance. This model allows for greater flexibility in vehicle configurations than current pro forma designs, but this model is limited to the low-speed standards (de Saxe, 2012).

Berman *et al.* presented a predictive model for the low-speed performance of a B-double (Berman, et al., 2015). The inputs for their low-speed PBS model were also based purely on vehicle geometry, and the model is able to predict the PBS level that a specific design was able to achieve. Once again, this analysis was limited to the low-speed PBS.

Following on from this, Benade *et al.* presented an analysis of techniques to determine the roll stability of heavy vehicles (Benade, et al., 2016). This work identified the New Zealand Land Transport Rule (New Zealand Government, 2014) as a relatively accurate and computationally cost-effective approach to predicting static rollover threshold (SRT). This analysis considered only heavy vehicle roll stability, but can be used in conjunction with one of the low-speed PBS tools. This may be considered suitable to applications such as car-carriers which are more sensitive to the low-speed standards and rollover than the other PBS standards. However, for heavier combinations, the other high-speed standards may be critical.

Dessein *et al.* presented a model to estimate two of the high-speed standards, SRT and rearward amplification (RA) for four vehicle configurations (Dessein, et al., 2012). This work allowed for vehicle configurations to be optimised for payload as well as these two standards, but did not include estimates for the entire set of standards.

4. Research Method

As has been shown, there exists a gap between current pro-forma designs, light-weight assessment tools and the need in industry, as well as amongst transport regulators, for determining the performance of heavy vehicles using the PBS framework. Such a tool would not be intended to replace formal PBS safety assessments, but would be used as a guide and design tool, as well as a validation tool for transport regulators.

We propose a data driven approach as a methodology for developing such a tool, and we present a fully parameterised model for a 9-axle B-double Smart Truck, illustrated in Figure 1. The model we present is one such example of the application of the methodology, which can be applied to any other heavy vehicle configuration.

4.1 Data Driven Approach

A data driven approach, using techniques from the field of machine learning, allows for the development of a fully parameterised multi-variate model to predict the performance of a previously unseen vehicle. This prediction is based solely on data describing the performance of similar vehicles. Such an approach is agnostic to the source of the data and the model underlying it, and in addition is adaptive to different conditions.

The general data driven methodology we present involves the development of a mathematical model to predict the PBS performance of a new vehicle. The model we developed (a variant of an artificial neural network) is trained on data in the form of thousands of randomly generated vehicles with different parameters (as input variables) and PBS performance (as output variables). This training process modifies the model parameters so as to provide the best fit of the model to the training data, in a way that allows it to generalise to new and unseen vehicle combinations.

The hyperparameters of the prediction model (internal tuning parameters that affect the model's performance and accuracy) were optimised using a Bayesian optimisation regime. This optimisation process used Gaussian Processes to determine the optimal combination of hyperparameters that gave the greatest accuracy of the prediction model. Using this optimisation regime allowed for the global optimum of the non-convex optimisation problem to be found (Kawaguchi, et al., 2015).

The B-double is one of the most common work-horse heavy vehicles in South Africa. Recently, there have been numerous applications for PBS B-double combinations and as such, a 9-axle B-double was chosen as the vehicle configuration for this study. A number of PBS B-double combinations which comply with the legal length limit (22 m) but exceed the legal mass (>56 tonnes) have been proposed and implanted, as have, many B-double combinations that exceed both the legal length and mass limits. The prediction model was developed to account for both of these cases. Figure 1 shows the typical layout and axle masses of a 9-axle PBS B-double combination.

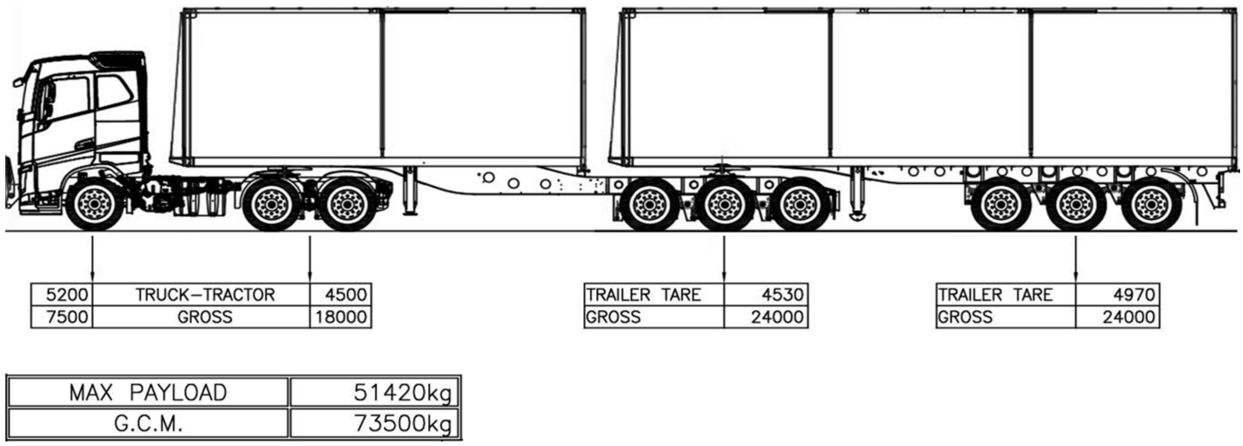

Figure 1: Typical PBS B-Double configuration

4.2 PBS Simulation

All vehicle combinations considered in this study were assessed in line with the rules of the Australian PBS Scheme, as compiled by the Australian National Transport Commission (NTC, 2008), subject to the additional requirements and amendments prescribed by the RSA RP.

The PBS standards considered in this investigation are: static rollover threshold (SRT), high-speed transient offtracking (HSTO), rearward amplification (RA), tracking ability on a straight path (TASP) and yaw damping (YD). The dynamic simulations were all conducted using the TruckSim 8.1 multibody dynamics simulation (MDS) package, with all post-processing conducted using Matlab®.

In order to limit the complexity of this investigation, a number of assumptions regarding the vehicle combinations and input data were made. It was decided that all combinations would use the same tyres: 385/65 R 22.5 for the steer axle and dual 315/80 R22.5 tyres on all other axles, as is standard in RSA. The tyre data for the tyres used in this analysis was obtained directly from a tyre manufacturer under non-disclosure agreement and was held constant for all combinations.

Similarly, the type and layout of suspension was fixed. It was decided that mechanical suspension would be used for the steer and drive axles of the truck tractor, and a common air suspension layout was used for both trailers. The vertical stiffnesses (airbags for the trailers) were fixed for the study, but the auxiliary roll stiffnesses were used as input variables.

Underslung suspension was used for the leader trailer, with overslung suspension used on the follower trailer on all combinations. All dampers, as well as roll centre heights and roll steer coefficients for all axles were likewise fixed.

The list of parameters that were selected as variables, with their corresponding upper and lower bounds are given in
Table 1.

Table 1: List of vehicle parameters used as input variables

Truck Tractor	Minimum Bound	Upper Bound
Steer Track (mm)	1 950	2 200
Steer Aux Roll (Nm/deg)	0	7 000
Drive Track (mm)	1 700	1 900
Drive Aux Roll (Nm/deg)	0	20 000
Wheelbase (mm)	3 800	4 000
Axle Spacing (mm)	[1350,1360,1370]+	
Hitch Offset (mm)	-600	0
Hitch Height (mm)	1 100	1 400
Front Ovrhng (mm)	1 200	1 700
Front Width (mm)	1 100	1 300
Rear Width (mm)	1 000	1 250

Payload	Minimum Bound	Upper Bound
Total Mass (kg)	41 000	51 800
CoG Height (mm)**	500	1 400

Leader Trailer	Minimum Bound	Upper Bound
Deck Length (mm)	6000	8500
Front Ovrhng (mm)	1400	1900
Wheelbase (mm)	7500	9200
Axle Spacing (mm)	[1350,1360,1370]+	
Axle Track (mm)	1800	2000
Aux Roll (Nm/deg)	5000	25000
Hitch Offset (mm)	-150	150
Hitch Height (mm)	Tractor	
Rear Ovrhng (mm)	WB + 1.5*AS	
Rear Width (mm)	1100	1300
Deck Height (mm)	Hitch Height + 150	
Deck Width (mm)	1200	1300
Payload Mass (kg)	0.36*Payload	

Follower Trailer	Minimum Bound	Upper Bound
Deck Length (mm)	11000	14500
Front Ovrhng (mm)	1400	1900
Wheelbase (mm)	7800	9500
Axle Spacing (mm)	Leader	
Track (mm)	Leader	
Aux Roll (Nm/deg)	Leader	
Rear Ovrhng (mm)	Deck - FO - WB	
Rear Width (mm)	1200	1300
Payload Mass (kg)	0.64*Payload	

+ Discreet values
** Above deck height

From these inputs, 36 470 unique vehicle combinations were created, by randomly sampling across each range using a uniform distribution. In the case of the discrete variables, three bins were chosen and sampled randomly, again from a uniform distribution. A number of checks were performed on each combination to ensure that the resulting vehicles were physically possible, and also to ensure that the axle loads did not exceed the RSA legislated limits of 7 700 kg for a steer axle, 18 000 kg for a twin axle group and 24 000 kg for a tridem axle group.

Each combination was systematically simulated in TruckSim, according to the PBS requirements of the NTC. The performance of each combination in all five high-speed standards was then calculated from the simulation data. These results were recorded and the next combination was simulated.

5. Prediction Models

There are two main types of prediction models, namely regression and classification. Classification is used for cases where the output or required result is given a label/class (categorical variable), such as male or female, and regression is used in case where the required output is numerical. PBS performance is recorded as both a numerical value and class with the resulting Level. It was decided that due to the relative simplicity in determining the class label from the numeric value, that regression would be used for the prediction model.

The goal of regression is to create a model, or function, to describe how the input parameters or variables combine to result in the output, which in this case was the PBS performance for each of the five high-speed standards. A unique model would be required for each standard. There is however a trade-off in that the desire is to choose a prediction model that represents as close an approximation as possible to the target function, with the caveat that the more expressive the representation, the greater the number of unique input combinations are required to learn the underlying function (Mitchell, 1997).

5.1 Development of Prediction Models

There are numerous mathematical models that can be used for regression problems; however the two models that were used in this study are both classed as neural networks.

Neural Networks

Neural networks (NN) are based on a biological model of neurons in the brain, comprised of a complex and dense web of interconnected neurons. Each neuron is a very simple unit which takes a number of real-valued inputs and produces a single real-valued output. Multiple layers of these interconnected neurons allow complex and highly non-linear functions to be modelled. These multiple layers are known as hidden layers, with only the input and output values being “seen” or known (Mitchell, 1997).

The mathematical operation that occurs at each neuron is a weighted linear combination of all inputs, known as a linear basis function (Bishop, 2006). The number of hidden layers and the number of neurons per layer will affect the performance of the NN model, and these parameters need to be tuned to find the network with optimal performance.

Radial Basis Function Neural Network

A specific type of NN, the radial basis function NN (RBFNN) utilises a radial basis function (a Gaussian distribution) in a single hidden layer as opposed to the weighted linear combination in a standard NN. RBFNN are very simple networks, but can accurately model multivariate non-linear functions, due to the Gaussian basis function.

5.2 Model Architecture

In total, 48 vehicle input parameters were modified for each unique vehicle combination that was simulated. Many of these parameters are interrelated, such as payload mass and the corresponding moment of inertia, and as such some parameters were a calculated combination of others.

The 36 470 vehicle combinations were split into two groups to model each high-speed standard. The first group (labelled training data) was used to tune the prediction model, and the second group (labelled testing data) was used to test the accuracy of the model. This is a machine learning technique known as validation, and is employed to ensure that the resulting model is not overly tuned to the specific set of training data used, and that the model can generalise to new and unseen combinations with high accuracy.

A unique mathematical model was developed for each of the PBS standard considered. RBFNNs were found to give the best overall accuracy for four of the five standards, with a multilayer NN selected for YD. The outputs from each model are then combined to determine the overall PBS performance according to the NTC rules. Figure 2 shows the architecture of the high-speed prediction model for a 9-axle B-double configuration.

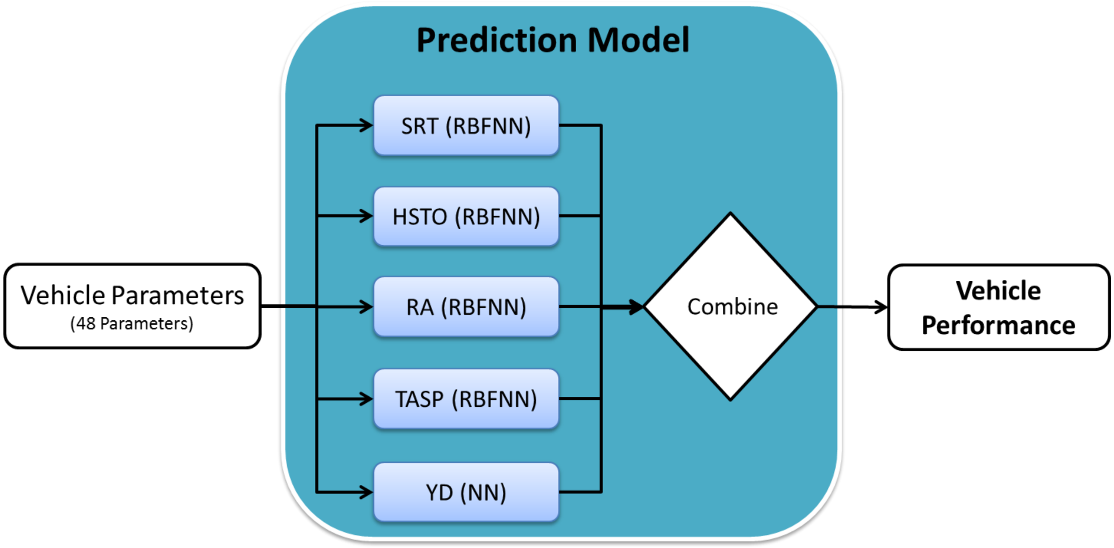

Figure 2: Architecture of the Prediction Model

6. Performance and Results

The input parameters were selected per standard, using so-called expert knowledge, with the number of unique input parameters for each standard listed in Table 2. The metrics used to determine the accuracy of each model were maximum absolute percentage error and average absolute percentage error. These errors were calculated as the difference between the actual performance value in the test data (determined from the TruckSim simulations), and the value predicted by the model.

Table 2: Model Parameters and Performance

	Number of parameters	Training Data	RBFNN Spread	NN Hidden Layers	Max Absolute Percentage Error (%)	Ave Absolute Percentage Error (%)
SRT (g)	27	10 000	41 039	-	5.39	0.4517
HSTO (m)	27	10 000	14 805	-	5.51	0.5059
RA (g)	27	5 000	19 298	-	6.41	0.3219
TASP (m)	30	1 000	95 506	-	0.56	0.0729
YD (-)	27	15 000	-	[20, 6, 12]	36.06	4.0140

Table 3 shows confusion matrices for the results of the five high-speed models. The top row headings represent the actual performance as simulated, and the last column headings represent the predicted performance. The values in the confusion matrices represent the number of combinations that were predicted for each performance level. For example all 971 combinations that had Level 2 performance for HSTO were correctly predicted as Level 2.

From the SRT confusion matrix, it can be seen that of the 21 791 combinations that achieved Level 1 performance, 135 were predicted to have failed; this is known as a false negative and is conservative. However, of the 14 679 combinations that failed the SRT standard, 210 were predicted as passing, this is known as a false positive and is not conservative.

Out of 36 470 combinations, 136 combinations that achieved Level 2 performance or higher overall were predicted as failing, 0.37% were false negatives. A total of 211 combinations that failed were predicted to have achieved Level 1 performance, 0.58% false positives.

Table 3: Confusion matrices for the high-speed standards

HSTO

Level 1	Level 2	Level 4	Fail	
35499	0	0	0	Level 1
0	971	0	0	Level 2
0	0	0	0	Level 4
0	0	0	0	Fail

SRT

Level 1	Fail	
21656	210	Level 1
135	14469	Fail

TASP

Level 1	Level 2	Level 4	Fail	
36470	0	0	0	Level 1
0	0	0	0	Level 2
0	0	0	0	Level 4
0	0	0	0	Fail

RA

Level 1	Fail	
36498	1	Level 1
1	0	Fail

YD

Level 1	Fail	
36470	0	Level 1
0	0	Fail

The accuracy of the NN for predicting YD performance, given in Table 2, was less than that of the other standards; however the following should be noted: B-double combinations inherently have good YD, as can be seen from only 1 out of the 36 470 combinations having failed the YD standard. Additionally, the YD value reported in the PBS scheme in the minimum value of three measures, the unit yaw rate, hitch articulation angle and hitch articulation angle. The critical YD value will vary per combination. The minimum operation used to report YD introduces additional complexity to the prediction of the value.

For the 9-axle B-double prediction model, the accuracy of the YD predictions was deemed to be acceptable. These factors will however need to be taken into account when developing prediction models for other vehicle configurations.

The computation time required to predict the PBS performance of a new, unseen combination by the presented model is less than a tenth of second. This is compared to several hours for a formula assessment by an accredited assessor using MDS software such as TruckSim. The model does not require an understanding of vehicle dynamics and can therefore be used directly by trailer designers or transport regulators. The model can be used to efficiently evaluate thousands of combinations in an optimisation regime to optimise certain parameters given a set of defined constraints. An example would be to determine the suspension parameters and trailer wheelbases required for a given payload to ensure that the combination meets Level 2 PBS requirements. This process would inform vehicle design and allow for PBS performance to be incorporated at the beginning of the design process and not the end, as is currently the case.

7. Conclusions

The process of assessing and implementing new PBS vehicle in RSA is a time consuming and costly process, usually requiring numerous vehicle design iterations. In addition to this, transport authorities have no means of verifying the results of PBS assessments, and as such, there is a need for a light-weight tool to quickly determine the full high-speed PBS performance of a vehicle combination. A methodology for creating such a tool was developed, and a model for a 9-axle B-double was presented. The model requires 30 unique vehicle parameters as inputs. These inputs describe the vehicle geometry, suspension stiffnesses and payload properties. The model was created using neural networks, and was able to predict the PBS performance in SRT, HSTO, RA, TASP with average errors of less than 1%, and errors less than 5% for YD. Further, the model correctly predicted the overall PBS Level in 99.42% of combinations, with only 0.58% of the combinations that did not pass the minimum SRT requirement being predicted as having achieved Level 1 performance. The prediction model presented in this paper is suitable for providing instant PBS performance feedback to trailer and transport regulators. The PBS prediction model we present can additionally be used with an optimisation regime to optimise vehicle design for a specific goal, such as maximum payload mass or volume. This model is not intended to replace the formal PBS assessment process, but is a tool that can be used as a guide to trailer designers as well as transport regulators for fast evaluation or validation.

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