

HYPERFORMANCE: Advanced PBS Performance Prediction



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Abstract

The ever increasing global freight task brings with it a number of challenges for road freight transportation. The combination of high-capacity vehicles and Performance-based Standards (PBS) is proving to be a viable and sustainable option in combatting some of the challenges, particularly environmental and safety. However, with the increase in the number of PBS initiatives as well as vehicles globally, there is an ever increasing demand on vehicle designers, PBS assessors and regulators. In this paper, we present an updated methodology for the development of PBS performance prediction or calculation tools: so-called “Hyperperformance” models. The methodology we propose uses a probabilistic machine learning technique called Gaussian Processes (GP), which provides both a prediction of vehicle performance, as well as an indication of the accuracy of the model for each prediction. This approach is ideally suited to efficient development of Hyperperformance models for new vehicle configurations. This has value in that they can be used to define new pro-forma or blueprint designs, as well as being used for optimisation of vehicle parameters for a given application. We also present a case-study in which we develop GP prediction models for a PBS B-double combination.

Keywords: Performance-based standards, high productivity vehicles, pro-forma designs

1. Introduction

As a result of the parallel global challenges of increasing freight volumes, and the need to reduce emissions, successful Performance-based Standards (PBS) initiatives have been implemented and investigated in Australia (National Transport Commission, 2008), South Africa (Nordengen *et al.*, 2018), and more recently in the European Union (Kharrazi *et al.*, 2017) and (Kural *et al.*, 2018). With the ever increasing number of new PBS combinations being developed under these initiatives, there is a growing burden placed on vehicle designers, trailer manufacturers, PBS assessors, and the relevant road authorities.

There are two options to fast-track the development and approval process of PBS-compliant vehicles: pro-forma designs, in New Zealand (De Pont, 2010), and “blueprint” designs in Australia (National Transport Commission, 2018). Both of these options have proven to be valuable to both industry and road authorities. However, there are still a limited number of vehicle combinations that are catered for by these options. They are also often region (or country) specific, and cannot easily be transferred to other PBS projects, such as in South Africa or Europe.

A set of simple pro-forma tools for South African car-carriers were presented by Benade *et al.* (2015, 2016a, 2016b). These built on the work of de Pont (2010), but were limited to the low-speed PBS standards, giving them limited application. Following this, Berman *et al.* (2015, 2016) presented a set of lightweight PBS performance prediction tools for both low and high-speed PBS standards: “Hyperperformance” models.

The low-speed performance was calculated using an approach developed by de Saxe (2012), and the high-speed performance was calculated using TruckSim, a multi-body dynamics software package for commercial vehicles. A set of mathematical models were developed using a collection of neural networks (NNs). These models were developed for the case of a typical South African 9-axle B-double, illustrated in Figure 1. It was shown that the PBS performance could be accurately calculated within seconds using these lightweight models.

These models provide three main benefits over existing approaches:

1. They provide a means for vehicle designers or road authorities to quickly evaluate the performance of a proposed vehicle.
2. They can be used to develop future pro-forma and blueprint designs.
3. They can be used to conduct advanced optimisation of vehicle layout and designs for a given application or set of constraints.

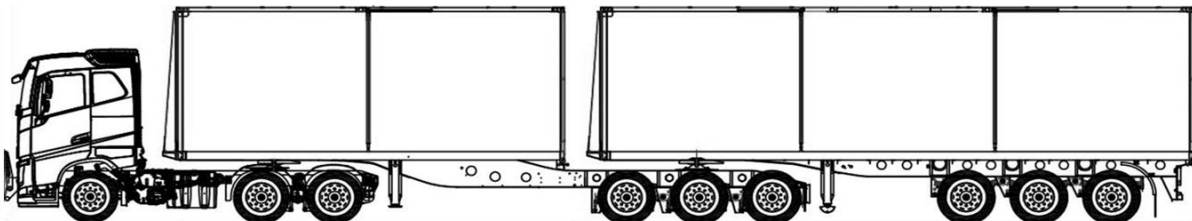


Figure 1 – Typical PBS B-double Configuration (Berman *et al.*, 2016)

In this paper, we present an updated, more sophisticated approach to developing lightweight PBS Hyperperformance models. The same dataset from Berman *et al.* (2016) will be used in this study, allowing for a direct comparison between methods. We also discuss the added benefits of using a new proposed method, as well as future work that is planned.

2. Methodology

Gaussian Processes are described by Rasmussen and Williams (2006) for a dataset \mathcal{D} , consisting of n observations for inputs x , and outputs y as:

$$\mathcal{D} = \{(x_i, y_i) | i = 1, \dots, n\} \quad (1)$$

Where in the case of PBS performance prediction, x corresponds to a set of vehicle parameters, such as unit wheelbase, payload centre of gravity (CoG) height, roll stiffness and so on. The output variable y corresponds to PBS performance in a particular standard, such as static rollover threshold or low-speed swept path. The goal is then to learn a function that mathematically maps the inputs x , to the output y , mapping vehicle parameters directly to PBS performance.

A GP is a generalization of the normal or Gaussian distribution, $N(\mu, \sigma^2)$, where μ is the mean and σ is the standard deviation of the set, is used to overcome the infinite combination of possible functions that could describe output y , in terms of inputs x .

For the case of mathematical regression, such as is required for PBS performance prediction, GPs rely on Bayesian linear regression with Gaussian noise (Rasmussen and Williams, 2006):

$$f(x) = x^T w, \quad y = f(x) + \varepsilon \quad (2)$$

Where x is the input vector, w is the weight vector of the linear model, f is the function value, and y is the observed target value. The Gaussian noise is denoted by ε , and follows an identically distributed Gaussian distribution with zero mean and variance σ_n^2 given as follows:

$$\varepsilon \sim N(0, \sigma_n^2) \quad (3)$$

GPs rely on a technique called conditional probability, which introduces the notion of a prior probability, which is initially set to a zero mean Gaussian. When an observation (in our case, PBS simulations) is made, a posterior probability can be calculated, which updates the knowledge of the distribution, f . The prior probability is therefore updated, and another observation can be made. This is achieved by using Bayes Rule (Rasmussen and Williams, 2006) as follows:

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{marginal likelihood}}, \quad p(y_A | y_b) = \frac{p(y_A)p(y_B | y_A)}{p(y_B)} \quad (4)$$

All of this is illustrated graphically in Figure 2, with part (a) showing four samples from the prior distribution (random and unknown), part (b) shows the update after four observations

(PBS simulations) shown by the dotted lines. The grey bounds depict the variance, or 95% confidence interval for $f(x)$ at each point x , with the function mean shown by the solid line.

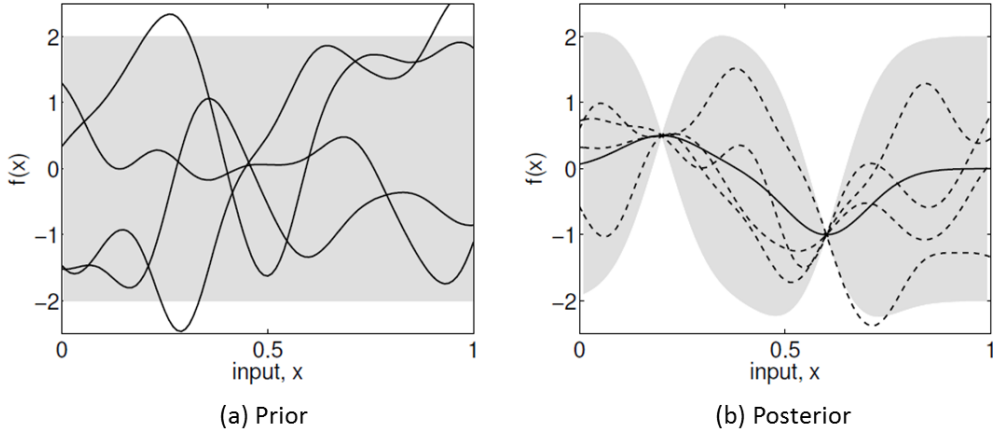


Figure 2 – Illustration of Gaussian Processes (Rasmussen and Williams, 2006)

The value of this approach for a PBS performance prediction model is that for any number of samples, $f(x)$ gives the mean, or predicted value, as well as the variance or model accuracy. It is this posterior probability that sets this approach apart from the previous parametric methods using NNs. Where the variance is low, the prediction accuracy is high. This provides valuable information to the user about the output of the prediction model, which is not available with the use of NNs. The posterior probability allows the user to know whether or not the calculated performance value can be trusted or not.

It is also interesting to note that an infinitely-wide, deep NN can be represented by GPs (Duvenaud *et al.*, 2014), it is therefore a natural evolution to use GPs in place of NNs for PBS performance prediction.

For this case study, we use the same parameters and PBS performance measures from the B-double in (Berman *et al.*, 2016). The following five high-speed PBS measures were again used: Static Rollover Threshold (SRT), High-Speed Transient Offtracking (HSTO), Rearward Amplification (RA), Tracking Ability on a Straight Path (TASP) and Yaw Damping Coefficient (YD). We also added the following five low-speed standards to the existing dataset: Low-Speed Swept Path (LSSP), Tail Swing (TS), Frontal Swing (FS), Maximum of Difference (MoD) and Difference of Maxima (DoM).

The dataset consists of 36 470 unique 9-axle B-double combinations, with a total of 48 input parameters and the PBS performance values for each of the ten standards. The vehicle parameters consist of physical and geometrical properties of the vehicles, such as mass and CoG location of the payload, unit wheelbase, suspension properties. These are discussed in greater detail in (Berman *et al.*, 2016). The input data were normalised by subtracting the mean and dividing the result by the variance of each input parameter. This helped with training the models, and to increase accuracy.

The analysis was conducted in Python, using the GPy (pronounced “G-Pie”) Gaussian Processes library (GPy, 2012). A single GP model was trained for each standard, giving a total of 10 individual models, which when combined, gave the overall resultant PBS performance.

The accuracy of the prediction models was calculated by comparing the predicted value to that of the simulation results from TruckSim for each vehicle combination. Each GP model was trained using a small subset of the overall dataset, and then tested for accuracy of prediction using the remainder of the dataset. During testing for accuracy, the model predicted PBS using the vehicle input data, which was then compared to the TruckSim simulation result.

3. Results and Discussion

The results are shown in Table 1, where predictions from the GP models are compared alongside to those of the previous NN from (Berman *et al.*, 2016). It can be seen that the probabilistic GP models offer equivalent performance to the NN models, but with a reduction in the number of data points required to train the models for each standard. This is a significant advantage, as the time required to perform each set of vehicle dynamics simulations is approximately six-and-a-half to seven minutes. A reduction of 7 000 simulations equates to over 31 days of total simulation time alone.

Table 1 – Model Parameters and Performance

Standard	No. of Params	No. of Training Data Points		Max Absolute Percentage Error (%)		Average Absolute Percentage Error (%)		Max Absolute Error
		NN	GP	NN	GP	NN	GP	
SRT (g)	27	10 000	3 000	5.39	9.69	0.45	0.51	0.03
HSTO (m)	27	10 000	3 000	5.51	4.08	0.51	0.04	0.01
RA (-)	27	5 000	3 000	6.41	3.40	0.32	0.17	0.04
TASP (m)	30	1 000	3 000	0.56	0.20	0.07	0.01	0.01
YD (-)	27	15 000	3 000	36.06	23.06	4.01	2.69	0.08
LSSP (m)	22	None	1 000	None	0.01	None	0.01	0.01
TS (m)	22	None	1 000	None	7.14	None	0.19	0.02
FS (m)	22	None	1 000	None	102.2	None	1.70	0.10
MoD (m)	22	None	1 000	None	0.11	None	0.01	2.4e-4
DoM (m)	22	None	1 000	None	499	None	0.09	0.14

In the cases where the maximum percentage errors are high, particularly the low-speed standards, the absolute error is relatively small. The magnitude of the absolute errors is still small relative to the performance limits for each standard. The models therefore provide acceptable performance without the need to significantly increase the number of data points.

The GP models resulted in a significant reduction in the time required to conduct the vehicle dynamics simulations, but they also gave a further reduction in time over that required to train the NN models. The time required to train the NN models was approximately 10 days of continuous CPU time, and that just for the five high-speed models. The GP models took from as little as a few minutes, up to a maximum of 1.5 hours to train each, with the total CPU time being approximately five hours. The benefits of this are numerous, with the main benefit being the ability to develop and then refine the prediction models for a particular vehicle

configuration in significantly less time that it would take to simply develop a single NN model.

The performance of the GP models cannot be entirely demonstrated by the table above. For the sake of brevity, only the models for SRT and LSSP will be investigated further. Figure 3 and Figure 4 below give greater insight into the value of the GP models. Part (a) of the figures below shows a histogram of the absolute error in the prediction for SRT and LSSP respectively. In both cases, the overwhelming majority of the predictions lie close to zero error, with very few predictions having a high error.

Part (b) of the figures gives a representation of the posterior probability or prediction confidence. In both cases, the PBS performance measure is shown versus one input variable which was normalised. Due to the large number of input parameters, the result cannot be visualised for all variables, thus one parameter was selected to illustrate the effect. In both cases, it can be seen that near the mean of the input variable (represented by 0), the GP models provide high accuracy in predicting performance, with increasing variance further away from the mean.

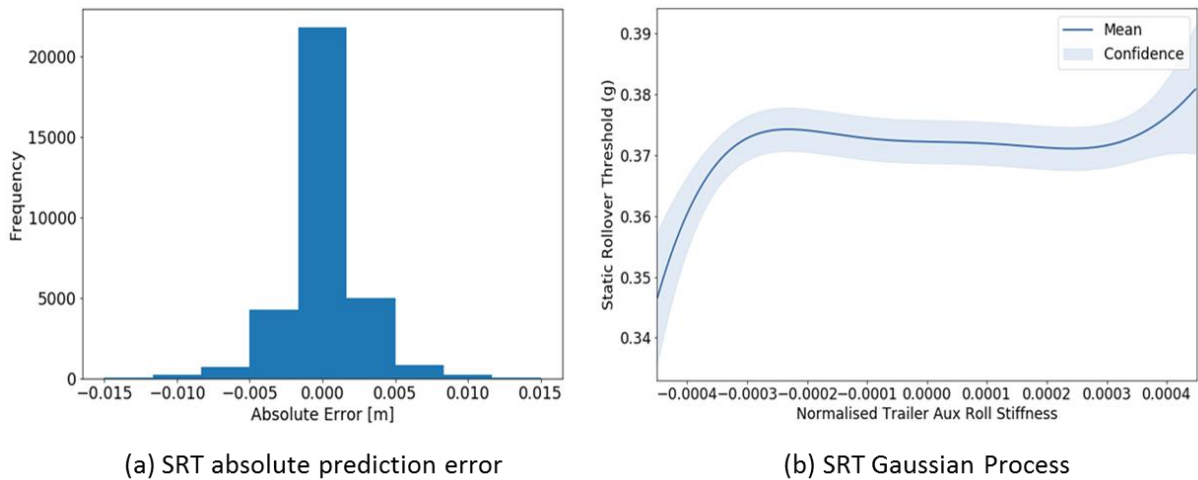


Figure 3 – GP Performance for SRT

For each prediction of vehicle performance, a variance is given as described by Equation (4), meaning that GPs can be built into the vehicle dynamics performance calculation phase, to develop a prediction model with high prediction accuracy across a wide variety of vehicle parameters, but for a minimal number of vehicle dynamics simulations.

In practice, this means that a GP model can be trained, starting with only a very small number of vehicle dynamics simulations. The model will not be highly accurate, but it can be used to calculate the performance of wide array of vehicle input parameters, recording the posterior variance for each prediction, the higher the variance, the lower the confidence in the performance prediction. The vehicle combinations that result in the highest posterior probability can then be used as input into vehicle dynamics simulation (TruckSim in this case) to determine the exact performance. These data can then be added to the existing dataset, and the GP models can then be re-trained on the updated dataset. In this way, the dataset can be incrementally increased, and the GP models updated at regular intervals, with the accuracy increasing until it has reached an acceptable level.

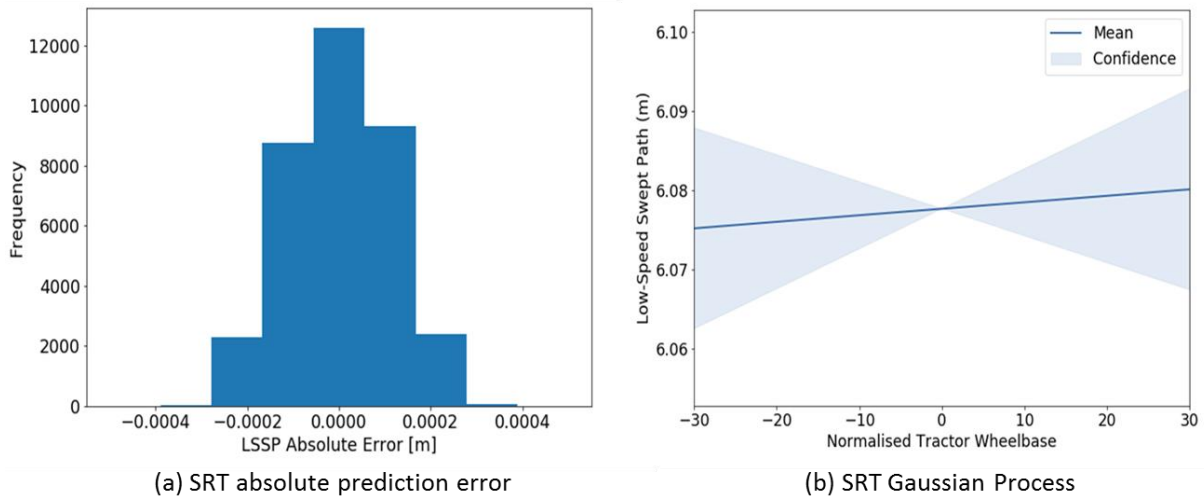


Figure 4 – GP Performance for LSSP

This approach will result in a robust model that is able to accurately predict PBS performance across the entire range of each vehicle input parameter, whilst minimising the CPU time required to achieve that result.

4. Conclusions and future work

We have presented a methodology for the development of lightweight probabilistic prediction models for PBS vehicle dynamic performance. The proposed technique for the prediction model is the probabilistic approach known as Gaussian Processes. GPs have the benefit of giving an indication of the confidence of the prediction, in addition to an accurate performance value. GPs are well suited to mathematically describing a complex high-dimensional problem, such as vehicle dynamics performance, with fewer data than other techniques such as neural networks. A case study of a 9-axle B-double was given, presenting GP prediction models for the low and high-speed PBS standards.

The unique posterior probability that GPs offer, results in this approach being ideally suited to the creation of these so-called “Hyperformance” prediction models for PBS performance. GPs can be used to ensure a Hyperformance model will give high accuracy across the full range of vehicle parameters, whilst minimising the number of vehicle dynamics simulations required to do so.

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