Lateral dynamics of a SUV on deformable surfaces by system identification. Part II. Models reconstruction

J Pytka

Lublin University of Technology, Mechanical Engineering Department, Nadbystrzycka 36, 20-618 Lublin, Poland

E-mail: j.pytka@pollub.pl

Abstract. The paper presents results of a study on lateral dynamics of a 1.6 tonne Sport Utility Vehicle *SUV* on deformable surfaces performed by means of system identification method. Based on the results of the identification experiment, described in the first part of this study, autoregressive models have been reconstructed from the experimentally obtained data and the fit of the models output to the results of the experiments has also been determined. Results show that autoregressive models, being simple, are useful for lateral dynamics of the test vehicle running on three different deformable surfaces: loess and sandy soils and wet snow. It was noticed the fit between the simulation and experimental results vary from 15 to 90% for various types of models applied to the data. It was also concluded the open-loop test method supported with the use of a steering robot instead of a human driver can be very useful, mainly due to high repeatability of manoeuvre in the tests.

1. Introduction

Studies on lateral vehicle dynamics on deformable, soft surfaces may give results of high importance for off road transportation safety or for prevention of rollovers during road departure. A traditional approach in vehicle dynamics modelling starts with a physical insight and model postulation, next describing the behaviour of the vehicle by means of differential equation system [1 – 4]. These equations are parametrized, taking into account vehicle parameters as well as wheel-surface interaction parameters, that determine dynamical behaviours of a vehicle on a given surface. In case of soft, deformable surfaces such as soils, snow, their deformability affect wheel-surface forces significantly [5 – 12]. Firstly, a deflection of surface under wheel loads causes an increased rolling resistance. Another problem is a loss of traction, caused mainly by shearing deformation in surface material [13, 2, 14 – 16] . These two phenomena are very difficult to analyse and model and, moreover, modelling of off-road vehicle dynamics with regard to all pronounced phenomena by means of a traditional approach seems to be complex and difficult.

The paper presents vehicle lateral dynamics models obtained with the use of system identification method, which has been applied to reconstruct autoregressive models of lateral dynamics of a Sport Utility Vehicle (*SUV*) running over soil and snow surfaces. The vehicle and its steering system has been treated as a black-box system, with no physical insight required, but the modelling was based on standard measures which describe lateral dynamics: lateral acceleration, side slip angle of the centre of gravity, yaw rate and steering wheel torque.

IOP Conf. Series: Materials Science and Engineering **421** (2018) 022029 doi:10.1088/1757-899X/421/2/022029

2. Methods

2.1. System identification method

System Identification (*SI*) is in fact a mathematical procedure in which a model and its parameters are reconstructed based on experimental data. There is a wide range of methods used for *SI*, from simple approximation to complex statistical analysis [17]. The method is widely used in modelling of aircraft dynamics and control [18, 19]. Also, modelling studies in vehicle dynamics have been performed by means of the *SI* method [8, 10, 11]. In general, the *SI* process is divided into five steps: model postulation, experiment design, data compatibility analysis, model reconstruction and verification. Model postulation in case of vehicle lateral dynamics is based on traditional approach and is assumes coupling input (steering wheel input) with output signals (lateral acceleration, yaw rate and side slip angle). Such model construction allows to analyse important properties of a vehicle within the general lateral dynamics. The second step, experiment design is a procedure that leads to capture experiment data describing the investigated features of a vehicle. Simply, all inputs and outputs have to be measured simultaneously, at a rate and resolution that ensure obtaining informative data. Data compatibility analysis is the next step in the *SI* method procedure and relies on data handling, filtering and checking procedures. It is important since the measured response data can contain bias and scale factor errors due to the characteristics of the sensors or measurements conditions. The most important stem in the *SI* process is the selection of an adequate model or a family of models that should have a structure sufficient to characterize the data and to estimate of unknown parameters and it should also have good prediction capabilities. Having selected a prospective model of the phenomena that we are analysing, there should be parameters to be estimated from the input and output data sets. The problem of state estimation is usually reduced to integration of vehicle equations of motion, provided that these equations represent a deterministic system—that is, with no process noise and no random parameters in the equations. Finally, the procedure ends with a validation test, in which the identified model must demonstrate that its parameters have physically reasonable values with enough accuracy and prediction capabilities. Model validation can be performed by comparison of output data with experimental data or with output data from other models of known performance. Prediction capabilities of the model can be checked on a set of data not used for system identification of this model.

2.2. Autoregressive models

One of the simplest models are linear, time-invariant autoregressive models. The most simple input – output relationship is obtained by describing it as a linear difference equation correlating y – output and u – input (see figure 1):

$$y(t) + a_1 y(t-1) + ... + a_{na} y(t-n_a) = b_1 u(t-1) + ... + b_{nb} u(t-n_b) + e(t) \tag{1}$$

with: $e(t)$ – disturbance acting on a given system. A vector, Θ of coefficients, a_n is given below:

$$\Theta = [a_1, a_2 ... a_{na}\ b_1, b_2 ... b_{nb}]^T \tag{2}$$

Introduce $A(q)$, $B(q)$ as:

$$A(q) = 1 + a_1 q^{-1} + ...\ a_{na} q^{-na} \tag{3}$$

$$B(q) = 1 + b_1 q^{-1} + ...\ b_{nb} q^{-nb} \tag{4}$$

so we obtain $G(q, \Theta)$ – transfer function from u to y and $H(q, \Theta)$ – transfer function from e to y:

$$G(q,\Theta)=\frac{B(q)}{A(q)},\quad H(q,\Theta)=\frac{1}{A(q)} \tag{5}$$

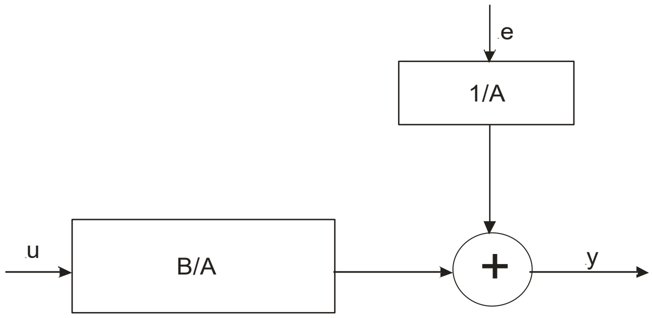


Figure 1. A schematic of a generalized autoregressive model *ARX*

In the presentation of the results – model calculation of lateral vehicle dynamics, the autoregressive models are designated as "*arx*", with usually three digits, i.e. "441", what means: the 4th order
The basic disadvantage with the simple model (1) is the lack of adequate description of the properties of the disturbance term. We can describe the equation error as a moving average of white noise:

$$y(t)+a_1y(t-1)+...+a_{n0}y(t-n_a)=b_1u(t-1)+...+b_{nb}u(t-n_b)+e(t)+C_1e(t-1)+...+C_{nc}e(t-n_c) \tag{6}$$

with:

$$C(q)=1+C_1q^{(-1)}+...+C_{nc}q^{(-nc)} \tag{7}$$

so:

$$A(q)y(t)=B(q)u(t)+C(q)e(t) \tag{8}$$

And corresponding to (5)we obtain:

$$G(q,\Theta)=\frac{B(q)}{A(q)},\quad H(q,\Theta)=\frac{C(q)}{A(q)} \tag{9}$$

where:

$$\Theta=[a_1,\ a_2...\ a_{na}\quad b_1,b_2\ ...b_{nb}\quad c_1,c_2...c_{nc}\ ] \tag{10}$$

So we have defined the *ARMAX* model family, in this study designated as "*arx*".

Suppose the relation between input and undisturbed output, *w*, which can be written as a linear difference equation, and that the disturbances consists of white measurement noise. We obtain the following description of a new model structure – called *Output Error* and designated "*oe*":

$$w(t)+f_1\ w(t-1)+...+f_{nf}\ w(t-n_f)=b_1\,u(t-1)+...+b_{nb}\,u(t-n_b) \tag{11}$$

$$y(t) = w(t) + e(t) \tag{12}$$

Introduce *F(q)*:

$$F(q) = 1 + f_1 q^{(-1)} + ... + f_{nf} q^{(-nf)} \tag{13}$$

and we can write the model as:

$$y(t) = \frac{B(q)}{F(q)} u(t) + e(t) \tag{14}$$

with the parameter vector:

$$\Theta = [b_1,\ b_2\ ...\ b_{nb} \quad f_1, f_2, ... f_{nf}]^T \tag{15}$$

A logical development of the output error model (14) is to a structure that describes the properties of the output error:

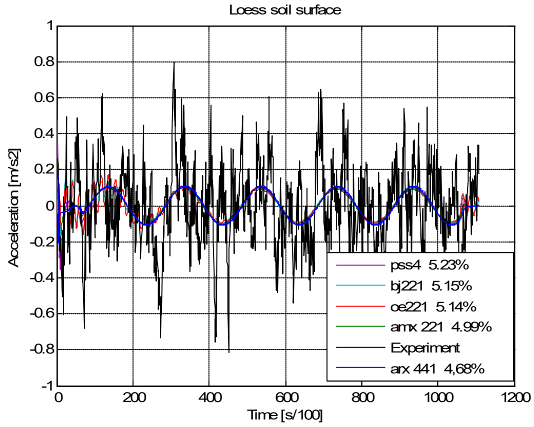
$$y(t) = \frac{B(q)}{F(q)} u(t) + \frac{C(q)}{D(q)} e(t) \tag{16}$$

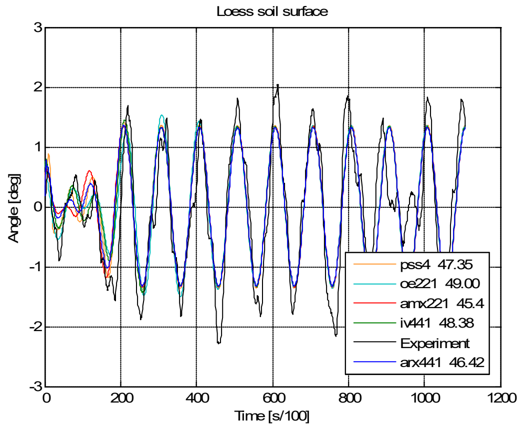
The transfer functions are independently parametrized as rational functions. This type of model was first introduced by Box and Jenkins, in 1970 [19]. In our figures, these model are designated with "*bj*".

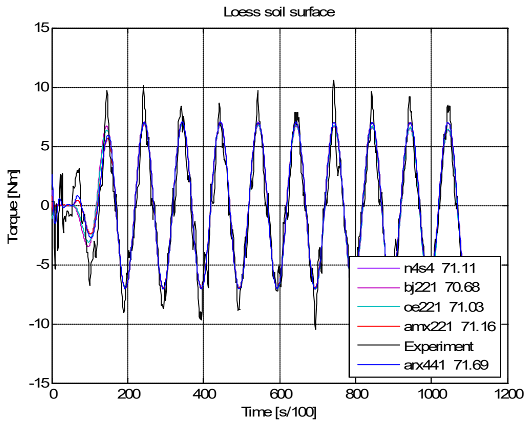
3. Results - Presentation and analysis of reconstructed models

The aim of the present study, reconstruction of autoregressive models of vehicle lateral dynamics has been done based on the above presented and other results from the field tests. The procedure is that a set of two data columns: input – the excitation signal, sine wave or ramp change of a given parameter, and output – measured wheel lateral force or lateral acceleration, slip angle, yaw rate, steering torque, is inserted into the *SI* software, then, before the identification procedure, data is checked for any irregularities, false point, etc. Then comes the most important step – model estimation, in which parameters of models (of model families) are obtained. The model families will be generally characterized in the following subsection. After the estimation procedure, the reconstructed models can be presented in a graphical form, typically on a graph containing simulation results for several models together with a course of experiment result, for visual comparison. The software enables to compare the estimated models based on the rule of fit between simulated and measured data and this fit is quantified by means of percentage similarity, where 100 is for ideal or full fit. For the purpose of the present study, linear autoregressive models have been chosen and sample results of model – experiment comparison for the two excitation modes are shown in figures 2 thru 5. It is to point out that linear autoregressive models are probably the simplest possible and generates lowest costs of computing.

Figure 12 includes graphs with time courses of simulated and measured data describing the lateral vehicle dynamics for sine wave excitation modes, here for the excitation with 1.0Hz frequency. Similarly, figure 3 presents those results for ramp change excitation mode, while in figures 4 and 5 we have results for wheel side force simulations. In each of the graphs in the four mentioned figures there is a legend box, in which we have graph line description – here are the acronyms of model families, presented in the previous section with digital data. That data describes the fit between a given model and the measured data ("*experiment*"). Generally, the higher the number, the better the model.


Loess soil surface
Acceleration [m/s2]
Time [s/100]
pss4 5.23%
bj221 5.15%
oe221 5.14%
amx 221 4.99%
Experiment
arx 441 4,68%


Loess soil surface
Angle [deg]
Time [s/100]
pss4 47.35
oe221 49.00
amx221 45.4
iv441 48.38
Experiment
arx441 46.42


Loess soil surface
Torque [Nm]
Time [s/100]
n4s4 71.11
bj221 70.68
oe221 71.03
amx221 71.16
Experiment
arx441 71.69

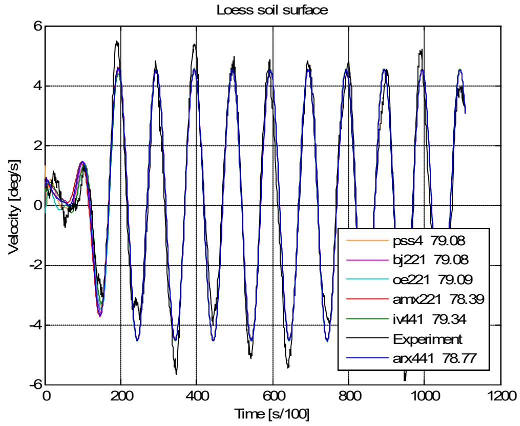
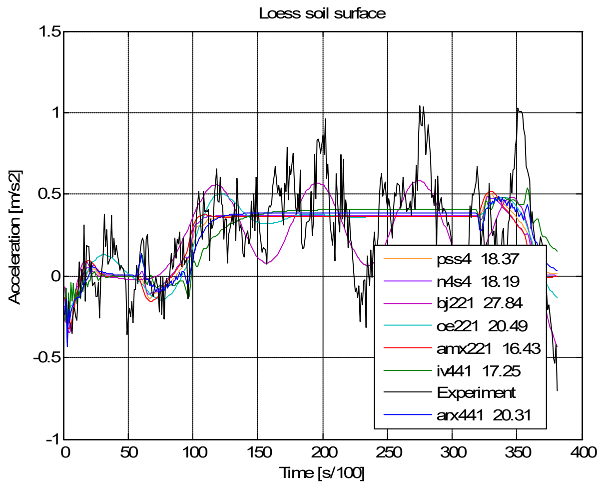
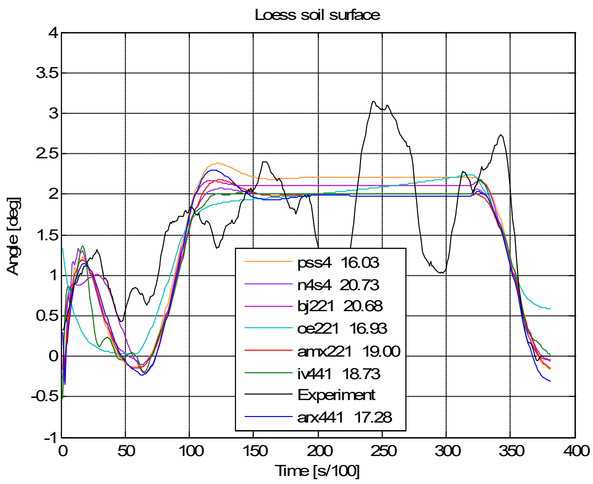


Figure 2. Reconstructed of models of vehicle lateral dynamics for the sine wave excitation mode

From above down: lateral acceleration, side slip angle, steering torque and yaw rate.





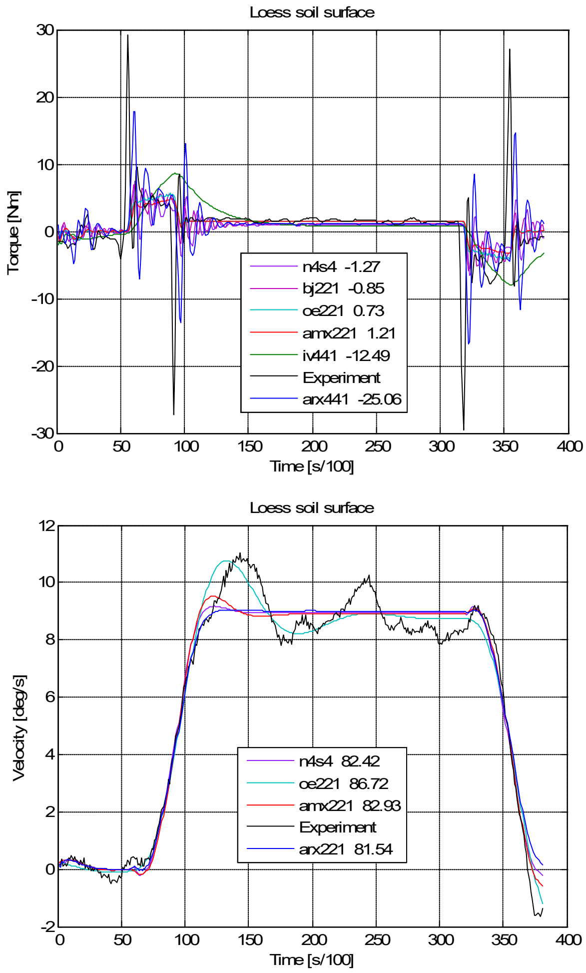
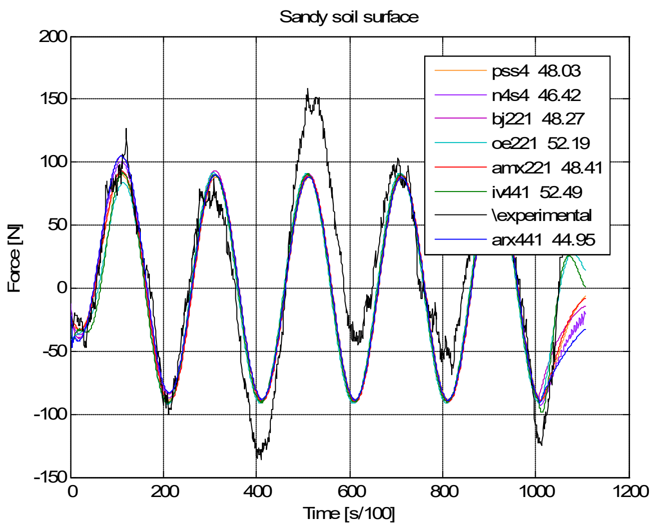


Figure 3. Reconstructed of models of vehicle lateral dynamics for the ramp change excitation mode From above down: lateral acceleration, side slip angle, steering torque and yaw rate.



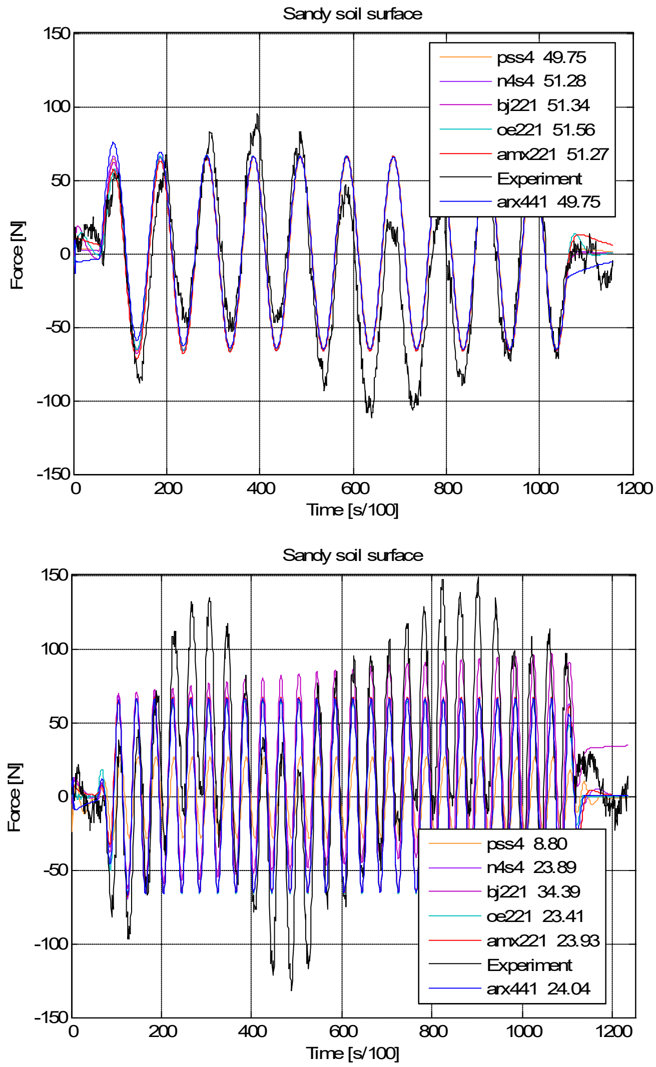
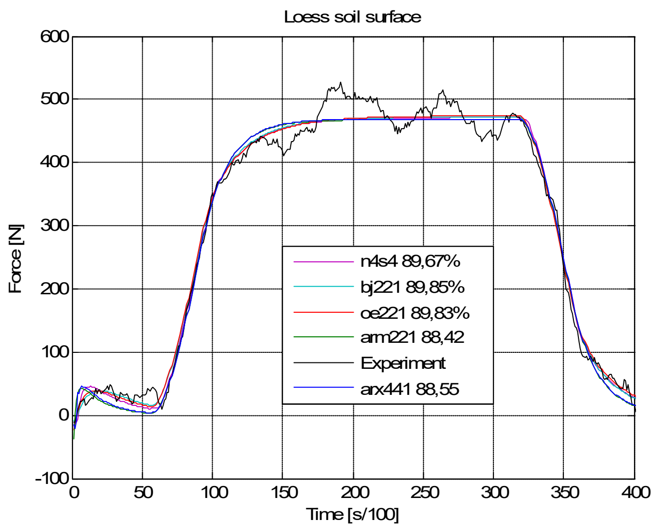


Figure 4. Reconstructed of models of wheel side force for the sine wave excitation mode: 0.5, 1.0 and 2.5Hz



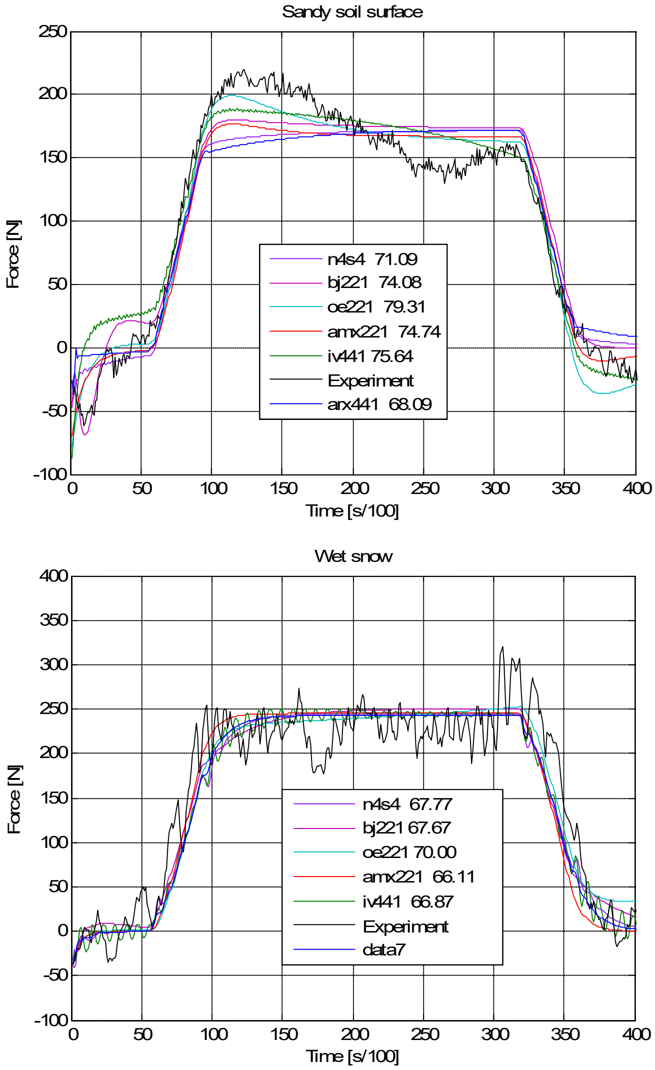


Figure 5. Reconstructed models of wheel side force for the ramp change excitation mode

It is to point out that the autoregressive linear models are well suitable for simulation of side slip angle, steering torque and yaw rate while not suitable for lateral acceleration of the vehicle running with sine wave excitation modes. This tendency has been observed for all the three deformable surfaces, loess and sandy soils and wet snow (although the results presented here does not include all cases).

For the ramp change excitation mode, the quality of results measured by means of the fit percentage is far worse than above. Only for the yaw rate, simulations are of acceptable fit percentage related to the experimental data, in the three remaining vehicle dynamics measures, models have given outputs that does not correspond with the base experimental data.

In the case of models for wheel side force, it seems that linear autoregressive models are a general good choice, since the results of the fit percentage are good or very good for all cases of excitation modes and parameters.

4. Conclusions

Study on vehicle lateral dynamics has been presented in this paper. Based on the results obtained in the field experiments, autoregressive linear models of lateral dynamics have been reconstructed using the system identification method. Simulation results have been compared to experimental data and the quality of models measured by means of fit percentage coefficient has been analysed. It has been concluded, simple and low-cost autoregressive models may be a good solution in modelling and simulation of vehicle lateral dynamics. In cases where the *ARX* models gave poor fits, probably non-linear models could be a good choice, until their higher cost would not be a concern.

It has been concluded that system identification method is a good useful tool for obtaining models of vehicle lateral dynamics running in off-road conditions. Its advantages over the classic modelling is that no physical parameters of the system are must to be known. This is especially of the importance for such a physically complex system as the tyre – soil.

Further research will be continued and the author is aiming to introduce a partially – physical, partially – experimental (a so called "gray box") model of the vehicle dynamics and the final application will be a simulating model of high accuracy yet low cost and computing time.

References

[1] M. Börner, R. Isermann *The characteristic velocity stability indicator...,* Veh. Syst. Dyn.
[2] C.W. Fervers *Improved FEM simulation...* J.of Terramechanics
[3] M. Mitschke, H. Wallentowitz, *Dynamik der Kraftfahrzeuge*, Springer
[4] H.B. Pacejka, *Tyre and vehicle dynamics*, Elsevier/Butterworth-Heinemann
[5] J. Pytka *Design consideration and calibration...* J. of Terramechanics
[6] J. Pytka *Determination of snow stresses...* Cold Regions Science and Technology
[7] J. Pytka *Determining and analysing the stress state...* IMechE J.of Automobile Engineering
[8] J. Pytka *A semiempirical model...* Int. J. of Auto. Technol.
[9] J. Pytka *An instrumented vehicle...*J. of Terramechanics
[10] J. Pytka *Stability...* Maintenance and Reliability
[11] J. Pytka *Steering effects upon ...* Int. J.of Vehicle Design
[12] J. Dąbrowski *Advantages of all-season versus snow tyres...* J.of Terramechanics
[13] S.A. Shoop *Finite Element Modeling of Tire...* ERDC-CREEL Technical Report
[14] S.K. Upadhyaya, M. Sime, N. Ranghuwanshi, B. Adler *Semi – empirical traction prediction equations ...* J.of Terramechanics
[15] S. Wanjii, T. Hiroma, Y. Ota T. Kataoka *Prediction of wheel performance...* J.of Terramechanics
[16] D. Wulfsohn, S. Upadhyaya *Prediction of traction and soil compaction...* J.of Terramechanics
[17] S. R. James *Lateral Dynamics of an Offroad...*Vehicle System Dynamics
[18] V. Klein, E.A. Morelli *Aircraft System Identification. Theory and Practice* AIAA Education Series, Reston, USA
[19] L. Ljung *System Identification. A theory for the user* Prentice Hall, New York, USA