Experimental Study on the Influence of Certain Parameters over Vehicle's Dynamic Behavior

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Abstract

Tougher request that are being formulated again and again regarding a vehicle?s dynamic performances and its fuel efficiency require a deeper study over the influence of various parameters over to the vehicle dynamic behavior. In the specialty literature we find appreciations both quantitative and qualitative regarding the influence of certain functional parameters, and how their adjustments have an impact on to the vehicle?s performances. We have to mention that the literature guides its self when analyzing the influence of certain parameters after a very restrictive methodology: when studying how a parameter influences a certain behavior all the other parameters are considered to be constant, which obviously does not happen in reality.

Index terms— vehicle dynamics, correlation analysis, variance analysis, information theory, sensitivity analysis.

1 I. Introduction

hroughout the paper, a study is being carried out onto the main functional parameters and how do they influence the dynamic and economy performances of vehicles. The performed study eliminates the mentioned restriction, that regarding that the other parameters but the observed one remain constant, especially in the case of onboard computer fitted vehicles which is the main object of this paper. There are accentuated functional interdependencies and the experimental research confirms that the parameters are not constant in time, their dynamic behavior being the predominant one during normal vehicle operation. Likewise, throughout the paper the study is based on experimental data gathered when testing a vehicle that has onboard computer, transducer and actuators that are already building since fabrication and using specialized data acquisition equipment.

2 II. Correlation Analysis

In order to show if functional parameters are independent or not and in order to establish the character of their dependencies (linear or nonlinear), frequently the correlation coefficient comes into focus defined through relation [1]:(0) (0) (0) xy xy xx yy R R R ? =**(1)**

That ranges[1;1] ? ? ?

, a perfect linear dependency is described by 2 1 ? = . If ?=1 than a perfect direct linear dependency is described and if ? =-1 than we are dealing with a perfect indirect linear dependency; if 0 1 ? < ? there is a direct dependency and if 1 0 ? ? ? < there is an indirect dependency.

Finally if ?=0, than the two parameters x and y are independent. So, if ? 2 is further distanced from the value of one (without reaching zero), the nonlinearity is accentuated. Furthermore, in expression (1), on the counter side we have the inter correlation function in the origin of discreet time, that ? =0, and under the square root we have the self-correlation functions for the same value of ? =0.

In order to exemplify, figure **??** presents the values for the correlation coefficients in the case of 50 acceleration test-runs and 50 regular runs (usual vehicle behavior) for the Logan Laureate vehicle; the parameters (influencing parameters) are engine speed n, throttle's position ? (describing engine load), and the resulted parameter is vehicle speed V.

As we can see from these charts, there is no experimental test run that has the correlation coefficient zero, thus the analyzed parameters are not independent, which was expected from a functional point of view. Also, observing that in the case of all test runs the correlation coefficients have sub unitary values, we can draw the conclusion that between these parameters there are non-linear dependencies; the most obvious one is between the throttle's position and vehicle speed in the case of normal operation, the correlation coefficients having the lowest values, including the overall average ?=0.418. This last aspect leads us to the conclusion that the vehicle movement needs to be described by nonlinear differential equations in order for the afferent model to precisely describe the phenomenon. A simple correlation was applied on the presented example, where one influencing parameters was considered (engine speed or engine load); if they are both, or even more, taken into consideration at the same time or we have to rely on multiple correlation analysis [1].

3 III. Variance Analysis

Studying the influence of functional parameters calls on variance analysis (ANOVA -ANalyse of Variance, MANOVA -Multivariate ANalyse of VAriance); variance is of outmost importance when analyzing the influence of certain parameters that describe a dynamics process [1].

Ronald Fisher, mathematician and statistics specialist, which is the creator of variance analysis, proved that estimating a certain characteristic's variance undergoing a certain parameter's influence, and afterwards eliminating this influence and comparing the two variances we get quantitative information regarding that influence. So, variance analysis is all about comparing the two types of variances, residual and factorial. If factorial variance is greater than the residual one, than that specific parameter has a sensitive influence over the analyzed process. Backwards, if factorial variance (individual or interacting with another parameter) is smaller than the residual one, than that specific parameter has a negligible influence over the targeted process. This comparison actually sets the percentage contribution of each parameter to the total variance.

Figure **??** presents the results when applying the generalized MANOVA algorithm (the analyzed parameters and their afferent interactions are considered) studying how engine speed n and throttle's position ? influences vehicle speed V. Similarly, figure **??** highlights the results of generalized MANOVA application studying how engine speed and throttle's position influences hourly fuel consumption C h .

From figure **??**a we can see that in the case of acceleration test-runs, the residual variance is practically zero (so all targeted parameters need to be taken into consideration), higher values than this is specific for engine speed (25.42%), throttle's position (65,38%) and the interactions between engine speed -throttle's position (9.2%). So in the case of accelerated test-runs the throttle's position (giving information about engine load) has the highest influence over the vehicle's speed, almost 2.6 times higher than the influence of the engine speed.

Fig. **??** Fig. **??** From figure **??**b we can observe that in the case of non-accelerated test-runs, the residual variance has a lower value, of 0.12%, all targeted parameters having grater contributions to the total variance. But this time, engine speed has the largest influence over the vehicle's speed (with a 67.4% contribution to the total variance), the throttle's position now has a 4.9 times less contribution than the previous case (13.63%). From the graph also we can see that interaction between engine speeds -throttle's position has an important contribution of 18.85%, which is higher than the case of throttle's position; this aspect shows the necessity that when analyzing the influence of certain parameters onto vehicle dynamic behavior we have to take into consideration the parameter's interactions.

The graphs from figure **??** shows that in the case of hourly fuel consumption, the highest influence is due to engine speed, both in the case of accelerated (fig **??**a) and non-accelerated (fig. **??**b) test-runs; this influence is much more important in the case of non-accelerated test-runs. Besides, as we can see from figure **??**b, the interaction between engine speeds -throttle's position has a higher influence (9.21%) than that of the throttle's position (3.12%).

4 IV. Information Theory

The information analysis of vehicle dynamic behavior, based on experimental data gathered during test-runs, allows for establishing the relevant parameters that define vehicle movement, so those parameters that need to be taken into consideration when establishing mathematical models. Information analysis is based on two main concepts of the field's theory: entropy and information [2]. Information represents the fundamental concept when predicting and is characterized by a probability distribution p. Hartley define information contained in n events i x X ? using the following relation:2 ( ) l ( ) i i I x p x = ? (2)

In order to characterize the uncertainty of an event happening, the concept of entropy is being used; Shannon himself, the one who introduced the notion, used the term of uncertainty. Entropy is the product between the probability and the available information overall events i x X ? :

(3)

The higher the entropy gets, the higher the uncertainty is and thus the prediction is less and less precise. When a certain system evolves, entropy is at its maximum when the systems find itself at a static equilibrium; so a dynamic system behavior, characterized by the reduction of its entropy ensures a good prediction, better than the case of static system.

Taking into consideration two parameters X and Y, for which we have a common probability density p(x,y). In this case, the common entropy of the two variables (co entropy) is calculated with the relation: (;) ( ) ( ) I X Y H X H X Y = ? (6)

and represents a quantitative measurement of X's uncertainty if Y is known. Mutual information is a concept that offers a quantitative measurement of how much the uncertainty is reduced, or how much the accurate prediction level increases. As higher the mutual information is, the uncertainties reduce thus better predictions. For this reason, mutual information is a basic concept when studying system's dynamic behavior and represents a measurement of parameter's interdependencies. From this reason, when establishing mathematical models, those parameters that are characterized by the highest mutual information need to be chosen because they ensure the highest prediction levels; these are called relevant parameters, regarding the concept of relevance. From the mentioned reasons, we consider that information theory is a generalization of the classical correlation analysis and mutual information represents a measurement of relevance. For exemplification, figure **??** presents a graph that show the result of an information analysis in the case of fuel consumption when covering 100 kilometers as a deduced parameter (placed on the top) and taking into account other 6 parameters (influence factors): engine speed and engine load (the latter expressed by the throttle's position), injection duration, intake air pressure, ignition timing and the quality of air-fuel mixture (expressed by the air excess coefficient). The graph's nodes present the H entropy values. We can see that the highest entropy is specific for engine speed, of 7.7 bits, and the lowest one is characteristic for fuel consumption and injection duration: H=1.5 bits;

according to what was said we can conclude here that using the engine speed in dynamic calculus results in lowering the prediction level. On the graph's arches mutual information of two parameters is presented. We can see that the first two relevant parameters (that have the highest influence over the fuel's consumption) are the throttle's position (mutual information with the consumption of 0.632 bits) and injection duration (I=0.409 bits). Figure **??** gives us the mutual information between 6 parameters; we can see that the highest mutual information is shared by the throttle's position and injection duration, of 0.654 bits, exceeding those that were previously presented; this confirms the necessity that when studying the vehicle's dynamic behavior the interdependency of certain parameters needs to be addressed, not only between them and the analyzed parameter but also between themselves, as presented the case of fuel consumption when covering 100 kilometers.

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Fig. **??** V. Sensitivity Analysis Sensitivity expresses a parameter's property to change its value under the influence of the factorial parameter [1]. If there is a single factorial parameter than the simple sensitivity is targeted, otherwise the multiple sensitivity is analyzed; in the first case, local sensitivity is defined (the classic one which calls on sensitivity function), and in the second case global sensitivity is addressed, which relies on variance and has Sobol index as its quantitative measurement [3]. In the second case, the Sobol index (marked here with S) represents the divergence afferent to the targeted parameter and the total divergence of the deduced parameter; thus we have the following relation:

... 1i ij ijk i i j i i j i k j S S S > > > + + + = ? ?? ???**(7)**

Where for the influencing parameter I there is the Sobol index S of first degree (or the main Sobol index), for the interactions between i and j parameters we have the Sobol index S ij of second degree etc. As we can see, global sensitivity takes into consideration the interactions between the targeted parameters, as information theory does.

For example, figure **??** presents the first degree Sobol index for vehicle speed and for vehicle acceleration. As we can see from the upper graphs, in the case of the accelerated test runs, vehicle speed is most sensitive when the throttle's position is modified (S=0.76), and in the case of non-accelerated test-runs is most sensitive to engine speed (S=0.634), aspect which is confirmed by the variance analysis from figure 2. Fig. **??** VI. Summary

We can conclude that the study of various parameters onto the vehicle's dynamic behavior needs to take into consideration the interactions between factors, as well as the fact that the factorial parameters vary simultaneously throughout vehicle movement, these two being the main differences compared to classical approach described in technical literature. [1] [2]

[2] Experimental Study on the Influence of Certain Parameters over Vehicle's Dynamic Behavior

Figure 1:

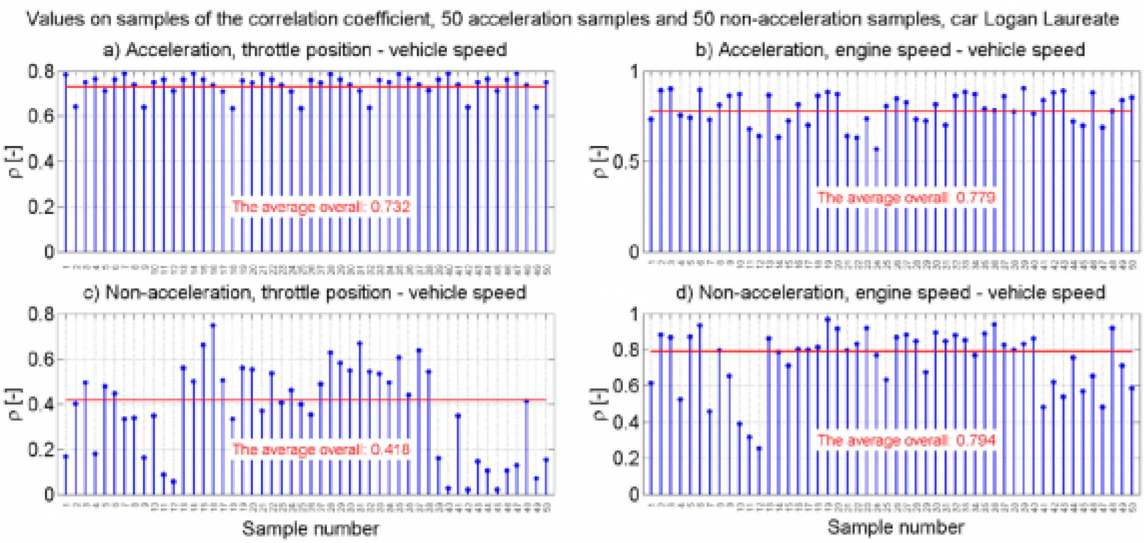

Figure 2:

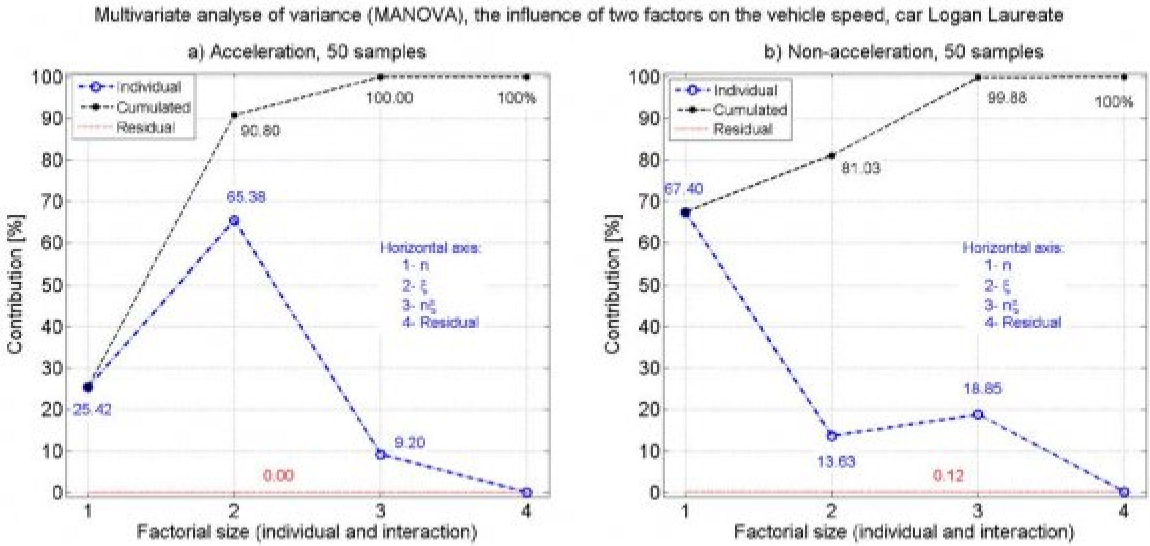

Figure 3:

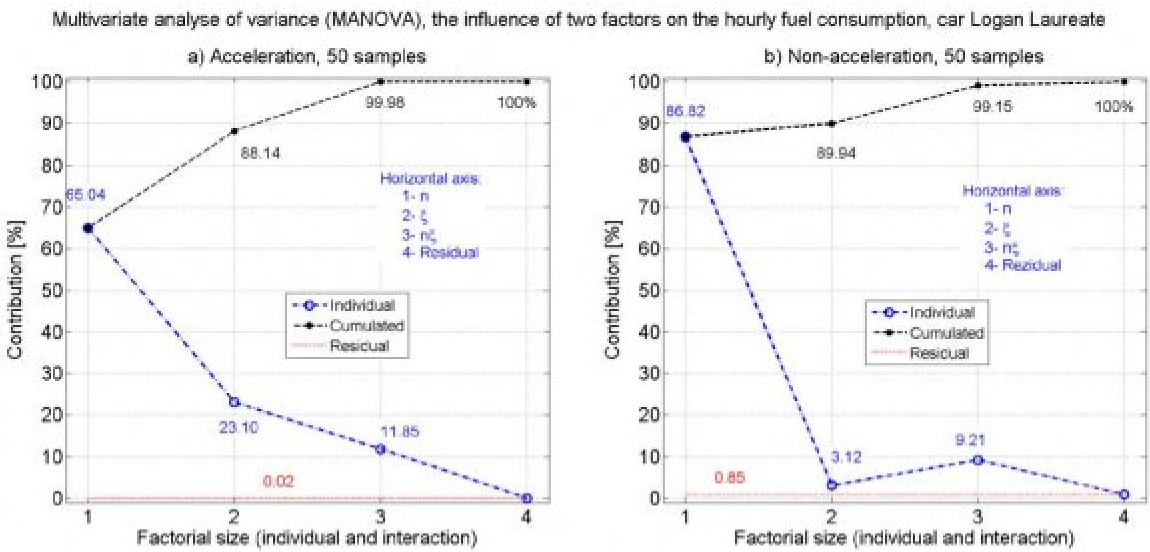

Figure 4:

$$H(X) = \sum_{i=1}^{n} p(x_i) I(x_i) \quad \Rightarrow \quad H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

Figure 5:

$$H(X) = \sum_{i=1}^{n} p(x_i) I(x_i) \quad \Rightarrow \quad H(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

Figure 6:

$$H(X,Y) = -\sum_{x}\sum_{y} p(x,y)\log_2 p(x,y)$$

Figure 7:

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