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Model to Predict Dynamic Performance of a Tractor Semi-trailer Car-carrier

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Abstract

A performance-based standards (PBS) framework evaluates actual on-road performance of a vehicle, allowing the length and mass of a vehicle to exceed prescriptive legislation, without compromising on vehicle safety and dynamic stability. This PBS approach is currently being piloted as a demonstration project in South Africa. As of June of 2018, 270 PBS vehicles are operational with a recorded 39% lower crash rate relative to conventionally-designed vehicles; testament to their improved safety. The PBS framework defines the safe performance envelope of vehicles but does not optimise their safety and productivity. The design process to achieve the optimal productivity of PBS vehicles is highly iterative. An initial design is evaluated using multi-body dynamics simulation. If the required PBS performance is not achieved, design iterations are made until the required PBS performance is achieved. The process is costly, time-consuming and computationally expensive. In this study, we simulate a range of tractor semi-trailer car-carriers representative of possible design configurations. Supervised machine learning techniques within H2O.ai driverless AI are used to develop prediction models for the low and high-speed PBS performance of a tractor semi-trailer car-carrier The vehicle design parameters that form the feature vector for each vehicle combination are chosen according to the results of previous studies which evaluated the impact of vehicle design parameters on vehicle dynamic performance. The number of design parameters is minimised to simplify the amount of input data required to train the vehicle performance models. The machine learning models for SRT, RA, HSTO, TASP, LSSP, TS, FS and STFD (PBS measures used to quantify vehicle safety) were accurately predicted for all configurations in the test dataset. The models for MoD, DoM and YDC (further PBS measures) were less accurate but produced a negligible number of false pass results where the absolute percentage errors were significant. It is envisioned that with further development and validation the simplified machine learning model will be used by the car-carrier industry to determine the preliminary PBS performance of their combinations before submitting the design for the final PBS performance assessment. Reducing or eliminating the iterative design process for optimal PBS vehicles will accelerate the design process of safer and more productive vehicles; leading to a reduction in the cost of transport in South Africa.

Keywords: Vehicle dynamics, Performance based standards, Predictive models, Machine learning, H2O.ai

1. Introduction

As part of the car-carrier road map, all car-carriers in South Africa registered after the 1st of April 2013 are required to be Road Traffic Management System (RTMS) certified and compliant with Level 1 performance-based standards (PBS) requirements. Under the car-carrier roadmap, tractor semi-trailer car-carriers are allowed a maximum combination length of 18.5 m unladen and 19.0 m laden (an additional 0.5 m relative to the prescriptive legislation) with a maximum rear overhang of 1.0 m. The maximum front overhang is governed by the maximum of difference (MoD) and difference of maximum (DoM) performance measures. The combinations are allowed a maximum height of 4.6 m (an additional 0.3 m relative to the prescriptive legislation) [1].

As of June 2018, 270 PBS vehicles are operational and have a recorded 39% reduction in crash rate relative to conventionally-designed vehicles. Car-carrier combinations evaluated within the PBS framework benefit from the improved safety but are unable to realise the significant productivity benefits using PBS that other vehicles such as coal carriers do since they are volume constrained rather than mass constrained. Recovering the costs of a PBS assessment of a car-carrier takes longer. When a car-carrier design is submitted for a PBS assessment and does not achieve the required PBS performance, it is required to undergo design changes and a re-assessment process. This becomes a significant financial burden to the car-carrier industry and should be avoided wherever possible.

A need for the reduction of the costs of PBS assessments for car-carriers has been identified and thus a simplified PBS pre-assessment tool for car-carrier manufacturers would reduce the risk and cost of re-design and re-assessment should the combination not achieve the required PBS performance. The tool should be made accessible to all and thus needs to be developed in such a way as to require as little technical know-how as possible to use.

2. Literature Review

Car-carriers are typically stable from a vehicle rollover point of view since the maximum payload is limited by volume constraints rather than mass constraints. The main points of concern for tractor semi-trailer car-carrier combinations tend to be the low-speed standards, particularly the MoD and DoM performance. As a result, most studies conducted in the past focus on low-speed performance, as highlighted by Kienhofer et al. in 2016 [2]. In this study on the MoD/DoM performance of car-carriers in South Africa, the PBS framework adopted from Australia was shown to be too strict for the South African car-carrier fleet, resulting in many combinations failing the original standard. It was recommended in this study that the MoD and DoM standards be relaxed to better suit the South African infrastructure and legislation and subsequently this recommendation was formally approved by the SMART truck review panel. The relaxed standard allows for a larger number of car-carriers to be approved without being penalised by overly strict MoD/DoM criteria. There are, however, still cases where car-carrier combinations fail one or more low-speed standards, resulting in time delays and additional costs for re-assessment of the combination.

Several studies have investigated ways to simplify the PBS assessment process to ease the computational, financial and expertise requirements.

Dessein et al. [3] developed simplified mathematical models for eight performance measures (static rollover threshold (SRT), rearward amplification (RA), low-speed swept path (LSSP), frontal swing (FS), tail swing (TS), startability (STA), gradeability A (GRAa)) to automate the optimisation of vehicle design based on a given payload density. Vehicle designs were optimised by varying the number of axles in each axle group, wheelbases of all vehicle units, hitch offsets, payload density and vehicle type (considering an A-double, B-double, truck and pig trailer, and truck and dog trailer). Using both prescriptive legislation and PBS Level 2 constraints, the automated design routine can be used to determine whether a PBS vehicle will have benefit over a standard baseline vehicle. If the PBS vehicle is found to be more productive, the optimised design can provide a starting point for the detailed design of a PBS vehicle.

De Saxe [4] developed a low-speed mathematical model (LSMM) capable of predicting the low-speed performance of articulated and combination vehicles. The LSMM requires significantly fewer inputs and runs in a shorter time than a multi-body vehicle dynamics software package such as TruckSim®.

Benade et al. [5] developed a pro-forma design approach for a truck and pig trailer type car-carrier using the LSMM developed by de Saxe. The pro-forma design approach consists of a set of geometrical constraints that if adhered to will ensure that the car-carrier performs according to Level 1 PBS requirements for the low-speed PBS performance measures (FS, TS and LSSP).

Berman et al. [6] developed a lightweight tool requiring only vehicle geometry to predict the low-speed PBS performance measures of a B-double combination. In total 22 input parameters were randomly selected to conduct 10 000 simulations on a B-double type combination. Supervised machine learning techniques were used to develop a model to predict LSSP, FS, MoD, DoM and TS performance measures from the simulated data. The model provides an accessible way for vehicle designers to quickly and accurately evaluate the low-speed PBS performance of their vehicle before a formal PBS assessment without the need for extensive mechanical knowledge of multi-body vehicle dynamics systems using only geometric parameters of the vehicle combination.

Following this initial research, Berman et al. [7] developed a lightweight prediction tool using neural networks to predict the high-speed performance of a 9-axle B-double combination. Upper and lower bounds were selected for 30 unique input parameters defining the vehicle geometry, payload and suspension. 36 470 vehicle configurations were created using random sampling within the range of each input parameter, assuming a uniform distribution. The model can rapidly predict the SRT, RA, high-speed transient offtracking (HSTO), tracking ability on a straight path (TASP), and yaw damping coefficient (YDC) PBS performance of a 9-axle B-double combination, as well as overall PBS performance level with a high degree of accuracy. The model is intended for determining preliminary PBS performance of a vehicle combination as a guide for vehicle designers and transport regulators as a precursor to a formal PBS assessment.

3. Objective

This paper aims to develop a simplified model using machine learning techniques to predict the high and low-speed PBS performance of a tractor semi-trailer car-carrier combination. The simplified model is intended as a tool for industry to predict the PBS performance of a tractor semi-trailer car-carrier design with a minimal number of design inputs and without the need for expertise in vehicle dynamics.

4. Simplified Car-carrier Model

Developing a simplified car-carrier model minimising the number of inputs used for the model presents two significant benefits:

1. The number of vehicle design configurations that need to be evaluated increases significantly with an increase in the number of design parameters, which results in an increased computational expense to build the model [8].
2. The user is required to enter fewer data to evaluate the PBS performance of the vehicle, making PBS more accessible to those with little or no experience and allowing the PBS performance to be evaluated early in the design process.

The simplified car-carrier model is intended to allow users with little technical knowledge to calculate the approximate PBS performance of a tractor semi-trailer type car-carrier with a minimal number of inputs.

4.1. Inertial and geometric parameters of the tractor semi-trailer car-carrier combination

The low-speed standards are influenced predominantly by the wheelbases and overhangs of the combination and therefore need to be included in the model. These can be easily determined from a well-dimensioned general arrangement (GA) drawing.

The inertial properties are difficult to determine since most vehicle designers use 2D computer-aided design (CAD) packages. If 3D CAD packages were used, the inertial properties could easily be determined from a well-built model of the vehicle structure. However, when 3D models are available they are seldom complete, and thus unreliable. Rules of thumb, proven to yield accurate performance, were thus used, with the reference being the wheelbase of each unit [9].

To minimise the number of inputs, relationships between the sprung mass and longitudinal centre of gravity (CG_x) location were determined from the database of PBS approved tractor semi-trailer car-carriers (see Table 11 and Table 12 in Appendix A). The average ratio was used for each of the relationships contained in Table 1.

Table 1. PBS approved tractor semi-trailer car-carrier properties

Car-carrier	Sprung mass / wheelbase (tractor) (kg/mm)	sprung mass / wheelbase (semi-trailer) (kg/mm)	Tractor *CGx* / wheelbase (mm/mm)	Semi-railer *CGx* / wheelbase (mm/mm)	Payload *CGx* / wheelbase (mm/mm)
1	0.968	0.784	0.199	0.669	0.657
2	1.480	0.776	0.222	0.662	0.607
3	1.480	0.849	0.222	0.663	0.682
4	1.250	0.789	0.216	0.493	0.689
5	1.428	0.905	0.191	0.646	0.669
6	1.428	0.876	0.191	0.714	0.569
Max.	**1.480**	**0.905**	**0.222**	**0.714**	**0.689**
Avg.	**1.339**	**0.830**	**0.207**	**0.641**	**0.646**
Min.	**0.968**	**0.776**	**0.191**	**0.493**	**0.569**

The inertial and geometric properties of the tractor and semi-trailer are summarised in Table 2. The minimum and maximum wheelbase was determined from the PBS car-carrier database, the CG_y was assumed to be at the centreline of the combination and the CG_z was assumed as the maximum from the PBS car-carrier database (see Table 11 in Appendix A). The CG_x and sprung mass are related to the wheelbase by the average ratio in Table 1.

The axle spacing was assumed to be 1360 mm in all cases as it has a low influence on vehicle performance relative to other vehicle design parameters [10]. The vehicle overall width at the centre of the trailer axle group and steer axle overall width have a significant effect on low-speed performance. However, these were found to be similar for the approved car-carriers at 2600 mm and 2343 mm respectively. Thus, to limit the number of possible vehicle configurations, these parameters were kept constant.

The radii of gyration of the tractor are determined from rules of thumb [9]. Estimations proven reasonable in previous PBS assessments of tractor semi-trailer car-carrier combinations were used for the semi-trailer.

Table 2: Inertial and geometric parameters of the tractor and semi-trailer

Parameter	Tractor		Semi-trailer	
	Min. (mm)	**Max. (mm)**	**Min. (mm)**	**Max. (mm)**
Wheelbase (mm)	3560	3700	9236	9700
Axle spacing (mm)	-		1360	
Hitch offset (mm)	350	650	-	
Hitch height (mm)	1250		-	
Sprung mass (kg)	1.339 x wheelbase		0.830 x wheelbase	
Longitudinal centre of gravity (CG_x) (mm)	0.207 x wheelbase		0.641 x wheelbase	
Lateral centre of gravity (CG_y) (mm)	0			
Vertical centre of gravity (CG_z) (mm)	1225		1514	
Roll radius of gyration (r_x) (mm)	760		1400	
Pitch radius of gyration (r_y) (mm)	0.5 x wheelbase		0.289 x length [1]	
Yaw radius of gyration (r_z) (mm)	0.5 x wheelbase		0.289 x length [1]	

[1] $length = wheelbase + 0.5 * axle\ spacing + \ (trailer\ front\ overhang) + (trailer\ rear\ overhang)$

Reference points which locate the front and rear extremities of the vehicle combination including the payload projections are used to evaluate the low-speed standards. These were generated within the ranges summarised in Table 3. Where there is a single value for the minimum and maximum coordinate, this is constant for all the reference points. For each reference point, the X and Y coordinate are independently randomised and together with the constant Z coordinate, locate the reference point on the combination. The tractor semi-trailer car-carriers are all structurally similar in design and thus the Z coordinates were set as a constant conservative value to simplify the input from the user.

Table 3: Reference points

Reference point	X coordinate		Y coordinate		Z coordinate	
	Min. (mm)	Max. (mm)	Min. (mm)	Max. (mm)	Min. (mm)	Max. (mm)
Tractor front overhang [1]	1100	1400	1000	1300	700	
Tractor rear overhang [1]	4454		1157		1000	
Trailer front overhang [2]	1300	1700	1200	1300	3800	
Trailer rear overhang [3]	3780	4680	1200	1300	2500	
Payload front projection [4]	400	1000	953		4200	
Payload rear projection [4]	800	1000	953		3800	

[1] relative to the steer axle; [2] relative to the hitch position; [3] relative to the last axle in the trailer axle group;
[4] relative to the trailer structure

4.2. Payload inertial and geometric parameters

A conservative payload of 6 Ford Expedition vehicles with the inertial properties as per Table 4 was used for each of the evaluated car-carrier combinations. The geometry of the payload vehicles was assumed to be 2000 mm wide with 350 mm radius corners.

Table 4: Inertial parameters of a single Ford Expedition [11]

Parameter	Value
Mass	2500 kg [1]
Roll radius of gyration (r_x)	677 mm
Pitch radius of gyration (r_y)	1430 mm
Yaw radius of gyration (r_z)	1462 mm
Longitudinal centre of gravity (CG_x) [2]	1459 mm
Lateral centre of gravity (CG_y) [3]	0 mm
Vertical centre of gravity (CG_z) [4]	777 mm

[1] reduced from the measured value of 2638 kg in [11] (removing driver and fuel);
[2] rear of the front axle; [3] relative to the vehicle centreline;
[4] above ground with the vehicle at rest on a flat surface

The inertial properties of the combined set of 6 vehicles were calculated for the payload arrangement shown in Figure 1. The locations of the payload vehicles are detailed in Table 13 in Appendix A. The longitudinal centre of gravity was assumed to vary with the trailer wheelbase with all other inertial properties constant for all configurations as shown in Table 5.

Table 5: Combined inertial parameters of the 6 payload Ford Expedition vehicles

Parameter	Value
Mass	15000 kg
Roll radius of gyration (r_x)	1458 mm
Pitch radius of gyration (r_y)	4626 mm
Yaw radius of gyration (r_z)	4452 mm
Longitudinal centre of gravity (CG_x) [1]	$0.646 \times (trailer\ wheelbase)$
Lateral centre of gravity (CG_y) [2]	0 mm
Vertical centre of gravity (CG_z) [3]	2650 mm

[1] measured rear of the hitch position; [2] measured relative to the vehicle centreline; [3] measured relative to the ground

4.3. Suspension parameters

Suspension and tyre properties are often difficult to source from original equipment manufacturers and require technical expertise to interpret. To make the model more accessible, a representative suspension design was developed and assumed to be constant for all vehicle configurations as per Table 6.

Table 6: Representative suspension parameters

Parameter	Steer	Drive	Semi-trailer
Tyres	315/80R22.5 (singles)	315/80R22.5 (duals 350 mm spacing)	245/70R17.5 (duals 280 mm spacing)
Axle load rating (kg)	8000	13000	9000
Unsprung mass (kg)	750	1300	746
Axle roll & yaw inertia (kg/m²)	529	619	466
Track width (mm)	2028	1837	1950
Wheel centre height (mm)	512	531	385
Roll centre height (mm) [1]	-15 (below)	+400 (above)	-114 (below)
Jounce / Rebound stops (mm)	+250 / -250	+250 / -250	+250 / -250
Spring type	Steel leaf spring	Airbag	Airbag
Spring track (mm)	815	756	1060
Damper track (mm)	1153	997	900
Stabiliser bar	Yes	Yes	No
Auxiliary roll stiffness (Nm/°)	2950	7487	12217
Steer/roll coefficient (°/°)	-0.087	-0.087	-0.051

[1] relative to the wheel centre height

The resulting simplified tractor semi-trailer car-carrier model has a total of 11 input parameters as illustrated in Figure 1 and tabulated in Table 7.

Table 7: Simplified tractor semi-trailer car-carrier model inputs

Category	Input (mm)	Description
Tractor geometry	XF_1	Longitudinal location of the furthest forward or outmost point
	YF_1	[1]Width of the vehicle at the furthest forward or outmost point
	WB_1	Wheelbase
	HO	Longitudinal location of the hitch point
Semi-trailer geometry	XF_2	Longitudinal location of the furthest forward or outmost point
	YF_2	Width of the vehicle at the furthest forward or outmost point
	WB_2	Wheelbase
	XR_2	Longitudinal location of the furthest rearward or outmost point
	YR_2	Width of the vehicle at the furthest rearward or outmost point
Payload projection	XF_P	Front payload projection relative to the front of the trailer structure
	XR_p	Rear payload projection relative to the front of the trailer structure

[1] The width is measured from the vehicle centreline as shown in Figure 1

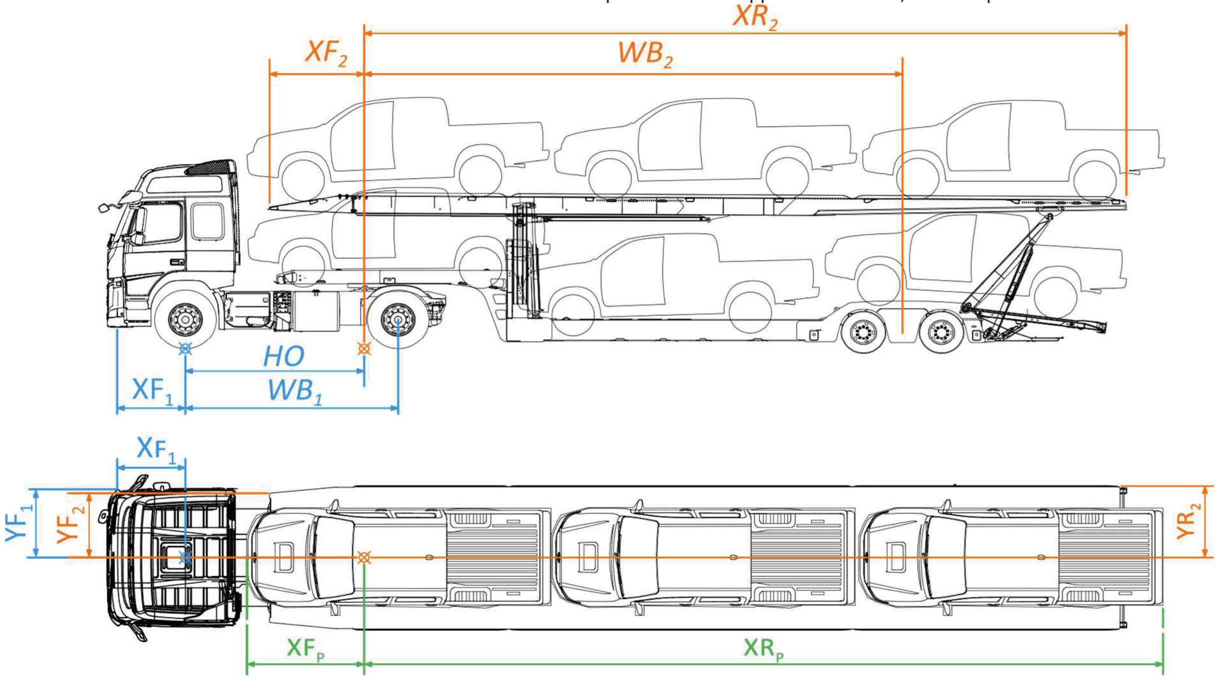

Figure 1: Simplified tractor semi-trailer car-carrier model input parameters

5. Methodology

A dataset of 4 149 randomly selected tractor semi-trailer car-carrier combinations was generated using the simplified car-carrier model as discussed in Section 4. MATLAB® 2018a and TruckSim® 2018.0 were then used to model and assess the PBS performance of each combination. MATLAB® was used to activate and control TruckSim® using a COM server. The process is summarised in Figure 2.

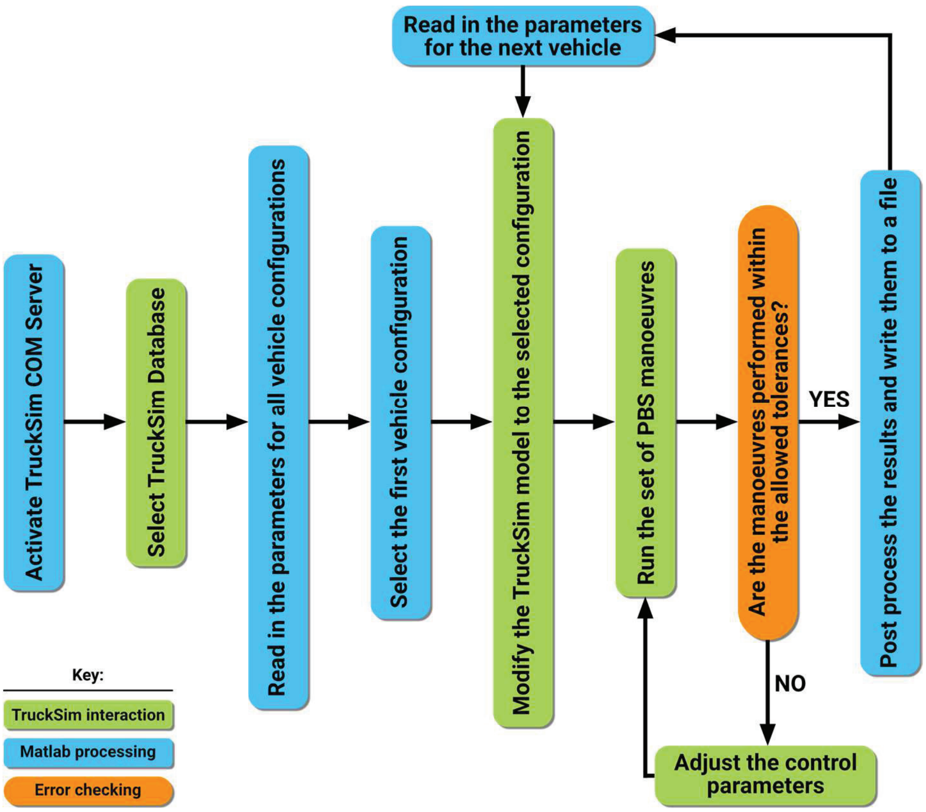

Figure 2: MATLAB® and TruckSim® COM server interaction

Driverless AI developed by H_2O.ai automates the process of machine learning (feature engineering, model building, visualisation and interpretability) [12]. The software was used to develop the machine learning models. The H2O.ai Driverless AI software was installed onto a google cloud platform virtual machine running Ubuntu 16.04 LTS with 8 vCPUs and 52 GB of memory.

The feature vector for each of the car-carrier combinations consisted of the 11 geometrical features described in Table 7 (all in units of mm). The high and low-speed PBS performance measures included in Table 8 form the dependant variables for each of the models. Longitudinal standards were excluded from the study as they can be calculated without a multi-body vehicle dynamics simulation package, reducing the value of training a machine learning model.

Table 8: Performance measures

Category	PBS performance measures
Longitudinal	Startability (STA)
	Gradeability A (GRAa)
	Gradeability B (GRAb)
	Acceleration capability (ACC)
High-speed	Static rollover threshold (SRT)
	Yaw damping coefficient (YDC)
	Rearward amplification (RA)
	High-speed transient offtracking (HSTO)
	Tracking-ability on a straight path (TASP)
Low-speed	Low-speed swept path (LSSP)
	Tail swing (TS)
	Frontal swing (FS)
	Maximum of difference (MoD)
	Difference of maximum (DoM)
	Steer-tyre friction demand (STFD)

The design matrix of 4 149 car-carrier feature vectors was split into a training (80%) and a test (20%) dataset. A model was then trained with the training dataset for each of the dependant variables (PBS measures) with the Driverless AI experiment settings detailed in Table 9. Once the model was trained, the test dataset was used to evaluate the accuracy of the trained model.

Table 9: H2O.ai Driverless AI experiment settings

Setting	Value
Accuracy	7
Time	2
Interpretability	6
Scorer	MAE (Mean absolute error)

6. Results and Discussion

The accuracy of the trained models is summarised in Table 10. The Level 1 PBS requirements for each of the performance measures are also listed to give a sense of the scale of the maximum absolute error in relation to the Level 1 performance requirements.

The mean absolute percentage error (MAPE) for the SRT, RA, HSTO, TASP, LSSP, TS, FS and STFD models are all below 1.5%, proving excellent predictors of the car-carrier performance for these performance measures. The maximum absolute percentage error (APE) for all these standards is below 4% indicating a good prediction of performance within the full test dataset. The models developed for these performance measures can be used to provide a reasonable estimate of the vehicle performance for the evaluated range of car-carrier combinations.

Table 10: Accuracy of the trained models

Trained model	Level 1 Requirements (varies)	Max absolute error (varies)	Mean absolute error (varies)	Max. absolute percentage error (%)	Mean absolute percentage error (%)
SRT (g)	≥ 0.35	0.00297	0.00043	0.12	0.81
YDC (-)	≥ 0.15	0.01088	0.00548	35.09	1.46
RA (-)	$\leq 5.7\times$SRT	0.00604	0.00112	1.01	0.11
HSTO (m)	≤ 0.6	0.03368	0.00088	1.29	0.08
TASP (m)	≤ 2.95	0.02241	0.00195	1.29	0.08
LSSP (m)	≤ 7.4	0.01651	0.00367	0.36	0.06
TS (m)	≤ 0.3	0.00552	0.00248	3.51	0.78
FS (m)	≤ 0.7	0.00552	0.00119	2.69	0.33
MoD (m)	≤ 0.55	0.05072	0.00674	7.31	1.33
DoM (m)	≤ 0.25	0.04328	0.00889	5792	19.39
STFD (%)	≤ 80	0.11363	0.01658	0.60	0.08

The DoM model had a large maximum APE of 5 792%. The absolute error at this datapoint was small at 0.01 m with an actual DoM of 0.0002 m resulting in the large percentage error. Similarly, large percentage errors occur at low or negative DoM values. The actual DoM versus predicted DoM values are shown in Figure 3. Large errors occurred for large DoM values (above 0.4 m). The split in the training and test dataset resulted in a portion of the test data exceeding DoM values present in the training data leading to a low-accuracy prediction in this region. However, at these high DoM values, the vehicle has failed by a significant margin and thus the accuracy is not critical. There is a high concentration of errors greater than 10% within the Level 1 performance region, however only a single datapoint predicted a false pass. As the DoM approaches the Level 1 performance limit, most of these points fall below the ideal prediction line indicating that the predicted performance is more conservative than the actual performance.

The actual MoD versus predicted MoD values are shown in Figure 4. The MoD model had a maximum APE of 7.31% with a MAPE of 1.33%. A single datapoint with an error larger than 5% predicted a false pass. Large errors occurred for large MoD values (above 0.7 m). This was again due to the small concentration of training data in this region. The remaining errors larger than 5% are all predicted conservatively relative to the actual result in the region which achieves Level 1 PBS requirements. The models are considered to reasonably estimate DoM and MoD with only 0.12% of the predicted results in each predicting a false pass where the error was significant.

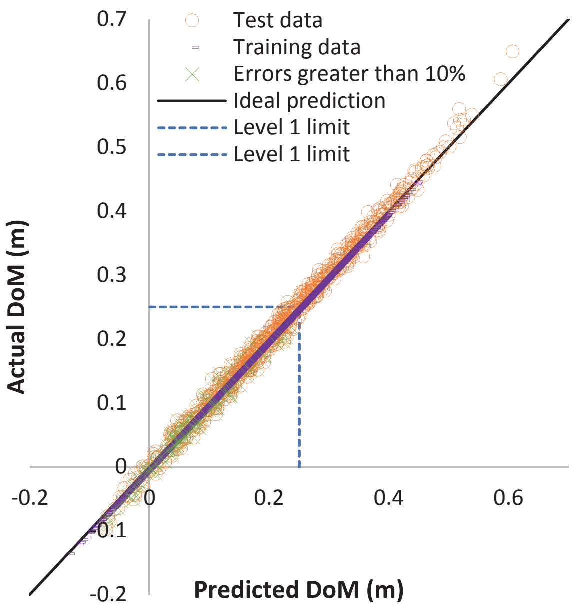

Figure 3: Actual versus predicted DoM

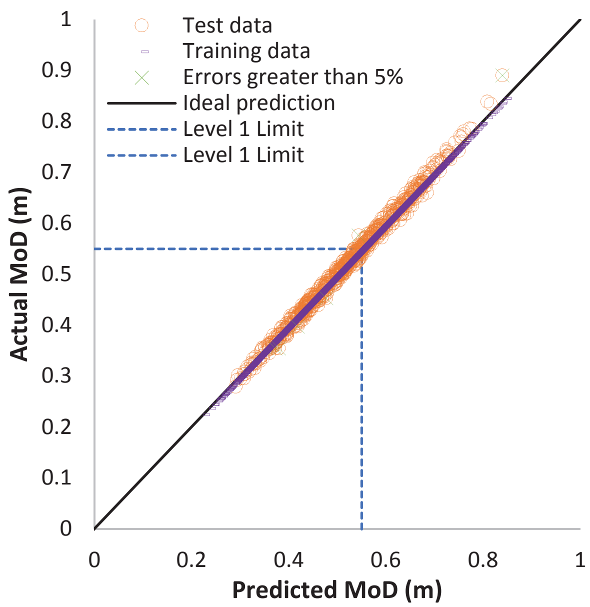

Figure 4: Actual versus predicted MoD

The yaw damping coefficient model has a MAPE of 1.46% and maximum APE of 35.09%. Figure 5 shows that there is a group of datapoints where the actual YDC is significantly higher than the predicted value. Logical operations are applied in the calculation of the YDC and therefore it is expected that a prediction model will have some outliers, which in this case are predicted to be conservative, and are thus acceptable. In addition, tractor semi-trailer combinations are expected to have good YDC performance, which is displayed in the results since no combination comes close to the Level 1 limit which in the case of YDC must be exceeded for safe performance.

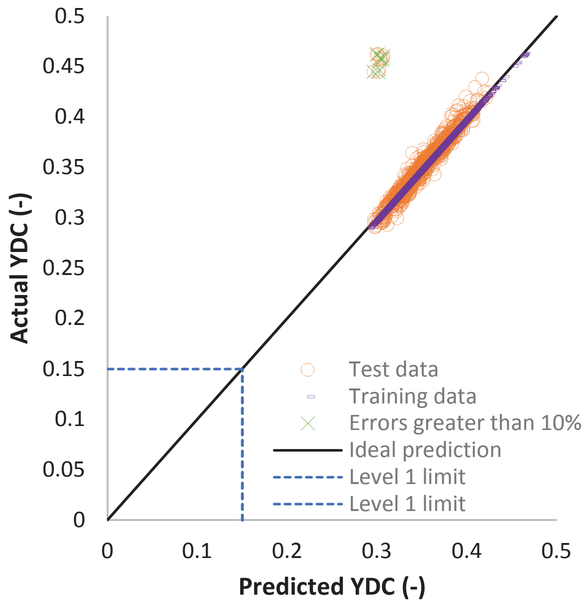

Figure 5: Actual versus predicted YDC

7. Conclusions

A dataset of 4 149 tractor semi-trailer car-carrier combination configurations was generated using simplifying assumptions and ranges developed from the database of approved PBS car-carriers (see Section 4). Each of these combinations was then modelled with TruckSim® and assessed within the PBS framework as adopted in South Africa.

The processed dataset consisted of a feature vector with 11 geometric vehicle parameters (illustrated in Figure 1) for each vehicle configuration. A separate machine learning model was developed within H2O.ai driverless AI for each of the high and low-speed PBS performance measures as the dependent variables. The overall dataset was split into a training (80%) and test (20%) dataset.

The models developed for SRT, RA, HSTO, TASP, LSSP, TS, FS and STFD showed excellent accuracy with a MAPE of below 1% and a maximum APE of below 5%. These models can accurately predict vehicle performance within the range of vehicle configurations evaluated.

The model developed for DoM has high APE (maximum APE of 5 792%), however the actual value and absolute error is small. The model has low accuracy at higher values of DoM due to the split in the training and test dataset which resulted in few training datapoints residing at the higher values. At these points, the combination has a clear fail result and the larger absolute differences are insignificant in this region. Only a single test datapoint with an error of greater than 10% predicted a false pass. Near the Level 1 PBS performance limit, most of the predicted results were below the ideal prediction line indicating a conservative estimate of performance. Thus, while this model is the least accurate of those trained, it is still capable of predicting a vehicle's MoD performance.

The models developed for MoD and YDC had significantly larger MAPE values of 7.31% and 35.09% respectively. Further investigation of these models showed that of the MoD errors greater than 5%, only a single point was predicted as a false pass, while the remaining errors of this magnitude were predicted conservatively. As with DoM, there were some larger absolute errors at high values where there were few training datapoints. The YDC model was found to have a group of datapoints predicted very conservatively by the model (resulting in the high MAPE) and with the YDC performance of all the configurations being well within Level 1 performance requirements, the model was deemed suitable as a prediction of vehicle performance.

The models developed in H2O.ai driverless AI have proven to be sufficiently accurate predictors of the PBS performance of a tractor semi-trailer car-carrier, while requiring only 11 geometric parameters that can easily be read off a detailed drawing of the vehicle combination. The DoM, MoD and YDC models are not as accurate as the other performance measure models. Nevertheless, they are typically conservative predictors of vehicle performance with a negligible number of false pass predictions (0.12%) within the test dataset for the MAPE values above 5% for MoD and 10% for DoM.

The success of these models indicates that further development with a larger dataset and improved machine learning techniques would lead to more accurate models capable of reliably predicting vehicle performance for any tractor semi-trailer car-carrier. The model can be used by anyone with access to a detailed drawing of a vehicle combination which will allow designers to predict PBS performance of their combination without the need for expensive multi-body vehicle dynamics software or expertise in vehicle dynamics.

To extend the simplified model, it is suggested that in addition to the 11 geometric vehicle parameters, vehicle overall width at the centre of the trailer axle group as well as steer axle overall width be considered. To improve the accuracy of the model predictions for vehicle configurations with performance on the upper and lower limits of the model as well as to encompass a wider range of vehicle configurations, it is suggested that the design parameters be evaluated beyond those found in the database of approved PBS tractor semi-trailer car-carriers.

It is recommended that the model be validated against tractor semi-trailer car-carrier PBS assessments in the future to determine whether the simplified tractor semi-trailer car-carrier model is a reasonable prediction of vehicle performance particularly for the high-speed standards where the inertial properties have a larger influence on performance.

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Appendix A. PBS approved tractor semi-trailer car-carrier parameters

The parameters of the six unique PBS approved tractor semi-trailer car-carriers are summarized in Table 11 to Table 12.

Table 11. Approved PBS car-carrier tractor and semi-trailer parameters

Car-carrier	Tractor				Semi-trailer			
	Wheelbase (mm)	Sprung mass (kg)	CG_x (mm)	CG_z (mm)	Wheelbase (mm)	Sprung mass (kg)	CG_x (mm)	CG_z (mm)
1	3560	3446	708	1000	9600	7527	6424	1514
2	3700	5477	820	1067	9700	7527	6424	1514
3	3700	5477	820	1067	9600	8150	6361	1361
4	3560	4450	768	1225	9500	7500	4687	1478
5	3700	5282	706	1170	9236	8358	5971	1470
6	3700	5282	706	1170	9350	8188	6678	1467
Max	3700	5477	820	1225	9700	8358	6678	1514
Average	3653	4902	755	1117	9498	7875	6091	1467
Min	3560	3446	706	1000	9236	7500	4687	1361

Table 12. Assessed payload parameters for approved PBS tractor semi-trailer car-carriers

Car-carrier	Sprung mass (kg)	CG_x (mm)	CG_z (mm)
1	15372	6305	2458
2	15372	5890	2618
3	14800	6550	2494
4	13390	6543	2234
5	15000	6179	2301
6	12900	5323	2558
Max	15372	6550	2618
Average	14472	6132	2444
Min	12900	5323	2234

Table 13: Tractor semi-trailer car-carrier payload vehicle locations

Vehicle	Location	CG_x (mm)[1]	CG_y (mm)	CG_z (mm)[2]
1	Top deck	437	0	3969
2	Top deck	5902	0	3949
3	Top deck	11384	0	3752
4	Bottom deck	1977	0	703
5	Bottom deck	5880	0	1756
6	Bottom deck	11491	0	1770

[1] relative to hitch location; [2] relative to the ground