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Design of Experiment based on VMEA (Variation Mode and Effect Analysis)

Kent Cronholm*

Department of Mathematical Statistics, Chalmers University of Technology, 412 96 Göteborg, Sweden

Abstract

This paper presents a method where the Variation Mode and Effect Analysis is used to convert subjective knowledge about variation and importance of parameters for a certain characteristic among practicing engineers into numerically comparable values. In a case study, with fuel consumption of an articulated hauler as the target function, the method is used to quantify and arrange external parameters in order to design an experiment. A suggestion of a test plan describing a fractional factorial test at two levels intended to investigate the influence of the external parameters is presented. Performance and analysis of the experiment are discussed together with assumptions and uncertainties.

Keywords: VMEA; GTA; construction equipment; customer usage; design of experiment;

* Corresponding author. Tel.: +46-455-53557.
E-mail address: kentc@chalmers.se

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1. Introduction

A great part of off-road transports are performed by construction equipment such as wheel loaders, articulated haulers, dump trucks and trucks.

More energy efficient solutions of these applications could be accomplished by 1) more efficient usage of existing products by operator training or system supporting the operator, or 2) development of new products with more efficient transmissions and energy recovery. In both cases, it is necessary to have a good knowledge about the operation conditions in service.

The usage of construction equipment performing off-road transports varies greatly. The response, product characteristics, of the machines in terms of performance, fuel consumption, durability etc. is largely an effect of this variability. Thus, a machine with good performance and good fuel efficiency for one type of operation does not necessarily have the same response for another type.

In order to develop machines that meet or exceed customer expectations of a specific product characteristic in their application, e.g. fuel consumption, it is required that designers have a good knowledge about the actual usage and also understand what affects the product characteristic in mind.

A common approach to increase the knowledge of a product characteristic of a machine is to perform tests during service operation and during these tests measure the characteristic in question and then draw conclusions about the usage effect. These tests are generally resource intensive.

The questions one should ask before these tests are what to measure and where.

The product characteristics are typically dependent on the operation. Thus if this is known the product characteristics for different designs and concepts can be estimated by aid of simulation tools. The common usage of this type of machines, e.g. articulated haulers, is to move material from one point to another along a route. This can be described with a set of operation characteristics. This approach has been used within the Volvo Group, where a set of 20 Global Transport Application (GTA) parameters [1] have been defined to describe the operation.

If a certain product characteristic is to be investigated one must know which parameters affect and to what degree, i.e. the sensitivity of the parameters with regard to the product characteristic. Then if the values of these parameters during service are known, the product characteristic can be quantified.

Performing a test to define sensitivity for all 20 parameters demands a large amount of resources and it is important to use all possible prior knowledge in order to find a proper test plan for studies of service usage.

There is often a good sense among practicing engineers of what is important based on years of experience of product usage. The problem occurs when this subjective knowledge should be structured and translated into numerically comparable values. Here we will put forward the Variation Mode and Effect Analysis method [2,3,4] to structure and quantify the different user parameters that affect fuel consumption of an articulated hauler during service use. This method is used to go from subjective in-house knowledge into measurable quantifications where both variations during service and sensitivity of the particular product characteristic in question are included in the analysis. These quantifications are compared and a reduced number of parameters are selected for further investigation.

For this investigation we only have a limited number of resources for different measurements. In order to get the most out of the measurements, a rational test plan based on statistical design of experiments [5] is created. As a base for the design, a fractional factorial design at two levels is used. The underlying assumption in such a design is that interaction effects are considered to be small compared to the main effect. It has to be kept in mind that the more the test is reduced the fewer interaction effects can be detected. One benefit of this type of design is that the test can be expanded later to estimate interaction effects and reuse the results from the first test set.

The procedure during the two-level factorial design is that the parameters are set to the two levels chosen, e.g. high or low, and then according to a pattern tests are performed so that the effects can be distinguished. Since this test is reduced this pattern must be created in such a way that possible interactions do not interfere with the results. One issue to deal with here is that when performing test during service operation the parameters cannot be controlled and fixed as in laboratory tests, which forces the analysis of the test result to be other than the standard two-level test method. Still, we believe that the powerful two-level test methodology is useful for the test planning.

This paper proposes a method using results from the Variation Mode and Effect Analysis to design a test plan for investigating usage effect on a product.
As a case study an articulated hauler is used as a product, and fuel consumption is used as product characteristic.

The outline of the paper is:

First the Variation Mode and Effect Analysis methodology and the Global Truck Application approach are described.
Then the procedure of the case study is presented with a following discussion. Finally some conclusions are given.

2. Theory

2.1. Global Transport Application (GTA)

As mentioned in the introduction, transport can be described by a set of operations characteristics. The Volvo group has defined a set of 20 GTA-parameters [1] and divided them into following groups:

Transport mission	Vehicle utilization	Operating environment
• Vehicle type • Body and load handling equipment • Gross Combination Weight (GCW), Technical weight	• Operating cycle • Speed changes • Maneuvering • Yearly usage • Quality of diesel fuel	• Road condition • Road type • Topography • Altitude • Ambient temperature • Curve density • Dirt concentration • Dust concentration • Bug concentration • Rolling resistance • Coefficient of traction • Load-bearing capacity of the ground

Figure 2.1 GTA-parameters from Booklet accessible by Volvo group

These parameters are mainly developed in order to describe the user and then make it possible to offer the right product to increase the efficiency and thereby the profit for the customer [6]. This material covers a large span of products from heavy construction machines, such as wheel loaders and articulated hauler, to buses and trucks. In this study, the parameters are used with the purpose of analyzing the fuel consumption of an articulated hauler.

2.2. Variation Mode and Effect Analysis (VMEA)

The Variation Mode and Effect Analysis method (VMEA) is a statistically based method [2]. The method is used to analyze the effect of different sources of variation on a specific process or product.
The principle of the method is that the process or product (Y) is treated as a target function (g), a function of *n* variables or even underlying functions ($X_1, X_2, \ldots, X_n$).

$$Y = g(X_1, X_2, \ldots, X_n) \tag{2.1}$$

Using the Taylor expansion around the mean values for the underlying functions (X_1, X_2, ,X_n) leads to the following expression for the variation of Y:

$$Var[Y] = c_1{}^2 \cdot \sigma_{X_1}{}^2 + c_2{}^2 \cdot \sigma_{X_2}{}^2 + \cdots + c_n{}^2 \cdot \sigma_{X_n}{}^2 + \textit{covariance contribution} \tag{2.2}$$

Where

$$\sigma_{X_i}{}^2 = Var[X_i] \tag{2.3}$$

And sensitivity coefficient (c_i)

$$c_i = \left.\frac{\partial g}{\partial X_i}\right|_{\mu_i} \qquad \mu_i = E[X_i] \tag{2.4}$$

Covariance contribution appears when (X_1, X_2, , X_n) are not stochastically independent.

When all the terms in expression 2.2 are given, it is possible to highlight which sources one needs to control or at least know the variation of. When estimates are available by means of variances and sensitivity coefficients, Probabilistic VMEA should be used [2]. In case such estimates are difficult to obtain, other related measures may be used leading to Basic, Enhanced or some other type of VMEA. That is one of the benefits of the VMEA-method; even if the information is incomplete, one can still use the material at hand and achieve guidance on how to proceed. In this study, a variant of Basic VMEA is used since the information available is limited.

A concise description of the procedure using the VMEA method primarily means that critical product characteristics (Y) are identified, here called Key Product Characteristics (KPC). They are identified as KPCs since their variation might affect the product performance or function. To easily understand the effect of the variation, the KPC can be broken down to sub-KPCs (X_i) and if needed even more levels. For each sub-KPC, one or more noise factors (NF) are identified. The NFs are sources of variations that cause deviations in sub-KPCs. A common way to visualize this is to use an Ishikawa diagram (see Figure 2.2). In order to achieve the best results, this work should be performed in a cross-functional group with several people.

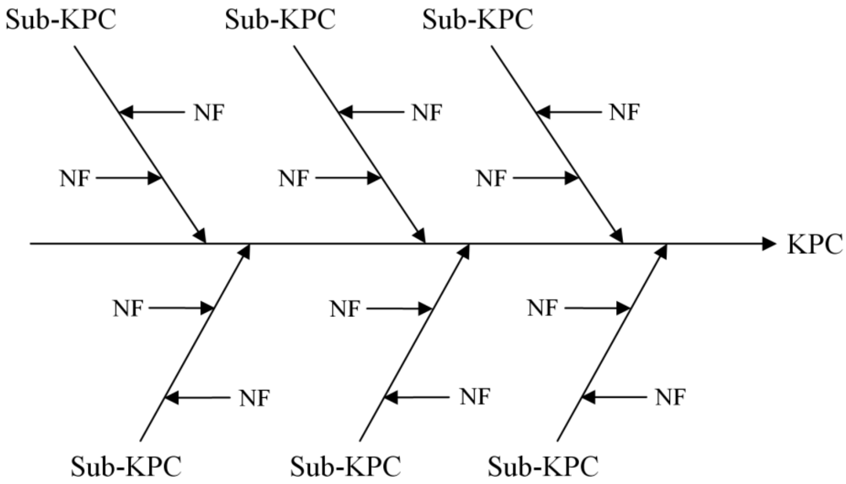

Figure 2.2 An Ishikawa diagram visualizing relations between KPC, sub-KPC and noise factors (NF)

When the sub-KPCs with corresponding NFs are identified, the effect on the product should be calculated. Here, the procedure diverges for the different VMEA levels (Basic, enhanced and probabilistic) slightly. For the Basic VMEA, one uses a fixed scale, e.g. 1-10, for the assessment of the variation and effect. For the two other levels of VMEA, one uses the known physical values for estimating the variation and effect.
When the variation and effect are assessed or calculated, depending on the method used, it is possible to calculate a Variation Risk Priority Number (VRPN), which is the last step in the VMEA-procedure.

A general working structure for VMEA contains four steps:

1. *KPC causal breakdown*
2. *Sensitivity assessment*
3. *Variation size assessment*
4. *Variation Risk Assessment and Prioritization*

3. Performance of VMEA

3.1. KPC causal breakdown

In this analysis, it was stated that fuel consumption is a Key Product Characteristic (KPC), so the breakdown operation was about determining the Sub-KPCs.
For this purpose, the GTA material was used.

GTA parameters

The 20 GTA parameters (figure 2.1) are treated as Sub-KPCs for the KPC fuel consumption according to the VMEA-methodology [2].
Initially, we wanted to sort out the Sub-KPCs that have the lowest effect on the KPC, i.e. to find the sources with low sensitivity. Here, we used a survey among experienced people within the company.

Cross-functional Survey

A survey was performed by sending out a questionnaire to co-workers in different fields such as testing, design, calculation, and sales & marketing. In the document sent out, the participants were asked to study the GTA parameters with fuel consumption of an articulated hauler in mind and divide the parameters into three groups:

A. The parameter does not affect significantly
B. The parameter affects to some extent
C. The parameter affects to a large extent

The response rate was 13 replies out of 15 sent out questionnaires.

Parameter	Class A	B	C
1 Rolling resistance			**13**
2 Topography		1	**12**
3 Operating cycle	1	1	**11**
4 Road condition		3	**10**
5 Speed changes		4	**9**
6 Load-bearing capacity of the ground		4	**9**
7 Gross vehicle Weight (GVW)	1	3	**9**
8 Coefficient of traction	1	5	**7**
9 Road type	2	5	**6**
10 Curve density		**8**	5
11 Vehicle type	4	4	**5**
12 Maneuvering	4	**7**	2
13 Altitude	4	**7**	2
14 Quality of diesel fuel	4	**7**	1
15 Body and load handling equipment	6	**6**	1
16 Ambient temperature	6	**6**	1
17 Yearly usage	**8**	4	1
18 Dirt concentration	**12**	1	
19 Dust concentration	**12**	1	
20 Bug concentration	**12**	1	

Figure 3.2 Results from the survey: To what extent does the parameter affect the fuel consumption of an articulated hauler? A: nothing, B: somewhat, C: much

Results from the survey was compiled and the parameters were ordered by how high a score they got in the ranking (See figure 3.2). One can see a difference and divide the parameters into two groups. At the top of the second group one can notice that the parameter “Vehicle type” received almost the same number of points in all classes. It seems that this parameter was hard to classify. In the GTA documents, which participants were given besides the questionnaire, one can see that the parameter “Vehicle type” is aimed to determine whether it is a loader, articulated hauler, bus or a truck. In this survey, it was stated from the start that the participants were supposed to have an articulated hauler in mind. This parameter will therefore not be taken into account during further evaluations.

3.2. Sensitivity assessment

The second step in the VMEA process is to establish how the sub-KPC affects the objective function, i.e. calculate coefficient of sensitivity c_i, defined in 2.4. In this case, we do not have measured data which means that we have to use the result from the survey and make an estimate of c_i:
First the class indexes, A, B and C were given numbers; 1 for class A, 2 for class B and 3 for class C. This was done in order to be able to use them in numerical calculations. The class number, k, was multiplied by the number of votes, N_k, the class received for each parameter, i. For each parameter, these products were summarized and divided by the total number of votes the parameter got, N_i. See equation 3.1. This equation gives a mean value of the judgement for each parameter and this will be used as the coefficient of sensitivity c_i.

$$c_i = \frac{\sum_{k=1}^{3} N_{k,i} \cdot k}{N_i} \tag{3.1}$$

Where $N_{k,\,i}$ = *number of votes in class k for parameter i*
and N_i =*total number of votes for the parameter i*

	Parameter, *i*	*k*	1	2	3	c_i
1	Rolling resistance	N_k			13	**3.1**
2	Topography			1	12	**2.9**
3	Operating cycle		1	1	11	**2.8**
4	Road condition			3	10	**2.8**
5	Speed changes			4	9	**2.7**
6	Load-bearing capacity of the ground			4	9	**2.7**
7	Gross vehicle weight		1	3	9	**2.6**
8	Coefficient of traction		1	5	7	**2.5**
9	Road type		2	5	6	**2.3**
10	Curve density			8	5	**2.4**
11	Vehicle type		4	4	5	**2.1**
12	Maneuvering		4	7	2	**1.8**
13	Altitude		4	7	2	**1.8**
14	Quality of diesel fuel		4	7	1	**1.6**
15	Body and load handling equipment		6	6	1	**1.6**
16	Ambient temperature		6	6	1	**1.6**
17	Yearly usage		8	4	1	**1.5**
18	Dirt concentration		12	1		**1.1**
19	Dust concentration		12	1		**1.1**
20	Bug concentration		12	1		**1.1**

Figure 3.3 Estimated coefficient of sensitivity, c_i, for the parameters (Sub-KPCs)

3.3. Variation size assessment

In this step, the NF's are examined in order to assess their variation. As in the sensitivity assessment we do not have any information available to calculate the variances. We have to use another approach: The assessment was performed by having a cross-functional meeting with co-workers. During this meeting we went through the parameters and made a judgment of how these vary during usage in a specific application. The assessment was based on the classification within the GTA material [1] and performed on the ten parameters with the highest value of the coefficient of sensitivity. The result is shown in figure 3.4

GTA-Parameter	levels, *j*	*x*	*p*	**GTA-Parameter**	levels, *j*	*x*	*p*
1	ROLR-1	1	0.05	**6**	1 - Very Good	1	0.20
Rolling resistance	ROLR-2	2	0.25	Load-bearing capacity	2 - Good	2	0.35
	ROLR-3	3	0.30	of the ground	3 - Moderate	3	0.40
	ROLR-4	4	0.20		4 - Poor	4	0.03
	ROLR-5	5	0.20		5 - Very Poor	5	0.02
2	Flat	1	0.05	**7**	Nominal	1	0.50
Topography	Pred. Flat	2	0.35	Gross Vehicle Weight	Overload	2	0.50
	Hilly	3	0.40				
	Very Hilly	4	0.20				
3	Stop n Go	1	0.35	**8**	FRIC-1	1	0.15
Operation Cycle	Local	2	0.62	Coefficient of traction	FRIC-2	2	0.50
	Regional	3	0.03		FRIC-3	3	0.30
					FRIC-4	4	0.05
4	Smooth	1	0.05	**9**	Min. R. - Public	1	0.05
Road Condition	Rough	2	0.20	Road Type	Min. R.- Enclosed	2	0.45
	Very Rough	3	0.35		Off-road	3	0.50
	Cross-country	4	0.40				
5	Low	1	0.05	**10**	Low	1	0.05
Speed Changes	High	2	0.35	Curve density	High	2	0.95
	Very High	3	0.60				

Figure 3.4 Assessment of variation during operation in a specific application.

In order to find an expression of the variances, we define a discrete distribution, x, based on the classification and judgement of probability, *p*:
For each parameter, the levels were numbered from 1 to n with step 1, n = number of levels. Then the assessment led to a distribution, where the *p* values show the number of customer using the machines at the different levels.
Since the parameters have different number of levels, we use a coefficient of variance, r_i, defined by:

$$r_i = \frac{\sigma_i}{\mu_i} \tag{3.2}$$

Where mean, μ_i, is calculated by:

$$\mu_i = \sum_{j=1}^{n} p_{i_j} \cdot x_{i_j} \tag{3.3}$$

and variance, σ_i^2, is calculated by:

$$\sigma_i^2 = \sum_{j=1}^{n} p_{i_j} \left(x_{i_j} - \mu_i\right)^2 \tag{3.4}$$

3.4. Variation Risk Assessment and Prioritizing

In this last step the Variation Risk Priority Number (VRPN) is calculated for each sub-KPC according to equation 3.5. The numbers are shown in figure 3.5.

$$VRPN_i = c_i^2 \cdot r_i^2 \tag{3.5}$$

	Parameter, *i*	**c**	**r**	**VRPN = $c^2 \cdot r^2$**
1	Rolling resistance	3.0	0.36	**1.18**
6	Load-bearing capacity of the ground	2.7	0.38	**1.07**
2	Topography	2.9	0.30	**0.78**
7	Gross vehicle weight	2.6	0.33	**0.76**
3	Operating cycle	2.8	0.31	**0.75**
8	Coefficient of traction	2.5	0.34	**0.70**
4	Road condition	2.8	0.29	**0.63**
5	Speed changes	2.7	0.23	**0.39**
9	Road type	2.3	0.24	**0.31**
10	Curve density	2.4	0.11	**0.07**

Figure 3.5 Calculated VRPN values for the top ten parameters (sub-KPCs)

3.5. Results

From the VMEA the total variation of expected fuel consumption at customer site can be calculated by taking the sum of the VRPN from each parameter. This value of the total variation is hard to interpret since the analysis comes from subjective figures and not physical values. However, the result gives a possibility for relative comparisons between the sub-KPCs.

4. Design of Experiments

4.1. Prerequisites

The objective was to create a test plan to investigate fuel consumption of an articulated hauler. The resources available were enough to perform up to ten measurements at customer sites.
Results from the VMEA described in the previous chapter give a value of expected variation of fuel consumption at customer sites and also the contribution from each parameter (Sub-KPC). This information is used for creating a test plan.
Studying the VPRN for each sub-KPC shows that number one and six have high values; 1.18 resp. 1.07. Then come three with around 0.75. Seven sub-KPCs have a VRPN over 0.50 and it was decided to investigate these further.
By means of VMEA, the number of parameters considered to be important for fuel consumption has been reduced from twenty to seven.

	Parameter, *i*		**VRPN**	no of levels
1	Rolling resistance	**(RR)**	**1.18**	**5**
6	Load-bearing cap.	**(LB)**	**1.07**	**5**
2	Topography	**(To)**	**0.78**	**4**
7	Gross vehicle weight	**(GVW)**	**0.76**	**2**
3	Operating cycle	**(OC)**	**0.75**	**3**
8	Coefficient of traction	**(CT)**	**0.70**	**4**
4	Road condition	**(RC)**	**0.63**	**4**

Figure 4.1 The seven selected GTA parameters with VRPN value and number of levels

4.2. Fractional factorial design

To fully investigate all the parameters, main effects and all interaction effects, requires a full factorial test. In a full factorial test, all possible combinations of the parameters (factors) and their levels are tested. The number of test runs during this type of test is calculated by taking the product of all levels. In this case this implies $5 \cdot 5 \cdot 4 \cdot 2 \cdot 3 \cdot 4 \cdot 4 = 9600$ test runs, see figure 4.1. The theory behind this is described for example in ref [5].

To perform this number of test runs is not possible; the test has to be reduced. One conceivable approach is instead to use just two levels of each factor, high and low. This is a so called factorial designed test at two levels. This would also make it possible to measure the effect of all factors. To be able to estimate all orders of interaction effects, it would mean $2^7 = 128$ test runs. From this test runs we would be able to estimate:

1	mean value
7	main effects
21	two-factor interactions
35	three-factor interactions
35	four-factor interactions
21	five-factor interactions
7	six-factor interactions
1	seven-factor interaction

But 128 test runs require more resources than are available in this project.

A way out of this problem is to use a method called fractional factorial design [5].
The fractional factorial designed test is a well-established statistical methodology and has been shown to be very effective since the number of tests can be reduced compared to full factorial tests.

This method is based on the assumption that some interactions are insignificant compared to the main effects. This is so because possible interaction effects will be confounded with main effects during analysis.

The procedure is that a test plan is created by carefully selected parts from a full factorial design test. The number of test runs extracted from the full factorial design depends on what order of interaction one can neglect.

One benefit of this type of experimental design is that if, after analysis of the performed test, it is considered that there are non-negligible interaction effects, one can expand the experiment with more test runs and then reuse results from previous tests together with the new during further analysis.

4.3. Test design

Due to resource limitations, the design selected for this experiment is a 2^{7-4} fractional factorial design at two levels. The test plan for this type of test design will include eight different test setups, where the levels for each factor should be set to high or low. With this experimental design, it is possible to estimate seven main factors. Since this is a reduced test, it will yield results where possible interaction effects will be confounded with main effects. These interaction effects are considered to be small.

Reducing experiments to this degree demands careful considerations in order to get useful results. It has to be thoroughly studied which interaction effects one can confound with which main effect without jeopardizing the reliability of the results.
Here it has been decided to let the main effect of LB be confounded with the two-factor interaction between To and OC, the main effect of GVW confounded with two-factor interaction between To and RC, the main effect of CT with two-factor interaction OC and RC and the main effect of RR with the three-factor interaction of To, OC and RC. Abbreviations are taken from figure 4.1.

In order to simplify the interpretation of the test plan and further analysis, the factors are given indices from A to G as they appear in the test plan. The index AB stands for interaction between A and B, AC between A and C etc.
The test plan is developed by first creating a 2^3 full factorial test plan with factors A, B and C setting the eight runs with all possible combinations of plus and minus signs as symbols for high and low. Then new columns for the factors D, E, F and G are added where the signs for each row are set by taking the product of the signs. For example: sign(D) = sign(A)*sign(B).
The test plan is shown in figure 4.2.

Test	To A	OC B	RC C	LB D (AB)	GVW E (AC)	CT F (BC)	RR G (ABC)
1	-	-	-	+	+	+	-
2	+	-	-	-	-	+	+
3	-	+	-	-	+	-	+
4	+	+	-	+	-	-	-
5	-	-	+	+	-	-	+
6	+	-	+	-	+	-	-
7	-	+	+	-	-	+	-
8	+	+	+	+	+	+	+

Figure 4.2 The test matrix of the 2^{7-4} fractional factorial two levels design for the seven factors. Indices in brackets show which interaction effect will be confounded with the search main effect.

The level indices from figure 3.4 define the levels in 4.2. For the parameter LB, there was very low probability assessed for the two highest levels, 4 and 5, so it was decided to exclude those from the test plan. The test plan with level indices is shown in figure 4.3.

Test	To	OC	RC	LB	GVW	CT	RR
1	Flat	Stop n Go	Smooth	3-Moderate	Overload	FRIC-4	ROLR-1
2	Very hilly	Stop n Go	Smooth	1-Very Good	Nominal	FRIC-4	ROLR-5
3	Flat	Regional	Smooth	1-Very Good	Overload	FRIC-1	ROLR-5
4	Very hilly	Regional	Smooth	3-Moderate	Nominal	FRIC-1	ROLR-1
5	Flat	Stop n Go	Cross-C	3-Moderate	Nominal	FRIC-1	ROLR-5
6	Very hilly	Stop n Go	Cross-C	1-Very Good	Overload	FRIC-1	ROLR-1
7	Flat	Regional	Cross-C	1-Very Good	Nominal	FRIC-4	ROLR-1
8	Very hilly	Regional	Cross-C	3-Moderate	Overload	FRIC-4	ROLR-5

Figure 4.3 The test matrix from figure 4.2 with defined indices of the levels from figure 3.4.

4.4. Estimating effects after performed test

When the test runs are performed, it is possible to estimate the main effects of each factor. This is done by calculating the difference between the mean of the test runs corresponding to the plus sign in the test matrix and the mean from the ones with the corresponding minus sign. See the example for factor A in equation 4.1. The same procedure is valid for all main effects.

$$main\ effect_A = \underbrace{\frac{(y_2+y_4+y_6+y_8)}{4}}_{\substack{mean\ value\ from \\ the\ tests\ corresponding \\ to\ the\ plus\ sign\ in \\ the\ factor\ A\ column \\ in\ the\ test\ matrix}} - \underbrace{\frac{(y_1+y_3+y_5+y_7)}{4}}_{\substack{mean\ value\ from \\ the\ tests\ corresponding \\ to\ the\ minus\ sign\ in \\ the\ factor\ A\ column \\ in\ the\ test\ matrix}} \qquad (4.1)$$

Where y_1 = test result from run 1, y_2 = result from run 2, etc.

5. Discussion

This paper presents a method where the Variation Mode and Effect Analysis (VMEA) are used to investigate and compare how external parameters influence the fuel consumption of an articulated hauler. The paper also suggests how a test plan could be constructed in order to investigate the influence further.

The VMEA method is based on the probability theory of the additivity of squared standard deviations and the mathematical theory of Taylor expansion. To fulfill the assumptions behind the theory, it is, therefore, important to obtain the right description of the inputs by means of standard deviations and partial derivatives (Equation 2.2). In our case, these properties are not available in their usual form, but must be assessed from engineering judgements.

For the partial derivatives, i.e. the sensitivity coefficients, we have neither a mathematical expression for the fuel consumption nor physical measurements. Instead, we assess the sensitivity by arranging a survey among experienced engineers and assign numerical values to the results.

One problem with such a sensitivity assessment is that the survey possibly answers the wrong question, namely the overall sensitivity on the fuel consumption for the different influentials, including their respective variation. Our method wants to distinguish between mathematical sensitivity and variation and the obtained sensitivity coefficient will be disturbed by an unknown extent of wrong question interpretations.

For the standard deviation, we have no samples of the population of usage for a standard deviation calculation, but must rely on engineering judgements about usages. By classification of usage profiles we can define a number of discrete distributions of usages, which makes it possible to estimate standard deviations.

The standard deviation estimates are based on an established classification of GTA parameters, which are not based on the actual application, articulated haulers, but on a general judgement of vehicle environments. This possibly influences the precision in the estimates together with subjective bias from the limited number of respondents to the survey.

Since tests in service are difficult to organize and expensive to perform, we needed a test plan that could extract maximum information from a highly limited experimental result. Although we will not be able to fulfill a pure two-level test in service, we will put forward the idea to use the powerful theory of two-level tests to find a proper plan. The simplified analysis that the two-level test offers (Equation 4.1), can however not be used; a more general regression methodology must be used for the future analysis of the result.

Highly limited test resources make it necessary to make maximal use of prior knowledge from engineering experience. Therefore, it is desirable to make use of statistical methodology such as the Variation Mode and Effect Analysis and the two-level factorial test design. But, prior knowledge is not available by means of statistical properties that suits as input to statistical procedures. Here, methods based on surveys among engineers have been used to approximate variances and sensitivity coefficients in order to make use of the statistical methodology. This first step of analysis for fuel consumption influences will be the basis for field experiments that in turn will give updated information on the importance of the different influences.

6. Conclusions

This paper proposes a method using results from the Variation Mode and Effect Analysis to design a test plan for investigating usage effect on a product.
As a case study, an articulated hauler is used as a product and fuel consumption is used as product characteristic. The case study shows that the VMEA method may be useful even if the information is limited.
The established experimental design methodology, a fractional factorial test design at two levels, is used to create a reduced test plan that focus the proceeding tests at the most interesting parameters.
All in all: a structured way of creating a test plan from subjective in-house knowledge and experience.

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8. References

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