GAUSSIAN PROCESSES AND PBS ASSESSMENT OF ARTICULATED VEHICLES

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Abstract

The design of High Capacity Vehicles (HCV) is a complex task, with many performance criteria to be considered, and where a large number of parameters can be varied. The aim is to find the envelope of parameters, which guarantees acceptable performance. In a second stage, one may search for parameters sets that lead to optimized performance, with the relative importance of the distinguished performance criteria to be decided by the designer.

This design process is usually a matter of trial and error, building on (and extending) valuable existing experience. Questions that can be raised are what parameters are key parameters for the different performances. To what extent are they dependent and act in the same way or conflict one-another. What are the sensitivities of the various vehicle design parameters for these performances and what are the boundaries for specific performance criteria (e.g. PBS: Performance Based Standards) or combinations of them?

HAN University of Applied Sciences has started the ENVELOPE project where, based on a Machine Learning approach, answers can be derived for these questions for arbitrary types of HCV's. In this paper, the first results are discussed for a truck-central axle trailer. Next steps are application for the truck-dolly-trailer combination and the A-Double, referred to in The Netherlands as the Super Eco Combi (SEC). The relationship between performances and vehicle parameters is determined through Machine Learning where we limit ourselves to Swept Path and Rearward Amplification. Next, this relationship is used to derive explicit second order relationships between performance and vehicle and operational parameters, from which parameter sensitivities are derived. A Monte Carlo analysis is used to find the boundaries of the parameter envelope for which the combined performance for low speed (swept path) and high speed (rearward amplification) is satisfactory. We have also examined factor analysis to understand possible dependencies between the vehicle parameters in the realization of performance.

Keywords: Performance Based Standards, Gaussian Process, Machine Learning

1. Introduction

Performance based assessment of articulated vehicles means that one judges vehicle performance according to a finite number of Performance Based Standards (PBS). Those standards are typically related to PBS areas such as high speed stability, manoeuvrability, performance under winter conditions, etc. (see also De Saxe et. al., [1]). To judge the performance, one may carry out experiments or perform virtual analysis using trustworthy (i.e. validated) models. Especially in the process of design, one will use the second approach, with the aim to set design parameters such that the vehicle performance complies with the requirements on the relevant PBS areas.

Two-articulated vehicles such as truck-trailer or tractor-semitrailer, are in general approved according to legal limits regarding loads and overall dimension, i.e. without considering performance. In other words, it is assumed that the envelope of this limited set of design parameters being loads and dimensions will guarantee the desired safe performance. For vehicles with more than two articulations, the freedom in design is increased significantly, and the designer must find a balance between conflicting criteria where easily over thirty different dimensions parameters can be distinguished, where one then still has to add the mass and payload conditions, axle configuration data, properties of chassis components, properties of intelligent control and driver support systems, and powertrain characteristics. Consequently, an enormous task for the designer. How to cover that in simple evaluation of dimensions and loads/masses is an impossible task. Therefore, the design of HCV's is in general a process of trial and error, building on (and extending) existing experience, starting from a limited requirement scope. This motivated the ENVELOPE project, initiated by HAN University of Applied Sciences, with the objective to find methodologies to establish envelopes of design and operational parameters (e.g. wheel basis, suspension, tyre properties, loading condition…etc.), ensuring the complete vehicle combination to comply with all of the appropriate infrastructure and safety performance requirements. In other words, to determine the boundaries in the (extensive) parameter space defined by the Performance Based Standards (PBS). Such enveloping process was explored earlier at HVTT15 in 2018, by Berman et. al (see [3]) and Kashampur at all (see [4]). This paper takes on the approach using Gaussian Processes as treated by Berman et. al and further develops that approach in a way that it fits within the practical design process for HCV's. This paper describes the total methodology in detail with application for the truck-central axle trailer, discussing parameters sensitivities, optimized parameter sets and parameter interdependencies. The truck-central axle trailer is just a start, and we give further outlook on (the established results for) EMS-vehicles (truck-dolly-trailer) and A-Double.

2. Objectives

The objective of the project ENVELOPE (ENhanced Vehicle Evaluation Leading to Optimized PErformance), discussed in the paper, is to define methodologies, leading to the specific envelope of design and operational parameters, ensuring the vehicle combination to comply with infrastructure and (PBS based) safety performance requirements. Obviously, certain parameters will be based on logistic constraints, and will be more or less fixed. We will ignore that for the time being, and focus primarily on the methodologies. An appropriate mathematical analysis tool is the use of Gaussian Processes for machine learning, as demonstrated in [3]. This potentially allows the assessment of these boundaries, based on a selected number of training situations. In contrast to [3], we will ask ourselves questions being relevant to make the Gaussian approach successful for practical design:

1. What is the expected accuracy in finding the relationship between design parameters and performance, also related to the minimum set of training situations? And how to optimize this?
2. How to deal with situations when many different parameters are included? How to visualize the outcome and make it more explicit, such that it can be included in the design process?
3. To what extent are parameters dominant in the design and/or interrelated? Can we identify clusters of parameters with similar impact on performance? And how to find the most optimal combination of performances.

3. Research approach

We have schematically shown the research approach in the scheme in figure 1, and treat the different steps below. A design case starts with the intended vehicle (some HCV: High Capacity Vehicle), a set of performance quantities $P_i, i = 1,2,..,N$ (typically swept path, rearward amplification, TASP,…), a selection of design parameters to be varied between

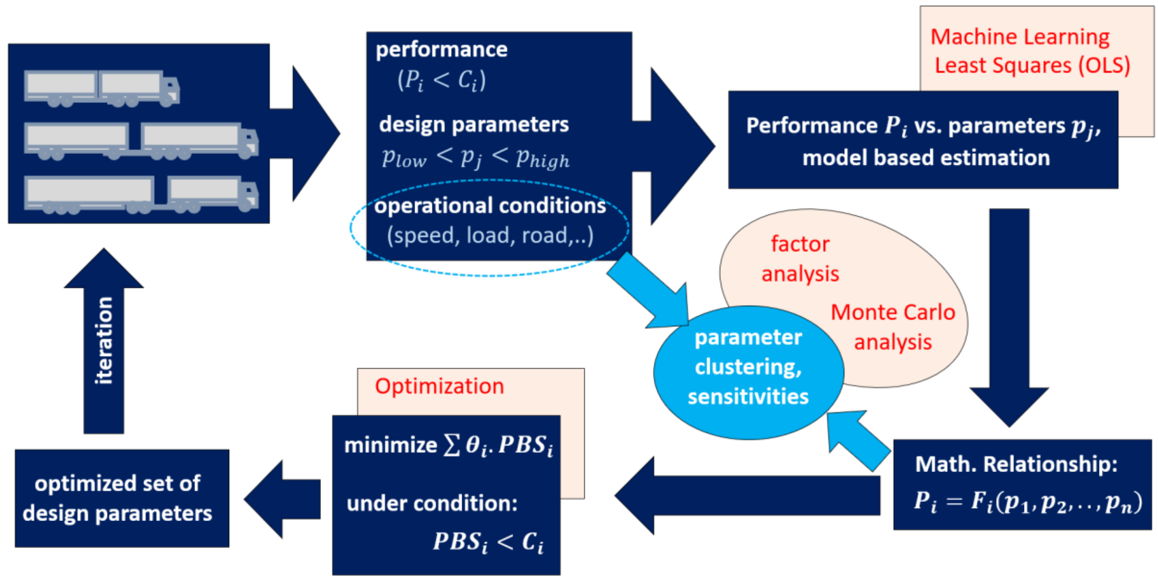

Figure 1.: Schematic layout research approach

lower and upper bounds, $p_{low} < p_j < p_{high}, j = 1, 2, \ldots, n$ and operational conditions referring to speed range, payload range, road conditions, etc. The performance quantities are constrained by maximum acceptable values, $P_i < C_i$. For example a rearward amplification which is demanded to be less than 1.8. It is up to the designer to set those demands, and maybe start with some more moderate values and reduce that later, to work from a large envelope of acceptable parameter values to a more restricted set. The first step is to prepare a mathematical model, preferably based on multi-body tools, but in this paper a mathematical model in Matlab. By taking a number of training sets in the selected parameter space, we can find an implicit, quite accurate, description of performance in terms of parameters $P_i = F_i(p_1, p_2, \ldots, p_n)$ using Gaussian Processes based on Machine Learning. Starting with a **prior** estimate of an n-variable function, a **posterior** estimate is established with improved expectation and minimized covariance. For a background on this AI-related mathematical approach, we refer to the book of Rasmussen and Williams [2], also used by Berman et. al [3].

In short, Machine Learning is a regression method to find patterns from raw data. Let us illustrate this for the one-dimensional case where we try to describe a stochastic function $y = f(x)$ with f known for m values of x. We call this set the training set, $\{(x_j, f_j)|j = 1, 2, \ldots, m\}$. When we assume a very basic (prior) Gaussian distribution (probability density function) for f with expected value 0 and variance 1, it may be expected that the conditional Gaussian distribution for f, that means under the condition of known training points (x_j, f_j), may lead to a more accurate expected value for f with significantly reduced variance (i.e. with high confidence. This is shown in figure 2 for 7 training points where samples of the prior estimate are shown in the left plot, and samples of the improved

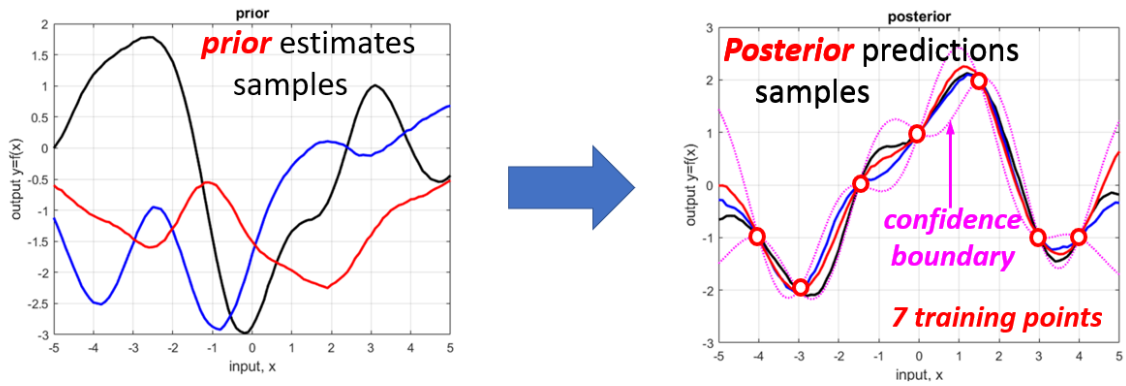

Figure 2.: Example of Machine Learning regression in one dimension

conditional (posterior) estimate in the right plot. In this paper, we consider the performance P_i as this function f, with x replaced by the n-dimensional set $(p_1, p_2, \ldots, p_n)$.

Once we have an accurate implicit description of performance in terms of parameters, we can make it explicit using OLS (Ordinary Least Squares). That means that we try to replace $P_i = F_i(p_1, p_2, \ldots, p_n)$, as resulting from Machine Learning, by an explicit expression $P_i = \sum a_{ij} . \varphi_j$ with φ_j being related to one of the parameters, being modified to

$$R(p_j) = \frac{p_j - p_{j,low}}{p_{j,high} - p_{j,low}} \quad (1)$$

(i.e. all ranging between 0 and 1, by weighting using the possible parameter range), its square or a product of two different modified parameters. Hence, we aim for a quadratic fit.

Next, we consider a linear relationship of the selected performance quantities to be minimized:

$$\sum_i \theta_i . P_i(p_1, p_2, \ldots, p_n) \quad (2)$$

with the performance explicitly expressed in linear or higher (second) order sense in terms of the weighted vehicle parameters $R(p_i)$. The coefficients θ_i can be chosen to express the relative importance of the individual performance measure.
We determine the minimum of this expression (optimized design) under conditions of $P_i < C_i$, where different methods can be used, for example linear programming, see [5] and chapter 8 in [6]. In this paper, we apply a Monte Carlo analysis for different ranges of operational conditions, and select the parameter sets minimizing the above relationship. That may lead to different optimal parameter sets. These different sets can then be used for a correlation analysis, where the resulting correlation matrix can be used for a factor analysis, see [7]. That means that we try to find a limited set of underlying factors (hidden features), being explained by a cluster of parameters meaning that a proportion of variances per parameter is accounted for by that factor. This helps to interpret the relationship between parameters and performance.

4. Results

In this section, we shall follow the scheme in figure 1 for a simple truck-central axle trailer. Just to get grip on the methodologies, we decided to start with a vehicle combination which is not extremely complex, and the combination, with the less stable central axle trailer, was expected to be a good start. The layout of this vehicle is shown in figure 3.

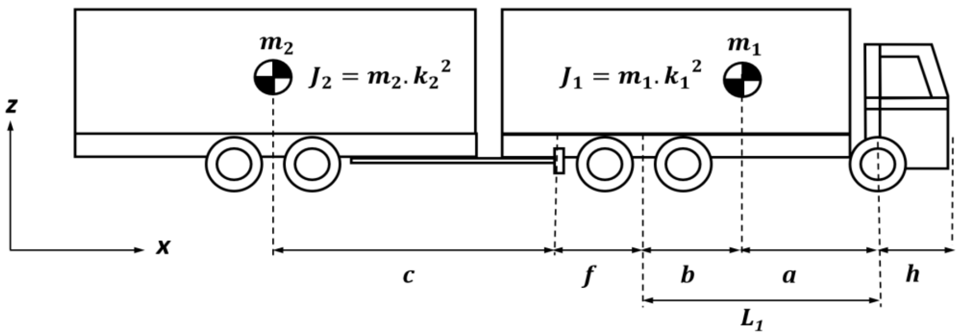

Figure 3.: Truck-central axle trailer

The vehicle will be described by a linear single track model, with the cornering stiffness C_i of axle i taken linearly in the axle load, $C_i = c_i . F_{zi}$ (normalized cornering stiffness c_i) and with the vehicle data as listed in table 1, where we also indicated the parameters to be varied and the range for that. Note that this paper aims to explain the methodologies, and that we therefore may vary parameters in a way, not always matching real practical designs and logistic requirements.
We restricted ourselves to two performance quantities, the Rearward Amplification and the Swept Path under steady state cornering conditions (RA and SWP for short, respectively).

	Reference		Reference	Range
m_1 [kg]	15000	m_2 [kg]	10000	5000-15000
a [m]	2.5	L_1 [m]	5.0	3 – 7
b [m]	2.5	f [m]	0.5	-0.1 – 2.5
c_1	4.5	c [m]	7.0	5 – 10
k_1 [m]	1.44	k_2 [m]	2.40	2.0 – 3.0
c_2	5.5	c_3	5.5	4.5 – 7.0
		h	1.4	1.2 – 1.8

Table 1.: Reference data

For the swept path we also varied the truck wheelbase, which we didn't for RA. The RA is derived from the acceleration to steering angle gain for both towing vehicle and trailer for

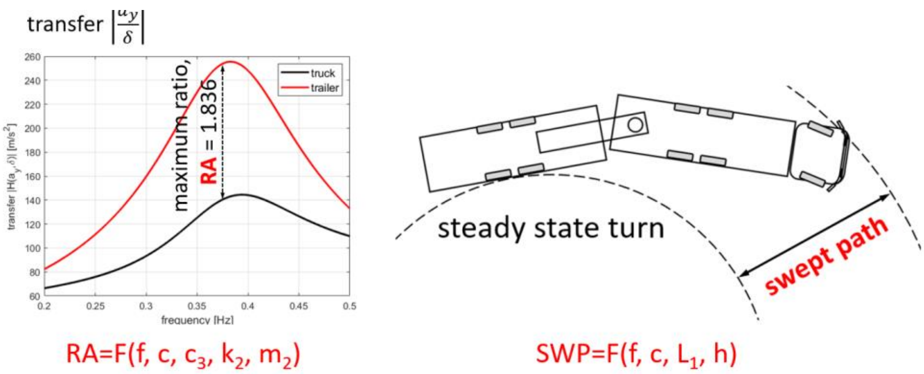

Figure 4.: Rearward Amplification (RA) and Swept Path (SWP)

varying frequency, with RA being the maximum ratio of them. see figure 4 for SWP and RA. Vehicle speed is taken as 88 km/hr.

4.1. Rearward Amplification

Gaussian process based machine learning estimates a posteriori regression description of a function, based on a prior estimate, for a number of training points for which the function is known. One would like to have a minimum number of training points such that still acceptable accuracy is obtained, which is basically a question on 'design of experiments'. Starting with only two varying parameters, c and f, and taking the other three equal to their

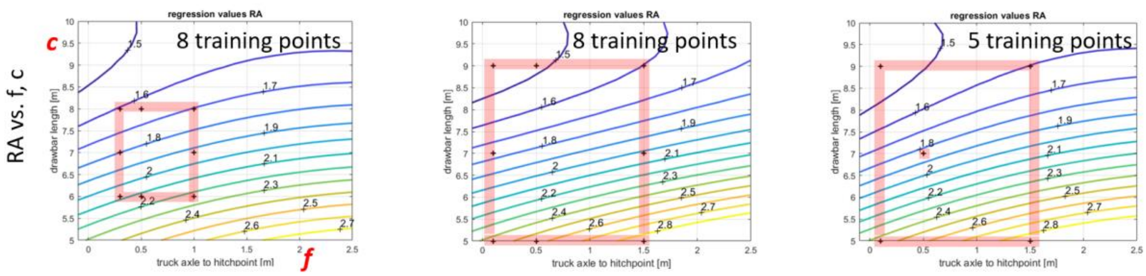

Figure 5.: Different contour plots for RA, resulting from machine learning using 8 or 5 training points

reference values, we can make contour plots of RA vs. (f, c) as resulting from the machine learning approach. Three cases are shown in figure 5.

One observes that even with five training points, the RA-values correspond well with the other plots. It was found that the standard deviation of the difference with the exact solution was order ≤ 0.02 in that situation.

The next step is to take all five parameters into account, with two or three values per parameter. Including the center point, this gives $2^5 + 1 = 33$ and $3^5 + 1 = 243$ training points in total, respectively. It is not possible to draw plots in terms of five parameters. Instead, we show plots of RA vs. trailer mass m_2, but based on the regression solution with all five parameters included, see figure 6. Clearly, 2 values per parameter is insufficient for a good match with the exact solution (indicated in red). We have also shown the 95 % confidence lines.

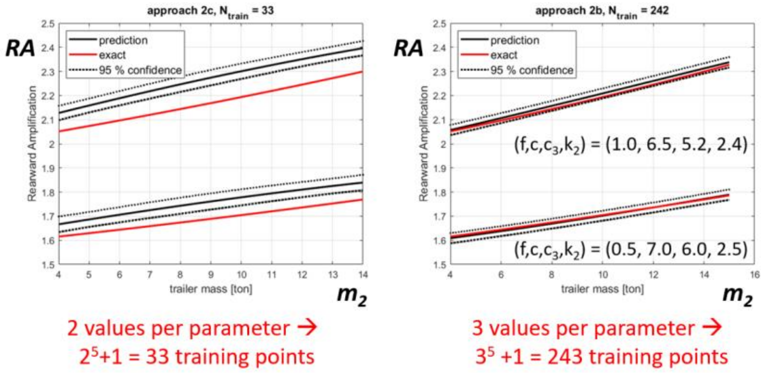

Figure 6.: RA vs. trailer mass m_2 for different parameters sets, based on five parameter regression using Gaussian Processing

The next step is to determine an explicit expression using OLS, which could be linear or second order. We have calculated the second order fit based on the previous regression results and taking 4 values for each relevant variable, meaning 1024 sets of five parameters and leading to the following expression:

$$\begin{aligned} RA = {} & a_0 + a_1.R(f) + a_2.R(c) + a_3.R(c_3) + a_4.R(k_2) + a_5.R(m_2) + a_6.R(f).R(c) + \\ & + a_7.R(f).R(c_3) + a_8.R(c).R(c_3) + a_9.R(c).R(k_2) + a_{10}.R(c).R(m_2) + a_{11}.R(c_3).R(k_2) + \\ & + a_{12}.R(c_3).R(m_2) + a_{13}.R(k_2).R(m_2) + a_{14}.R(c)^2 + a_{15}.R(c_3)^2 + a_{16}.R(k_2)^2 \end{aligned} \quad (3)$$

a_0	2.6069	1	a_{10}	-0.4723	$R(c).R(m_2)$
a_2	-2.3438	$R(c)$	a_4	0.4585	$R(k_2)$
a_3	-1.6441	$R(c_3)$	a_{12}	-0.3058	$R(c_3).R(m_2)$
a_8	1.0762	$R(c).R(c_3)$	a_{11}	-0.2923	$R(c_3).R(k_2)$
a_1	0.7590	$R(f)$	a_{13}	0.2917	$R(k_2).R(m_2)$
a_{15}	0.5803	$R(c_3)^2$	a_7	-0.2052	$R(f).R(c_3)$
a_9	-0.5237	$R(c).R(k_2)$	a_{14}	0.2002	$R(c)^2$
a_5	0.5086	$R(m_2)$	a_{16}	0.1076	$R(k_2)^2$
a_6	-0.5012	$R(f).R(c)$			

Table 2.: Coefficients, nonlinear approximation, RA

The coefficients are included in table 2 in order of absolute magnitude, where we have omitted the coefficients being very small. When we would have included all second order

terms (squares, cross-products), we would have 21 terms, whereas for a linear approximation, this would be only 6 terms. One clearly 'pays a penalty' when higher order is considered.
From the coefficient values, one can conclude that the linear terms for drawbar length and trailer slip stiffness are most dominant (largest sensitivity), followed by higher order terms, also related to this drawbar length and slip stiffness (coefficients a_{14}, a_8). Other parameters are entering with smaller coefficients. This shows already which parameters are more relevant for RA (drawbar length. trailer slip stiffness), but also that nonlinear performance is hard to neglect, especially if a significant range in parameters is considered.. We have checked the error in the second order RA approximation and we found that over 80 % of all 1024 values were closer to the exact RA-value than 0.1, that is less than 5 %. A linear OLS appeared to lead to errors being at maximum in the order of 12 %. Suppose, one aims for a critical value for RA of 1.8. The above analysis suggests that one might take a conservative RA-value (e.g. 1.7) and follow the above analysis to find the parameter values which guarantee a safe RA.

4.2. Swept path analysis

A similar analysis can be carried out for the swept path SWP = $F(c, f, L_1, h)$. Starting with the machine learning analysis for all four parameters, and taking either three or four values per parameter, but omitting the combinations for which no swept path exists (e.g. too large drawbar length), we arrive at a relationship between SWP and drawbar length c as shown in figure 7. Apparently, the accuracy for three different values per parameter is insufficient, due to the strong nonlinear behaviour. Using this regression result to carry out a (quadratic) OLS analysis taking 4 values for each relevant variable leads again to an explicit expression, now for SWP:

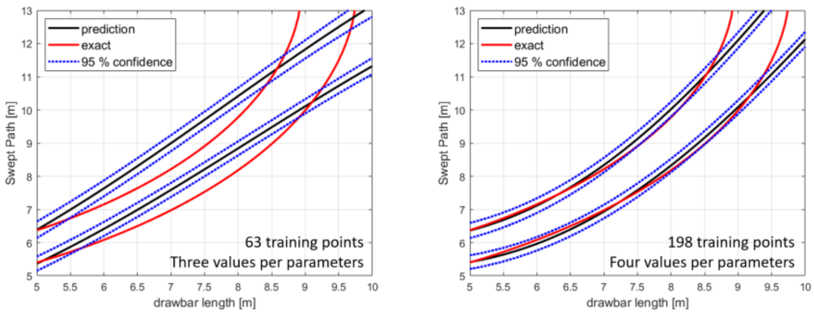

Figure 7.: Swept path vs. drawbar length, from regression based on 81 and 256 training points, respectively, including all four parameters. Prediction based on (*f*, *L*₁, *h*) =(0.2, 4.5, 1.3) and (0.8, 5.5, 1.7)

$$\begin{aligned} SWP = {} & b_0 + b_1.R(f) + b_2.R(c) + b_3.R(L_1) + b_4.R(h) + b_5.R(f)^2 + b_6.R(c)^2 + \\ & + b_7.R(L_1)^2 + b_8.R(h)^2 + b_9.R(f).R(c) + b_{10}.R(f).R(L_1) + \\ & + b_{11}.R(f).R(h) + b_{12}.R(c).R(L_1) + b_{13}.R(c).R(h) + b_{14}.R(L_1).R(h) \end{aligned} \tag{4}$$

The coefficients are listed in table 3 in the order of magnitude, omitting very small ones (magnitude < 0.01). This gives an impression of what (combination of) parameters are most relevant. This list suggests that wheel base and drawbar length are the most relevant parameters with high sensitivity with respect to swept path, as expected, followed by hitch point position and nose length. The nonlinear dependency on the drawbar length is very clear. This is by far the most dominant parameter.
Observe also the sign of the coefficient, indicating a positive relationship or a negative one.
We have again checked the error in the second order approximation (for SWP) and we found that over 80 % of all values were closer to the exact SWP-value than 0.2, that is less than 3 %.

b_6	**5.6797**	$R(c)^2$	b_{12}	**0.3617**	$R(c).R(L_1)$
b_0	4.7917	1	b_4	0.2641	$R(h)$
b_7	2.0277	$R(L_1)^2$	b_2	0.2083	$R(c)$
b_3	0.5201	$R(L_1)$	b_9	-0.1903	$R(f).R(c)$
b_{14}	0.5072	$R(L_1).R(h)$	b_{11}	-0.1384	$R(f).R(h)$
b_5	-0.4593	$R(f)^2$	b_1	0.1169	$R(f)$
b_{13}	0.4044	$R(c).R(h)$			

Table 3.: Coefficients, nonlinear approximation, SWP

4.3. Combining different performance quantities

We have considered two PBS criteria, but how can we combine them? We have seen that we are able to derive accurate descriptions of the relationship between a performance quantity and its underlying vehicle design parameters, through a machine learning approach with a minimum number of training points, followed by a fit based on Ordinary Least Squares. In general, we have N different performance quantities $P_1, P_2, \dots, P_N$, which have to satisfy criteria $P_i < C_i$ where lower values are better. That may be generalized to finding the minimum of a linear combination of these performance values:

$$M_{PBS} = \min Q(P_1, P_2, \dots, P_N), \;\; Q(P_1, P_2, \dots, P_N) = \left[\theta_1 \frac{P_1}{C_1} + \cdots + \theta_N \frac{P_N}{C_N}\right] \qquad (6)$$

where coefficients may be used to tune between the different performance quantities, as we mentioned earlier. Hence, we arrive at an optimization problem, which can be handled by linear or quadratic optimization, or through a Monte Carlo approach. In this paper, we follow the last approach. Since we fixed the parameters a and b in the RA-analyses, we keep L_1 constant and equal to 5 meter.

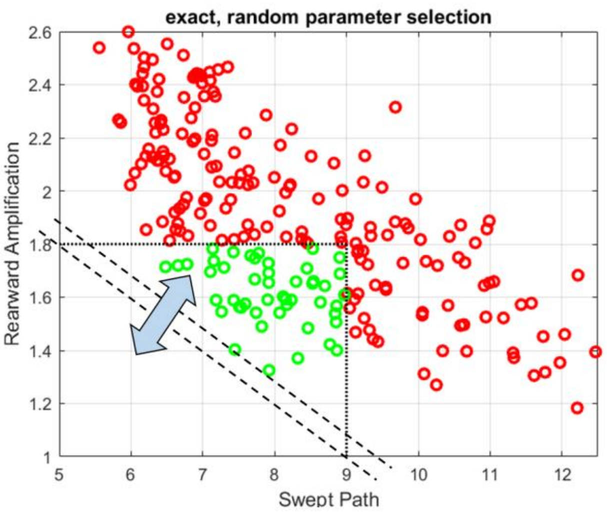

Figure 8.: Random parameter sets, RA vs. SWP.

We have varied the remaining parameters, f, c, k_2, c_3, h and k_2 within their relative range and determined the Rearward Amplification and the Swept Path. This was done 300 times in a random way, collecting 300 data sets. Some sets were cancelled because of unrealistic swept path results. The trailer mass was varied between 5 and 15 ton. The results are plotted in figure 8, with distinction between satisfactory results (identified in green) and results not satisfying the criteria $P_i < C_i$ (in red). We have selected $C_{RA} = 1.8$ and $C_{SWP} = 9.0$. Aiming for the best results we consider the line connecting the points (9.0, 0.0) and (0.0, 1.8) and shift that perpendicular to the orientation of this line. That means that we are considering values of $Q(P_{RA}, P_{SWp})$ as introduced in (6) with all coefficients equal to 1. The best solution is obtained for (f, c, h, c_3, k_2) = (0.659, 7.158, 1.209, 6.960, 2.106) for a trailer mass of 6.67 ton, leading to RA = 1.403 and SWP = 7.446.

It is of interest to examine the range for the parameters in the sets being acceptable, for the drawbar length c, hitchpoint position f and trailer axle slip stiffness c_3. These ranges appear to be much smaller than originally assumed. The updated and original ranges are included in table 4, giving interesting information to the designer on these three parameters.

	original range	**range acceptable sets**
f **[m]**	-0.1 – 2.5	-0.03 – 0.66
c **[m]**	5 – 10	5.7 – 7.5
c_3	4.5 – 7.0	6.0 – 7.0

Table 4.: parameter ranges, original and updated.

In other words, there are preferred value ranges for vehicle data in order to obtain a good balance between RA and SWP, i.e. between high speed and low speed performance. Especially the updated range for the trailer axle normalized slip stiffness is of interest, which is mainly due to the RA standard since it is of minor importance for manoeuvrability. The message here is, do not choose that cornering stiffness too low! Likewise, keep the drawbar length limited and the hitch point not too far off from the truck rear axle. For the other parameters, k_2, h this was less clear.

Observe the points in figure 8 in the sense that combinations of large swept path and large rearward amplification do not occur. We have either large RA and not too large SWP or large SWP and not too large RA. We already knew that RA (handling) and SWP (manoeuvrability) work against one another, and the figure confirms that.

The trailer mass cannot be chosen freely, and we can select the parameters sets restricted to a certain mass range, from 5 to 6 ton, from 6 to 7 to etc. Two situations are shown in figure 9, with $6 < m_2 < 7$ and $12 < m_2 < 13$ in tons.

In both cases, we find acceptable solutions, with optimal (RA, SWP) values listed in table 5.

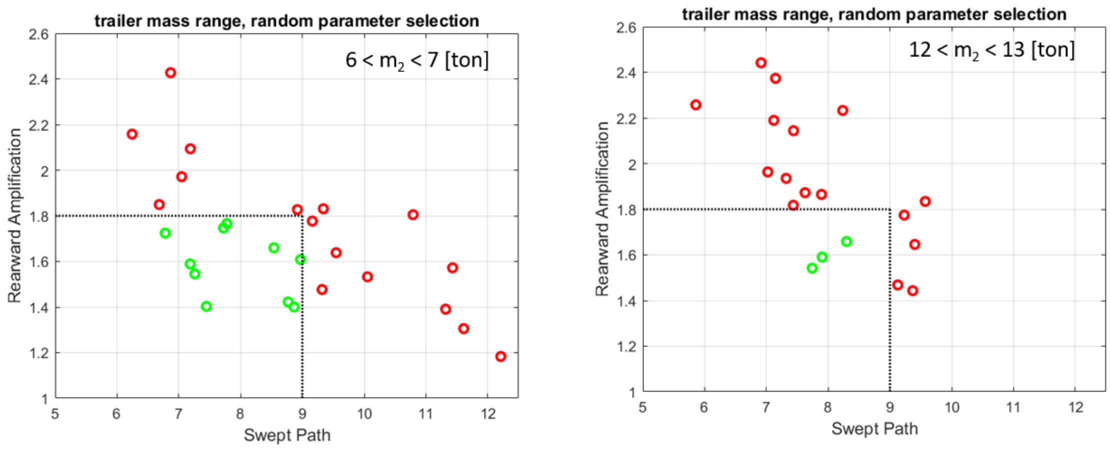

Figure 9.: Swept path versus Rearward Amplification for randomly chosen parameters sets, for two different trailer mass ranges.

	RA	SWP
6 < m_2 < 7 [ton]	1.403	7.446
12 < m_2 < 13 [ton]	1.542	7.741

Table 5.: Optimal RA and SWP values for two trailer mass ranges

A full list of optimal parameters, as derived from this Monte Carlo analysis is included in table 6.

m_2 (ton)→	**5-6**	**6-7**	**7-8**	**8-9**	**9-10**	**10-11**	**11-12**	**12-13**	**13-14**
RA	1.325	1.403	1.370	1.564	1.714	1.854	1.490	1.542	1.575
SWP	7.923	7.446	8.233	7.509	6.481	6.210	7.820	7.410	7.590

Table 6.: Optimal RA and SWP values for different load classes

A next step could be factor analysis meaning that one tries to find underlying factors $F_m, m = 1, 2, \ldots M$, explaining the parameter sensitivities and interdependencies. Factor analysis tries to find such factors such that variables (in our case vehicle parameters) can be expressed in these factors:

$$p_j = \sum_m A_{jm} . F_m \quad (7)$$

In more general terms, we are looking for hidden features for the vehicle, being essentially (and independently) responsible for its performance. In general, this number of features (called factors in factor analysis) is much smaller than the number of variables (parameters). One usually tries to give an interpretation of these factors, leading to further understanding of the interdependency and relative impact of the vehicle parameters. We have used the principal factor method together with rotation of the factors such that a maximum distinction in the factor pattern arises, see [7]. This analysis searches for combinations with maximum variances between factor and parameter. Assuming the factors to be non-correlated, the coefficients A_{jm} correspond to correlation between factor and parameter. We have assumed three factors and determined the weights A_{jm}, see table 7.

Factor →	***F_1***	***F_2***	***F_3***	***communality***
Hitchpoint position [m]	-0.1	***0.90***	-0.02	0.82
Drawbar length [m]	***-0.82***	0.03	0.21	0.71
Truck nose length [m]	0.01	-0.02	***0.99***	0.98
Trailer axle norm. slip stiffness [.]	***-0.78***	0.42	0.29	0.84
Trailer radius gyration	-0.38	***-0.88***	0.28	0.69
Percentage of variances	*23.9*	*29.0*	*23.2*	

Table 7.: Factor structure (weights), based on data from table 6

We have added two types of information, the *percentage of variances*, being the sum of squares of the weights for each factor divided by the number of variables (vehicle parameters)**,** explained by the relevant factor, and the *communality*, being the sum of squares for the factors, indicating to what extent the variable is explained by one or more factors. We highlighted the relevant weights in the table showing that factor F_1 is directly related to drawbar length and the trailer axle slip stiffness, factor F_2 is mainly combining the impact of radius of gyration and hitch point position, and factor F_3 is dominated by the nose length, i.e. corresponding to manoeuvrability. Comparing this with table 2, one may suggest that the relative dominance of parameters in RA, first c and c_3 being both most dominant, and second f and k_2 with less impact is confirmed by the outcome of the factor analysis. The interpretation in comparison with the SWP coefficients in table 3 is less clear. Please note that the results depend on the number of parameters sets in the analysis, and that we only considered two performance quantities and a total of five parameters, except for m_2 in the combined analysis. We expect to get more meaningful results when a larger number of parameters as well as performance quantities is considered.

5. Conclusions and discussion

In this paper, we have introduced a methodology to assist in the design of articulated, possibly high capacity vehicles (HCV) based on performance based standards (PBS). Our starting point is the set of selected performance criteria, and the vehicle and operational parameters to be varied within certain constraints. As a first step, we have considered the truck-central axle trailer combination. The research has been restricted so far to two performance quantities, Rearward Amplification and Swept Path, for a truck-central axle trailer, and a limited set of parameters. The approach is based on regression, first in an implicit way using Gaussian Processes for machine learning, being very effective in the sense that it requires only a limited number of training points to arrive at an accurate fit. Next, through Ordinary Least Squares, to derive an explicit description of the performance in terms of the vehicle and operational parameters, from which the sensitivities of the design parameters could be derived regarding the selected performance quantities, and based on the predefined parameter range of interest. Monte Carlo analysis has been applied to derive the parameter envelopes guaranteeing acceptable performance. Within that envelope, we have found the parameter values for which the most optimal performance is derived, based on the presetting of relative importance by the designer. In the paper, we have assumed swept path and rearward amplification of the lateral acceleration to be of equal importance, but that can be easily changed. This analysis has been carried out for different ranges of operational conditions (trailer load), allowing further analysis on hidden performance features of the vehicle (linear combinations of parameters), indicating dependencies between parameters leading to the vehicle performance.
Next steps will include more complex vehicle designs (EMS vehicles, A-Double,…), in combination with more performance quantities and a larger number of vehicle and operational design parameters, also accounting for logistic constraints. Follow-up research on the truck-dolly-semitrailer combination for six different performance quantities confirms the successful use of the mentioned methodologies in deriving parameter envelopes for acceptable performance, parameters sensitivities and interdependencies.

The project under which this work is done, ENVELOPE (ENhanced Vehicle Evaluation Leading to Optimized PErformance), was inspired significantly by the papers by Berman et.al. [3] and Kashampur et. al. [4], both presented at HVTT15 in 2018.

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