The Influence of Functional Factors on the Performances of Motor Vehicles

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***Abstract*—The paper highlights the main possibilities of studying the influence of the functional parameters on the vehicle's efficiency and its dynamic behavior. Mathematical algorithms are applied, which allow us to study these issues based on experimental data gathered throughout specific tests carried out on certain vehicles. These algorithms are applied on vehicles which have electronic control for various automotive systems, thus the data was gathered from the vehicles' built in CPUs. To this purpose we will show how to use sensitivity analysis, dispersion analysis, correlation analysis and information theory in automotive engineering.**

***Index Terms*—Correlation analysis, fuel saving, information theory, ANOVA, MANOVA, sensitivity analysis, vehicle dynamics.**

I. Introduction

Research on how various factors affect a vehicle's fuel efficiency and dynamic behavior has been a constant challenge for specialists in the automotive industry. In the field literature of vehicle engines and vehicles, we can always find both qualitative and quantitative appreciations regarding the influence of the construction factors (mass, shape and vehicle's transmission, cylinder's capacity, compression ratio, method of engaging the cooling fan and type of cooling system used on the engine etc.), of the exploitation factors (tire air pressure, the quality of the performed adjustments, engine and vehicle technical state, etc.) and the driving style.

Throughout the paper, we will look at how the functional factors (also called factorial parameters) affect the vehicle's dynamic behavior and efficiency regarding its fuel saving. To this purpose we use experimental data of the targeted parameters which we read from the vehicle's onboard computer. We have to mention that we analyzed data from vehicles that have gasoline injection systems; so we would look into those parameters measured while the vehicle is moving like: engine rotational speed n, engine load (measured by the throttle's position ξ), inlet air pressure pa, ignition advance β, the quality of gas - air mixture (measured by the excess of air coefficient λ), injection duration t_i, etc. [4].

Those parameters that are of interest regarding the influence of functional parameters can be fuel consumption (horary fuel consumption C_h, the fuel consumed when travelling a 100 km C100, actual specific fuel consumption c_e, etc.), vehicle's acceleration a, engine power P_e, engine torque M_e, etc.; these parameters are called deducted parameters.

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II. Results Obtained

A first method of studying the influence of functional parameters is by applying the sensitivity analysis [4; 8; 9]. Sensitivity is expressed as one's deducted parameter (the system's output) property to modify its value under the influence of the factorial parameter (also called as causative parameter, or the system's input) or of the system's parameter variation (its mathematical coefficients).

As we can see, a first classification of sensitivity is based on what has a certain influence on a deducted parameter: the factorial parameter variation, a case where we have non parametric sensitivity and which represents this paper's main study object. The parameter variation of the targeted system (the mathematical coefficients from the model which describes its dynamic behavior) is a case featuring parameter sensitivity.

According to the above defined data, we can deduct that non-parameter sensitivity calls on directly to experimental data.

If there is only one factorial parameter than we look only at the simple sensitivity, otherwise we deal with multiple sensitivity. Sensitivity represents a function which may vary (case which is known as hetero-sensitivity) or may be constant (case which is known as iso-sensitivity).

By definition, simple sensitivity is established by the following relation:

$$S\left(y/x\right)=\frac{\mathrm{d}y}{y}:\frac{\mathrm{d}x}{x}, \tag{1}$$

which shows that the $y=f\left(x\right)$ function's sensitivity is equal with the relative variation rate of the deducted parameter y caused by a unit of relative variation of the factorial parameter x.

From (1) we can see that sensitivity has no measurable dimensions; this is why S is known as sensitivity coefficient.

Expression (1) can also be written this way:

$$S\left(y/x\right)=\frac{x}{y}\frac{\mathrm{d}y}{\mathrm{d}x}. \tag{2}$$

Let us consider, for example, the following situation. If aiming to set the influence of the throttle's position and engine speed onto the fuel consumption when travelling 100 km (so we look at mileage), then the following sensitivity functions are established:

$$S\left(C_{100}/\xi\right)=\frac{\xi}{C_{100}}\frac{dC_{100}}{d\xi};\ S\left(C_{100}/n\right)=\frac{n}{C_{100}}\frac{dC_{100}}{dn}. \tag{3}$$

Similarly, if aiming to set the influence of the throttle's position and engine speed onto the vehicle's acceleration (so we analyze the vehicle's dynamic behavior), then the following sensitivity functions are established:

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$$S(a/\xi)=\frac{\xi}{a}\frac{da}{d\xi};\ S(a/n)=\frac{n}{a}\frac{da}{dn}. \quad (4)$$

Expressions (3) and (4) have all parameters known from experimental data or can be calculated based on it (including their respective derivatives).

As Fig. 1 obviously illustrates, the sensitivity function varies in time, so we can say that we deal with a hetero-sensitivity; the graphs show the instantaneous values of the sensitivity function taking into account 50 tests carried out on Logan Laureate vehicle. The deducted parameter is the horary fuel consumption.

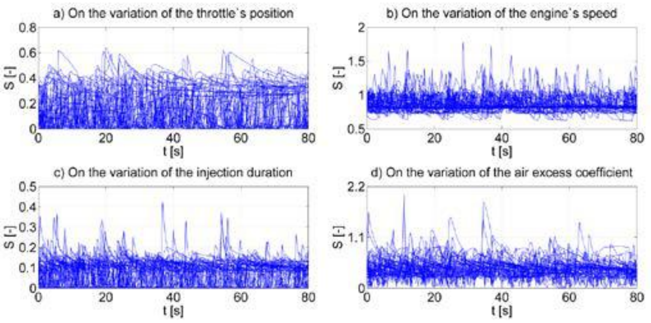


Figure 1. Instantaneous values for the sensitivity function of horary fuel consumption, 50 experimental tests, Logan Laureate

Fig. 2 presents the average values of the sensitivity function in the mentioned case (test LL-31 as example); the graphs show the existence of some average values that differ at various experimental tests. From Fig. 2 we can also deduct that throughout the entire tests, the least influence onto the horary fuel consumption is given by the injection duration, and the most important influence is given by the engine speed. The graphs reveal the fact that overhaul, the engine speed has twice as much influence as the quality of the fuel and air mixture (air excess coefficient) and almost five times the influence as the throttle's position has (engine load).

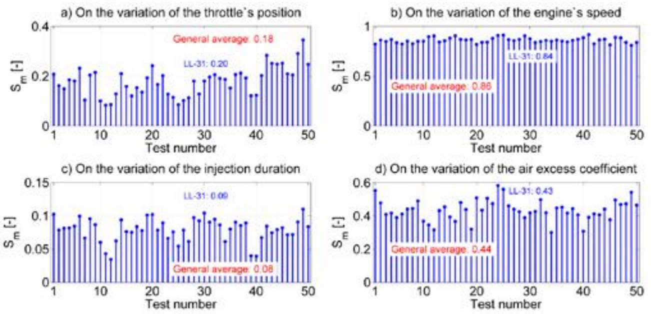


Figure 2. Average values for the sensitivity function of horary fuel consumption, 50 experimental tests, Logan Laureate

The study of the functional parameters can call on the dispersal analysis also known as the name of variance analysis (ANOVA – ANalyse Of Variance, MANOVA – Multivariate ANalyze Of VAriance). Dispersion also called variance, has significant importance in analyzing the influence of certain factors onto the development of dynamic process [2;3].

The English mathematician Ronald Fisher, the creator of dispersal analysis proved that estimating a certain characteristic under the influence of a parameter, and afterwards eliminating that influence and compare the two dispersions, this way we can get quantitative information regarding that parameter's influence. So, dispersal analysis is all about comparing two types of dispersions, factorial and residual ones. If the factorial dispersion is greater than the residual one, than that specific parameter has sensitive influence onto the analyzed process. Backwards said, if the factorial dispersion (individual on or interacting with another parameter) is smaller than the residual one, then that specific parameter has negligible influence onto the analyzed process. Practically this comparison can be made by setting each parameter's contribution rate and its residue to the total dispersion.

Fig. 3 presents the results obtained applying the generalized MANOVA algorithm (taking into account the targeted parameters and their interactions), studying the influence of the engine speed, throttle's position, injection duration and the air-fuel mixture onto the output engine power measured in experimental test LL31 performed with the Logan Laureate vehicle.

From Fig. 3 we can see that residual dispersion represents 1.4% from the total dispersion; engine speed dispersion has higher values than it (56.2%) also the quality of air-fuel mixture (30.4%) and the throttle's position (3.46%). Beside that, higher values than the residual dispersion have the interactions between the air excess coefficient and engine speed (4.37%) or between throttle's position and air excess coefficient (2.31%); all the others have smaller values and are no longer mentioned. So we can say that engine speed and the quality of the mixture have the most important influences onto the engine's output power. The first mentioned parameter has an influence of almost twice as important as the second one.

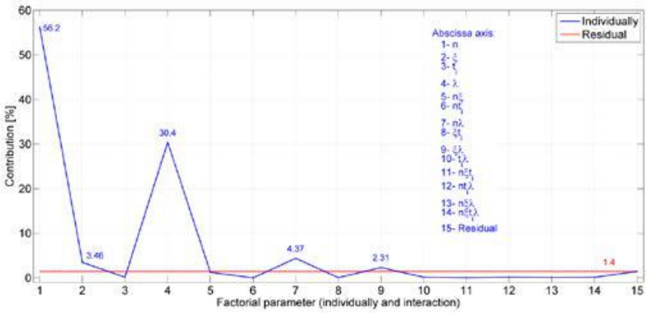


Figure 3. Generalised multifactorial dispersional analysis - certain factorial parameter's contribution in the total dispersion, engine`s output power, test LL-31, Logan Laureate vehicle

Studying the influence of the functional parameters has a direct interest but also can help when predicting; to this purpose we can apply concepts and algorithms from information theory, relying on entropy and information.

This way, in order to characterize the uncertainty of a certain event to appear we will use the concept of entropy, and the information represents the fundamental concept in prediction. As long as the entropy is bigger, the higher the uncertainty is and thus the prediction level is lower. Besides, mutual information is a concept that offers us the quantitative measure of reducing uncertainty, thus increasing the level of prediction. As long as mutual information has higher values, the uncertainty level is lower and the predictions are higher (more accurate).

Mutual information is a basic concept when studying the evolution of systems and processes and represents a tool to measure the inter-dependencies between parameters. For this reason, when establishing mathematical models we have to take into consideration which parameters are characterized by the highest mutual information that will ensure us highest predictions; these parameters are called relevant parameters, attached to the concept of relevance. For these reasons, it is considered that information theory is a generalization of the classic correlation, and the mutual information concept represents a measure of relevance.

Fig. 4 presents a graph that has in its nodes the analyzed parameters and their entropy values *H*, and on the connecting arches the value for the mutual information I_{xy}. The deducted parameter is the horary fuel consumption when traveling 100 km with the Logan Laureate vehicle, and it is presented in the superior side of the graph (so we target fuel efficiency); all the other parameters are functional parameters.

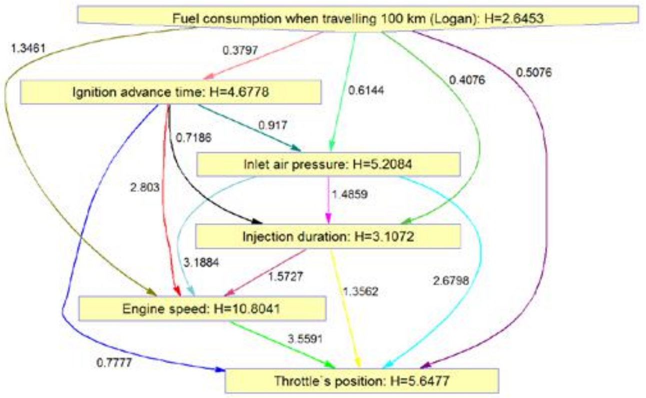


Figure 4. Graph that contains entropy and mutual information for fuel consumption at 100 km

The graph from Fig. 4 shows that the pair engine speed – inlet air pressure is characterized by mutual information taken from longer test runs (1.346 and 0.6144 bits) than the pair throttle's position – injection duration (0.5076 and 0.4076 bits). So we can say that the first two parameters are relevant parameters. If we are to establish two mathematical models regarding fuel efficiency, of this type $C_{100} = f(n, p_a)$ and $C_{100} = f(\xi, t_i)$, the first model will ensure a better prediction than the second one for the values recorded for fuel consumption.

In order to highlight the dependency character (linear or nonlinear) from the factorial parameters and the deducted ones, correlation analysis will be applied.

As it is known from the classical statistics, a simple correlation analysis looks at the link between a certain deducted parameter *y* and a factorial parameter *x* (influence factor). The index which is used in mostly all the cases when appreciating the linear dependency between two variables is the correlation index ρ (Pearson's coefficient), established with the following relation [4]:

$$\rho_{xy} = \frac{R_{xy}(0)}{\sqrt{R_{xx}(0)R_{yy}(0)}}, \tag{5}$$

with a maximum possible inter-correlation (a linear perfect dependency) for. If $\rho = 1$ then there is a linear dependency perfect directly, and if $\rho = -1$ then we deal with a linear dependency perfect indirectly; if we deal with direct dependency, and if we have indirect dependency. So, as long as ρ_2 is further away from the value of 1 (without reaching null value), non-linearity is much more present.

Expression (5) has in the abaci place the inter-correlation function with its origin in discrete time, meaning $\tau = 0$, and under the square root we can find the self-correlation functions also for $\tau = 0$ (meaning their maximum values).

In the case of multiple correlation we study the simultaneous influence of two or more factorial parameters (here functional parameters) onto the deducted parameter. In this case multiple correlation coefficient will be used, which is calculated based on simple correlation coefficients between pairs of parameters and taking into account the correlation function's expressions.

For example, Fig. 5 presents the multiple correlation coefficients in the case of 50 experimental tests that were carried out on a Nubira vehicle; the factorial parameters are the engine's speed n ant the throttle's position ξ (engine's load), and the deducted parameters are the vehicle's acceleration a and fuel consumption calculated when travelling 100 km C_{100}.

Similarly, Fig. 6 shows us the value for the correlation coefficients for the same factorial parameters, but in this case the deducted parameters are the engine's output power P_e and the horary fuel consumption C_h.

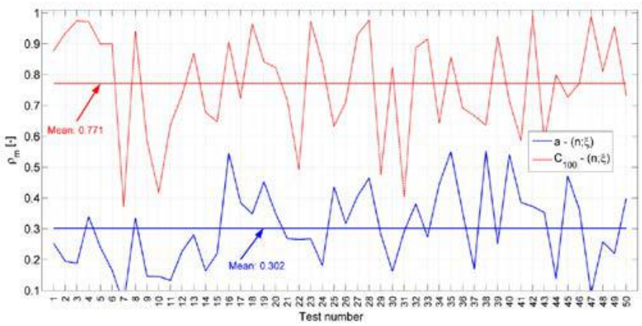


Figure 5. Multiple correlation coefficients (for C_{100} and *dv*/*dt*), test values and overall average, 50 experimental tests, Nubira vehicle

As we can see from the last two graphs, the most pronounced linear dependency is between the horary fuel consumption and the pair engine speed – engine load (Fig. 6), and the most pronounced non-linear dependency is between the vehicle's acceleration and the two analyzed functional parameters (Fig. 5).

Similarly we can study the influence of any functional parameter onto the vehicle's fuel efficiency and dynamic behavior. From what we have presented here, we can conclude that in order to make a realistic study, we have to take into consideration the simultaneous variation of more functional parameters especially when studying the vehicle's dynamic behavior or fuel efficiency.

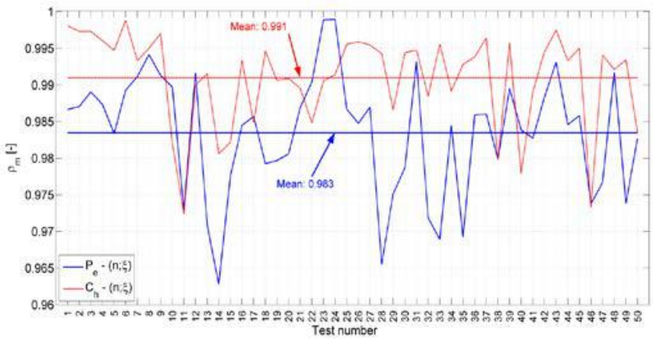


Figure 6. Multiple correlation coefficients (for P_e and C_e), test values and over hall average, 50 experimental tests, Nubira vehicle

We need to mention that beside the procedures presented throughout the current paper, there are others aimed at studying the influence of functional parameters onto the vehicle's dynamic behavior and fuel efficiency based on experimental data [1; 5; 6].

On the basis of these, mathematical models of vehicle dynamics and engine operation can be established. For example, Fig. 7 presents a graph the knots of which indicate the targeted parameters and their entropy values H, with the values for the mutual information I_{xy} *on the arches*. The deducted parameter is hourly fuel consumption in the case of 50 test runs carried out on a Logan Laureate vehicle. The mentioned parameter is presented in the graph's upper part (so we target the vehicle's efficiency); the other 5 parameters constitute factorial parameters [7; 10].

The graph in Fig. 7 shows that the pair hourly fuel consumption – engine speed has the highest value for mutual information (1.8357 bits), followed by the pair hourly fuel consumption – inlet air pressure (0.5287 bits); thus engine speed and inlet air pressure are the first top two choices which are relevant, the third one being spark ignition advance (0.5013 bits). Therefore if two mathematical models are established referring to efficiency, of type $C_h = f(n, p_a)$ respectively $C_h = f(n, \beta)$, the first one will ensure a better prediction (a smaller modeling error) than the second for the values of hourly fuel consumption C_h.

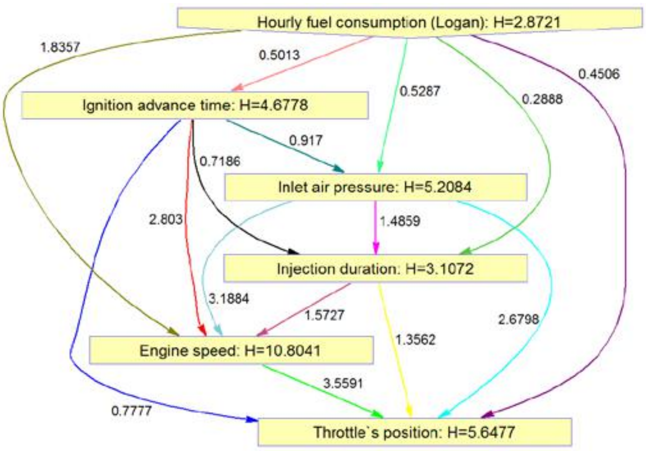
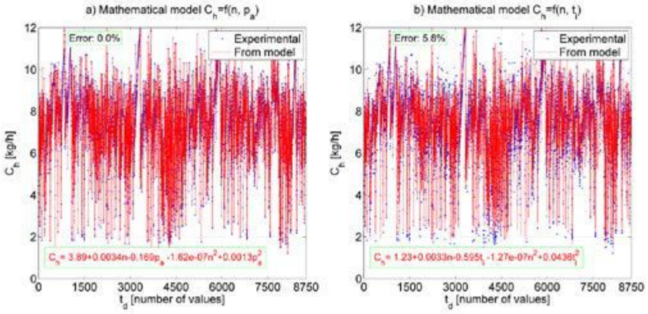


Figure 7. Graph that contains entropy and mutual information for hourly fuel consumption

The final issue hereby referred to is validated by Fig. 8, where results are being presented in the case of some mathematical models on which the factorial parameters that were used are engine speed n and inlet air pressure p_a (Fig. 8a), respectively engine speed n and injection duration t_i (Fig. 8b). On both models the resulted parameter is hourly fuel consumption C_h. As we can see maximum prediction (simulation error is virtually zero) is being ensured by the mathematical model from Fig. 8a, on which the factorial parameters are the two relevant parameters that have the highest value for mutual information from Fig. 7 (1.8357 and 0.5287 bits).

In exchange, the simulation error is higher in the case of Fig. 8b, where instead of inlet air pressure, the injection duration was used as factorial parameter, for which the mutual information has a lower value (0.2888 bits in Fig. 7).



a) b)

Figure 8. Mathematical model for fuel consumption of the engine

The graphs in the lower part of Fig. 8 present the expressions consistent with the two targeted mathematical expressions. Fig. 8a reveals that the generalized mathematical models (for 50 experimental test runs) equal

$$C_h = 3.89 + 0.0034n - 0.169 p_a - 1.62 \cdot 10^{-7} n^2 + 0.0013 p_a^2, \qquad (6)$$

which allows the calculus of hourly fuel consumption for the engine depended on engine speed and its load (the later through the inlet air pressure).

III. Conclusion

Quantitative appreciation regarding the functional factors influence on motor vehicles performances can only be obtained based on experimental data.

Equipping today's motor vehicles with control systems, transducers, actuators and on-board computers enables a thorough study of vehicle dynamics and engine operation and provides data on the influence of various factors on performances.

References

[1] R. Blahut, *Principles and Practice of Information Theory*, Addison-Wesley, Cambridge MA, 1988.

[2] G. Carey, *Multivariate Analysis of Variance (MANOVA)*, Colorado State University, 1998.

[3] B. Clarke, *Analysis of Multivariate and Time Series Data*, Colorado State University, 2003.

[4] I. Copae, I. Lespezeanu, G. Cazacu, *Vehicle Dynamics*, ERICOM Publishing House, Bucharest, 2006.

[5] R. Gray, *Entropy and Information Theory*, Stanford University, New York, 2007.

[6] B. Hoenselaar, *A Mutual Information as a Measure of Relevance. Thesis*, Providence, Rhode Island, 2007.

[7] O. Langsrud, *Entropy and Information Theory*, Division of Statistics, Depatarment of Mathematics, University of Oslo, Norway, 2003.

[8] F. Murtagh, *Multivariate Data Analysis*, Queen's University Belfast, 2000.

[9] G. Glenn, K. Isaacs, "*Estimating Sobol sensitivity indices using correlations*," Environmental Modelling&Software, 37, 2012, pp. 157-166.

[10] L. Paninski, "Estimation of Entropy and Mutual Information," *Neural Computation*, vol. 15, no. 6, pp. 1191-1253, June 2003.