A PARAMETRIC IDENTIFICATION OF STOCHASTICALLY LOADED STRUCTURES AND ITS SOFTWARE SUPPORT

Bohuš Leitner[1]

Summary: The paper contains descriptions of one possible approach of an identification of stochastically loaded structures. The purpose of this approach is to find an algorithm of a forecasting control of their working in real working conditions. It deals with a proposal of an application of vector time series moving average models (VARMA). Their parameters are possible to determine using the nonlinear modification of the least squares method. The paper contains a main theoretical principle of solved area and its application on a real testing structures. The main purpose of practical apllication is to identify the important parameters and to examine their relations to one another while gantry crane structure was modelled.

Key words: stochastic load, parametric identification, vector autoregressive model VARMA, cranes, software tools - ArmaGet, Matlab, ARMASA Package.

1. INTRODUCTION

It is well known that working of majority of machines is significantly influenced by different kinds of stochastic loads. There is possible to respect the tendency a limitation of energetically and material consumption to oversize their dimensions. But it is necessary to look for some more ingenious methods to deal with this problem. Some of them are the ways to control (influence) the working of a mechanical system in respect to their proposed behaviour. But it needs to follow of the system behaviour in the real time and to make some necessary controlling interventions. Gantry crane has been applied for moving container over variable paths within restricted areas. The review of the literature has shown that most of the previous studies focused on optimal ways to control the crane trolley position so that the swing of the hanging container can be minimized. Using the models with the full-sized or reduced-sized gantry crane in the laboratory is not new, but there are still constrains which have not solved completely.

Firstly, until now large gantry crane has specially designed for loading and unloading containers from the ships with 10 to 18 rows. However, in the future, there are significant needs for bigger gantry crane with 22 or higher rows. Therefore, how to change the frame length of gantry crane, which influences other elements, is a more considerable problem.

Secondly, the full-sized gantry crane with wind effect has not considered thoroughly in the studies results. The whole structure of gantry crane is divided into two sections: the moving substructure and the static framework. Following the balance of forces, the relationship between the fixed framework and the moving sub-structure can be simplified into time-variant moving point loads. During the operation of the gantry crane system, the moving substructure is subjected to wind flow; it may increase vibration or suddenly deflect its motion in wind flow around. Therefore, to

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understand the dynamical behaviours of the hanging container under wind excitation, the basic wind phenomena needs to be clearly understood. In addition, designing a gantry crane includes designing structure, testing vibration, making gantry crane, installing controller, and redesigning. In these steps, controllability has been ignored, even though this is an important parameter in operation of gantry crane in practical (1).

2. DYNAMIC SYSTEMS IDENTIFICATION AND AUTOREGRESSIVE MOVING AVERAGE MODELS

The procedure of dynamic modelling is shown in Fig.1. The inputs for system are measurements including wind pressure, motor torque, etc., while the inputs for system reaction are displacement, strain, stress. To model the system reaction as the output signal from the system inputs, a transmission through the object has been modelled.

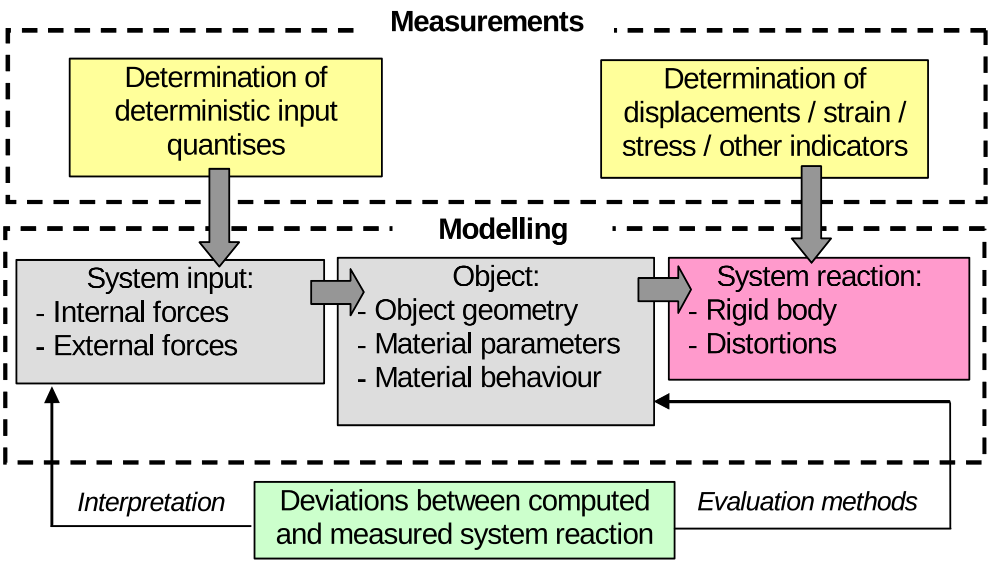

Fig.1 - Procedure of Dynamic Systems Modeling

Generally, process identification, which catches some of the most important properties of the process behaviour, is based on step response analysis. System identification, as shown in Fig. 2, can be achieved when the inputs as well as the output signals are available as measured quantities.

There are two kinds of models including parametric model and non parametric model. The parametric model (*white box models*) is the model in which the transmission of the signal through the object is supposed to be known and can be described by differential equations.

In non parametric model, on the contrary, modelling geometrical and the physical structure of a system can not be established except by the sense of regression and/or correlation analysis (behaviour model). System identification means that determining the regression or correlation coefficients. Non-parametric models are *called black box models* because system identification is based not only on measurements but also on mechanical model.

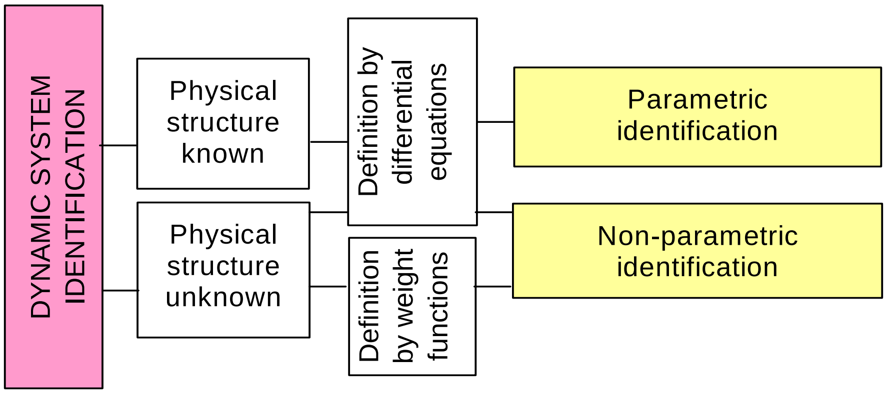

Fig. 2 - Parametric and Non-parametric identification

There is necessary to identify such a system at first. It means to get its statistically adequate mathematical model. There is possible by using this model and by developing sufficient fast and correct machine control system and suitable software to forecast behaviour of system in the near future. We can get in such a way the possibility of making some controlling corrections before the system reaches an unstable region.

It was found the as a suitable solution for a stochastically loaded mechanical structure identification can be used the autoregressive moving average models ARMA or their vector modification named VARMA (Vector Autoregressive Moving Average) models (2), (5), (6). A stochastically loaded part of structure and its behaviour during time can be described by using of scalar autoregressive moving average models (8). Its identification (stochastically adequate model) but gives just an information about its own behaviour without a relationship to the whole structure during acting of different working regimes.

We have found as one of possible ways the use of autoregressive moving average models ARMA and its adaptive modifications to improve accuracy of stochastically loaded mechanical structures identification. These models are suitable for stochastically loaded mechanical structures identification which outputs are reflections on stochastically loads in more number of points – vector time series.

3. ALGORITHM OF ADAPTIVE “ARMA” MODELS AND ITS APPLICATION IN PARAMETRIC IDENTIFICATION PROCESS

Algorithm for adaptive modelling [8] is based on a gradient method (steepest descent method) and can also be used for non-stationary processes. Model is able to adapt itself to the changes in process character. It is supposed that n-th order Vector Autoregressive model (2) is at any given time defined by the vector of its coefficients:

$$\mathbf{a}(k) = [a_1(k), a_2(k) \ldots a_n(k)]^T \tag{1}$$

Using the steepest descent method, point of least squares $\Sigma\varepsilon_{t2}$ is searched. Search begins with an initial guess as to where the minimum point of $\Sigma\varepsilon_{t2}$ may be.

Minimal sum of squares S is

$$\frac{\partial S}{\partial a_k} = \frac{\partial}{\partial a_k}\left(\sum \varepsilon_t^{\,2}\right) = 0\,. \tag{2}$$

The updated values of AR model coefficients are obtained from [7,8]

$$\mathbf{a}(k+1)=\mathbf{a}(k)+\eta.\frac{\partial S}{\partial a}, \tag{3}$$

where

$$\frac{\partial S}{\partial a}=-2\left[\varepsilon_{ft}.\mathbf{X}^T(k-1)\right]$$

is the gradient direction and positive value of η in equation (3) scales the amount of readjustment of the model coefficients in one time step. Then, the iterative corrections of coefficients are

$$\mathbf{a}(k+1)=\mathbf{a}(k)+\mu.\left[e_t.\mathbf{X}^T(k-1)\right]. \tag{4}$$

In (8) adaptive AR models were extended to include also MA part to adaptive Autoregressive models with moving average. To achieve this, vector of moving average coefficients must be considered

$$\mathbf{b}(k)=[b_1(k),b_2(k)...b_n(k)]^T. \tag{5}$$

Same procedure as for vector of AR coefficients was used to derive formula (4) for iterative corrections' calculations of MA part coefficients

$$\mathbf{b}(k+1)=\mathbf{b}(k)+\mu.\left[\varepsilon_t.\varepsilon^T(k-1)\right], \tag{6}$$

where ε_t is error from the last iterative step and $\varepsilon_{(k-1)}$ is vector of preceding errors

$$\boldsymbol{\varepsilon}(k-1)=\left[\varepsilon_{k-1},\varepsilon_{k-2},\dots\varepsilon_{k-n+1}\right]^T \tag{7}$$

Another problem arises when deciding value of convergence constant. It influences converging speed of algorithm and also its sensitivity to random or systematic changes in process environment character. Procedure for calculating μ constant, based on experimental work [8] was presented for use in area of adaptive control

$$\mu_k=\varphi+\beta.C_k \quad \text{and} \quad C_k=\left(1-\frac{1}{\alpha}\right)C_{k-1}+\frac{1}{\alpha}.\varepsilon_t^{\,2}, \tag{8}$$

where α is constant describing system memory, it influences model sensitivity to random process changes, β is constant characterising system dynamics and φ is constant for correction of numeric calculation errors. Actual values of these constants can be chosen so the model sensitivity to stochastic events and response speed to process character changes are as required.

The advantages of adaptive ARMA models:

- they can show the physically base of problem studied (this means that they to obtain the natural frequencies and natural modes of vibrations) (9),
- they can describe a wanted accuracy of real system (10) , (6), (7),
- the mathematical apparatus of methods is relative simple (4).

4. NEW SOFTWARE TOOL FOR PARAMETRIC AND ADAPTIVE IDENTIFICATION OF DYNAMICS SYSTEMS

The creation of a software support which is able to identify some stochastic loaded parts of structures is just the firs step for applying of the forecasting control of mechanical systems.

The final form of an identification software was created in such a way that it enables the use of an identification library and to realise the own identification of system parameters. The result of a proposed application of this methodology is software tool - **ArmaGet** (Fig.3).

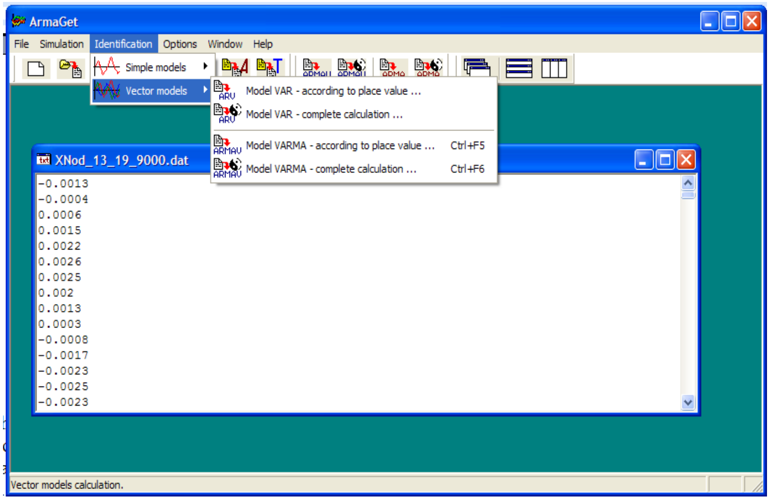

Fig. 3 - Main window of created software tool - ArmaGet

This developed software tool is able to create an adequate mathematical model for describing a matrix model of a tested stochastic loaded mechanical system. It contains users menu, which apart from basic functions with file, configurations, works with windows and help functions and contains two submenus – submenu of *"Simulation"* and submenu of *"Identification"*.

The heart of the program is submenu "*Identification*", by means, which is possible to make selection of the identification method and way of chosen time series, whereupon it is possible to use either adaptive algorithm of time series identification or make identification using non-linear least squares method. Item "*Simulation*" enables adjustment and conversion of incompatible input files of time series to compatible ones and simulation (generation) of time series basing on given AR or ARMA models order and parameters with possibilities of mean and dispersion selection of simulated series.

Because of the above stated reasons, procedure based on theory of adaptive and self-learning systems is used for describing system behaviour in real time.

5. VERIFICATION OF PROPOSED APPROACH OF IDENTIFICATION ON THE REAL STRUCTURES

5.1 Case A: Identification of Crane jib model parameters

Main problem in identification and modelling by autoregressive models is finding coefficients of AR and MA parts and determination of adequate order of the model. Coefficients of AR model can be simply found using least square method (LSM) [4]; for universal ARMA models non-linear LSM must be used. Both methods use matrix calculations for finding needed coefficients, which are very time-consuming and therefore not usable for on-line process, control or identification and they also can not be used for modelling of non-stationary time-varying process.

There was developed a FEM (Finite Element Method) model of a crane jib (Fig.4) and in MATLAB-environment was realised simulation of its loading. The acting loads were described as a stochastic excitation.

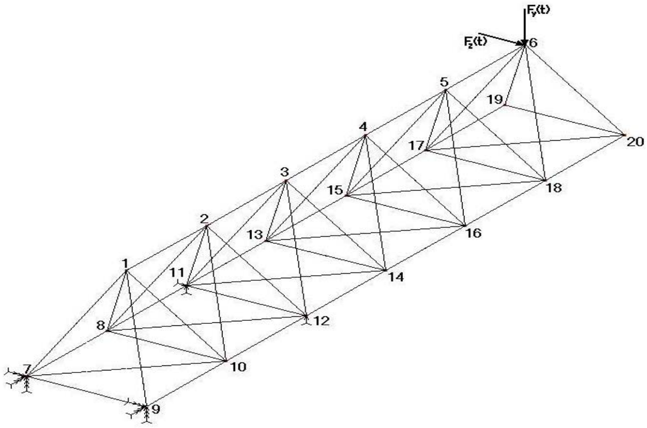

Fig.4 Testing model of crane jib

There were used as an application of a numeric Crank-Nicolson method (10) of direct integration the deformation of all nodes of model (20 nodes). The time intervals were selected as Δt v_z = 0.01 s. Resulting deformational outputs were organized in corresponding vector time series. There was selected in a testing example a vector time series of deflection in "z" axe direction.

The main window of inputs for determination of vector time series in direction of "z" axe is introduced on Fig.5 and results of its identification are introduced on Fig.6 (an optimal order of model - VARMA (6,5)).

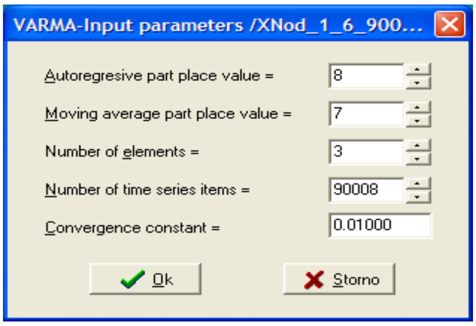

Fig. 5 - Settings of input parameters for identification process

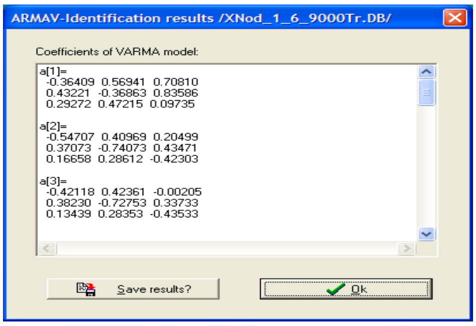

Fig. 6 - Results of a crane jib upper boom identification

The verification of developed identification support – software tool ArmaGet was realised by three different ways. At first it was a comparison with results of computing module Solver, from MS Excel. The second way to verify the correctness of software support was based on a comparison of obtained results with the application of software package ARMASA [3], working in Matlab© environment. As a third way of verification was chosen approach to generate new vector time series derived from the obtained parameters of VARMA models. This way means the simulation of time series with determined parameters and their "back way" identification. This option is available by menu item *Simulation→ Model VARMA* from developed tool ArmaGet.

In Tab.1 are results from identification through software tools by comparing values of sums of squares. In Tab.2 are presented results from a comparison of the application for three orders of VARMA models - namely orders (6,5) (8,7) and (10,9).

Tab.1 - The comparison of results - ArmaGet, ARMASA Package, Excel - Solver

	VARMA(6,5)	**VARMA(8,7)**	**VARMA(10,9)**
	ArmaGet	***ARMASA Package***	***Excel - Solver***
Node 1	$7{,}6591.10^{-6}$	$7{,}8991.10^{-6}$	$1{,}8398.10^{-7}$
Node 2	$1{,}0659.10^{-5}$	$1{,}1243.10^{-5}$	$1{,}1953.10^{-5}$
Node 3	$1{,}1204.10^{-5}$	$1{,}1868.10^{-5}$	$1{,}1307.10^{-5}$
Node 4	$1{,}4823.10^{-5}$	$2{,}1467.10^{-5}$	$2{,}0833.10^{-5}$
Node 5	$2{,}5955.10^{-5}$	$4{,}2690.10^{-5}$	$3{,}5906.10^{-5}$
Node 6	$4{,}1240.10^{-5}$	$6{,}4402.10^{-5}$	$6{,}2980.10^{-5}$

Tab. 2 - The verification of identification results for different orders of VARMA models

	VARMA(6,5)		**VARMA(8,7)**		**VARMA(10,9)**	
	ArmaGet	***Excel***	***ArmaGet***	***ARMASA***	***ArmaGet***	***ArmaGet***
Node 1	$7{,}6591.10^{-6}$	$1{,}8398.10^{-7}$	$7{,}6591.10^{-6}$	$7{,}8991.10^{-6}$	$7{,}8985.10^{-6}$	$7{,}8482.10^{-6}$
Node 2	$1{,}0659.10^{-5}$	$1{,}1953.10^{-5}$	$1{,}0659.10^{-5}$	$1{,}1243.10^{-5}$	$1{,}0365.10^{-5}$	$1{,}0402.10^{-5}$
Node 3	$1{,}1204.10^{-5}$	$1{,}1307.10^{-5}$	$1{,}1204.10^{-5}$	$1{,}1868.10^{-5}$	$1{,}0424.10^{-5}$	$1{,}0497.10^{-5}$
Node 4	$1{,}4823.10^{-5}$	$2{,}0833.10^{-5}$	$1{,}4823.10^{-5}$	$2{,}1467.10^{-5}$	$1{,}4028.10^{-5}$	$1{,}4183.10^{-5}$
Node 5	$2{,}5955.10^{-5}$	$3{,}5906.10^{-5}$	$2{,}5955.10^{-5}$	$4{,}2690.10^{-5}$	$2{,}2255.10^{-5}$	$2{,}5761.10^{-5}$
Node 6	$4{,}1240.10^{-5}$	$6{,}2980.10^{-5}$	$4{,}1240.10^{-5}$	$6{,}4402.10^{-5}$	$3{,}7822.10^{-5}$	$3{,}5980.10^{-5}$

For more information on selected practices and other functional outcome assessment prepared software support can be found e.g. in (2, 6, 8).

5.2 Case B: Parametric Identification of the Large Gantry Crane System

a) Parameters of Gantry Crane model: analytical model of examined gantry crane is on Fig.7, where *XY* is the fixed coordinate system and ($X\hat{}, Y\hat{}$) is the trolley coordinate system, which moves with the trolley.

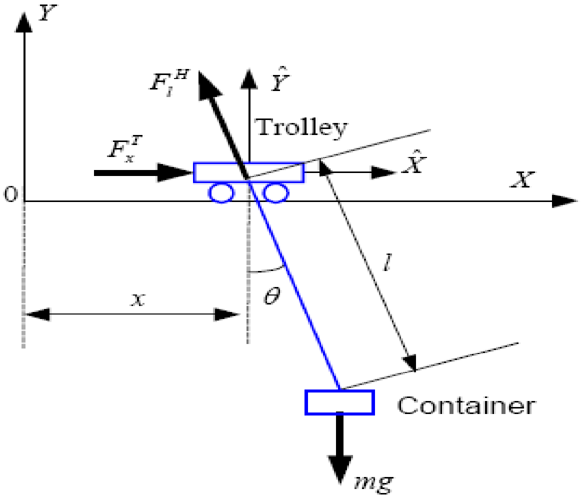

Fig. 7 Dynamic parameters of crane model

The equations of motion of a two-dimensional gantry crane are obtained by Lagrange's equation as follows (1):

$$\left(M_\theta + m\right).\ddot{x} + m.l.\cos\theta\ddot{\theta} + m.\sin\theta\ddot{l} + C.\dot{x} + 2.m.\cos\theta\dot{l}\dot{\theta} - m.l.\sin\theta\dot{\theta}^2 = F_\theta^T \qquad (9)$$

$$ml^2\ddot{\theta} + ml\cos\theta\ddot{x} + 2ml\dot{l}\dot{\theta} + mgl\sin\theta = 0 \qquad (10)$$

$$(M_l + m)\ddot{l} + m\sin\theta\ddot{x} + C_l\dot{l} - ml\dot{\theta}^2 - mg\cos\theta = F_l^H \tag{11}$$

From equations (9) and (11), the functions bellows are received

$$C_x\dot{x} - k_{mx}F_{xe}^T = -(M_x+m)\ddot{x} - ml\cos\theta\ddot{\theta} - m\sin\theta\ddot{l} - 2m\cos\theta\dot{l}\dot{\theta} + ml\sin\theta\dot{\theta}^2 \tag{12}$$

$$C_l\dot{l} - k_{mi}F_{le}^H = -(M_l+m)\ddot{l} - m\sin\theta\ddot{x} + ml\dot{\theta}^2 + mg\cos\theta \tag{13}$$

where $\mathbf{C_x}$, $\mathbf{C_l}$ denote damping on x - axis and along cable; k_{mx} k_{mi} denote stiffness along cable. We assume that we observe the set of outputs and inputs in form

$$\begin{bmatrix} \dot{x} & F_{xe}^T & 0 & 0 \\ 0 & 0 & \dot{l} & F_{le}^H \end{bmatrix} \begin{bmatrix} C_x \\ -k_{mx} \\ C_l \\ -k_{mi} \end{bmatrix} = \begin{bmatrix} -(M_x+m)\ddot{x} - ml\cos\theta\ddot{\theta} - m\sin\theta\ddot{l} - 2m\cos\theta\dot{l}\dot{\theta} + ml\sin\theta\dot{\theta}^2 \\ -(M_l+m)\ddot{l} - m\sin\theta\ddot{x} + ml\dot{\theta}^2 + mg\cos\theta \end{bmatrix} \tag{14}$$

and thus we obtain equation in form

$$\boldsymbol{\varphi}^T.\boldsymbol{\theta} = \mathbf{y}\ . \tag{15}$$

The experimental model used for this case is shown in Fig. 8.

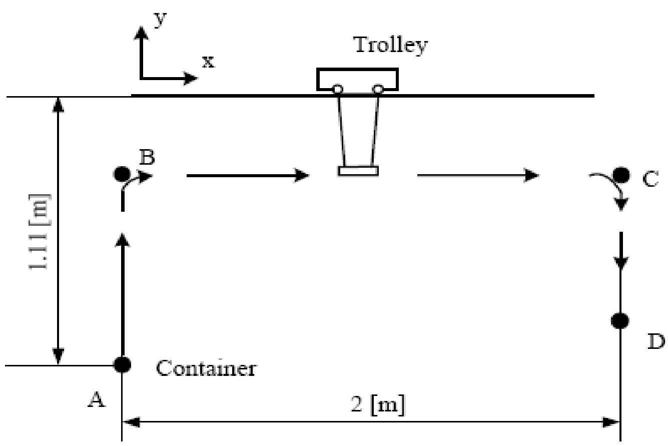

Fig. 8 - Transportation sequence of the container

Firstly, the container moves along the y -axis, from A point to B point, then travels along the x -axis, from B point to C point, and finally moves along the y-axis, from C point to D point. The experimental model with using microcontroller is defined in Fig. 9, where driving forces F_x^T and F_l^H is installed by joysticks.

Fig. 9 - Experimental model of gantry crane

Displacement of trolley and length of rope are obtained by two encoders.

The input parameters are as follows: *length of rope l = 1,11 [m], acceleration of gravity g = 9,81 [m/s^2], mass of trolley M = 100 [kg], mass of container m = 60 [kg].*

Results: Result for computing values of the identification parameters are in Tab.3 and the courses of driving force on x-axis and driving force along cable (in experiment by using joystick) for realized 4 basic cases (1 to 4) are referred to Figs. 10-13.

Tab.3 - Result for computing values of the identification parameters

Case 1 : Results	**Case 2 : Results**	**Case 3 : Results**	**Case 4 : Results**
$\begin{bmatrix} C_x \\ -k_{mx} \\ C_l \\ -k_{mi} \end{bmatrix} = 1.e^3 \begin{bmatrix} -2{,}417 \\ 0{,}422 \\ -0{,}749 \\ 0{,}350 \end{bmatrix}$	$\begin{bmatrix} C_x \\ -k_{mx} \\ C_l \\ -k_{mi} \end{bmatrix} = 1.e^3 \begin{bmatrix} -0{,}943 \\ 0{,}156 \\ 0{,}087 \\ -0{,}033 \end{bmatrix}$	$\begin{bmatrix} C_x \\ -k_{mx} \\ C_l \\ -k_{mi} \end{bmatrix} = 1.e^3 \begin{bmatrix} -9{,}600 \\ 4{,}475 \\ -3{,}899 \\ 0{,}436 \end{bmatrix}$	$\begin{bmatrix} C_x \\ -k_{mx} \\ C_l \\ -k_{mi} \end{bmatrix} = 1.e^5 \begin{bmatrix} 1{,}264 \\ -0{,}211 \\ -0{,}038 \\ -2{,}537 \end{bmatrix}$

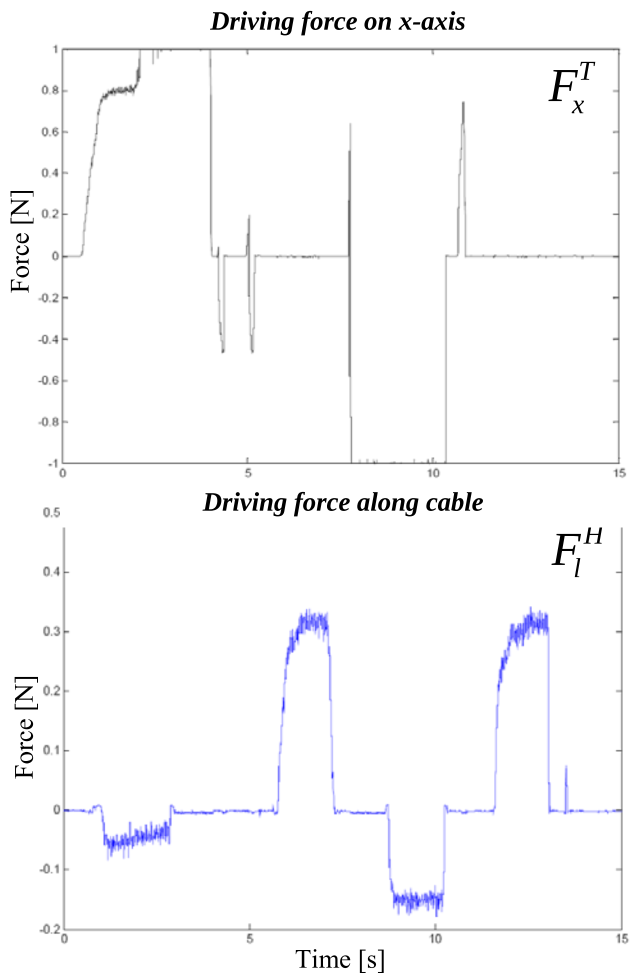

Fig. 10 - Driving force for Case 1

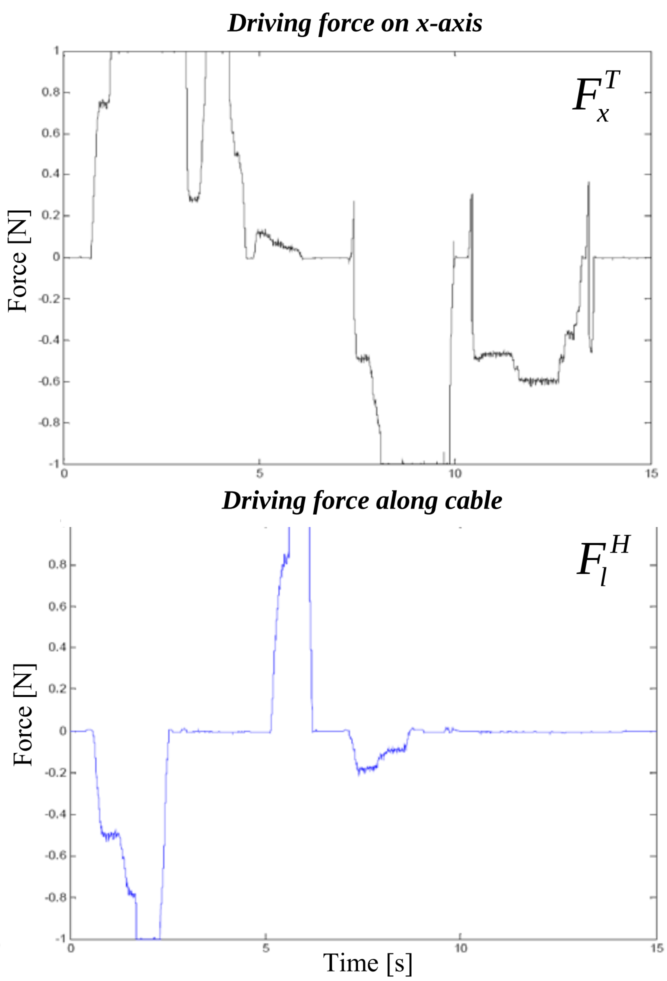

Fig. 11 - Driving force for Case 2

Depending on the experiment results, system identification is used to identify parameters of gantry crane including damping and stiffness matrices. MATLAB program is also applied, with the least squares method.

Depending on the experiment results, system identification is used to identify parameters of gantry crane including damping and stiffness matrices. MATLAB program is also applied, with the least squares method [10]. However, the least squares method can not be regarded as a suitable algorithm for parametric identification of the large-scale crane systems.

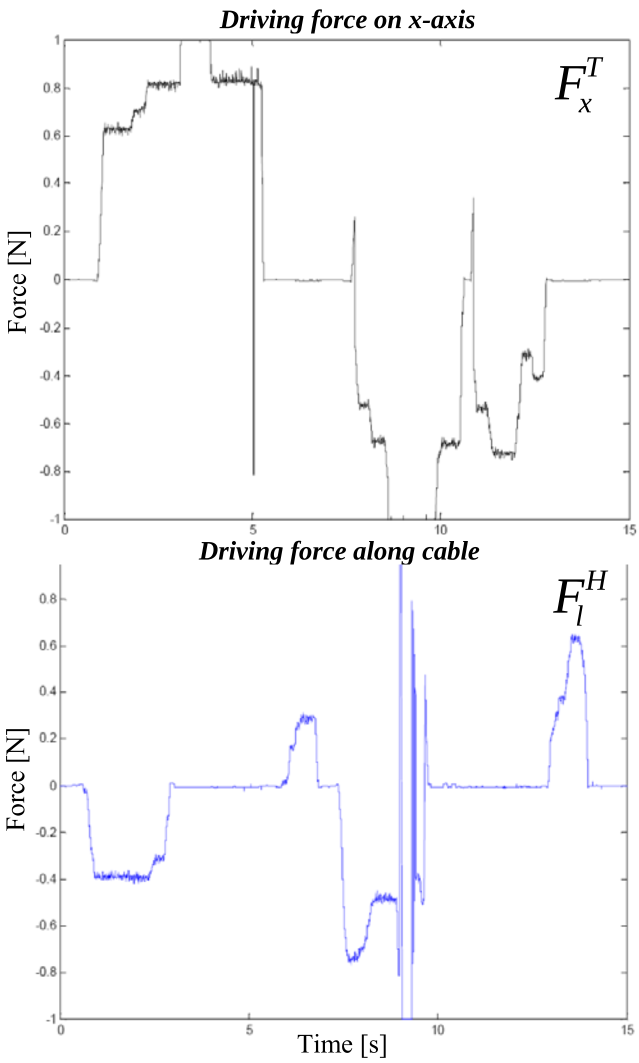

Fig. 12 - Driving force for Case 3

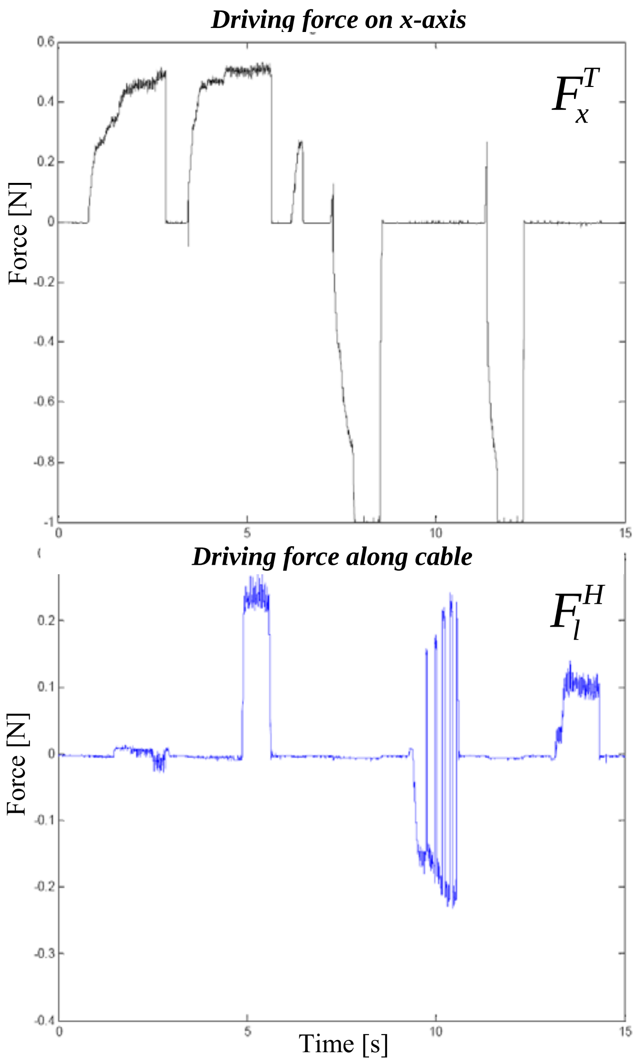

Fig. 13 - Driving force for Case 4

6. CONCLUSIONS

It was shown that by using of a suitable mathematical apparatus can forecast the future behaviour of a mechanical structure. The vector time series (Vector Autoregressive Moving Average Models – VARMA) were chosen as a suitable mathematical apparatus and the suitability of this choice were proven by use of computer simulation of stochastically excited mechanical systems (2). Procedure of statistically adequate models is getting concentrated in principle of output signals substituting (using non-linear least square method) with models of gradually increasing order until the decreased sum of squares becomes statistically non-significant on a chosen level of significance. Physical meaning of such a procedure is in that we are trying to substitute the system with a model with the lowest number of statistically significant modes of vibrations. During this procedure, each increase of model order by two introduces (a further degree of freedom). If its contribution in not significant, the former model is taken as statistically adequate. In detail is involved strategy described in (8).

It introduces problems were proposed and verified in a frame of grant research, where some possible applications of the proposed identification procedure were investigated. It was namely a connection of proposed identification procedure with systems of complicated machine structures solution using FEM.

In this paper, we have proposed a modelling method by using virtual simulation to identify the important parameters of large-scaled gantry crane. Depending on the experiment results, system identification is used to identify parameters of gantry crane including damping and stiffness matrices. MATLAB program is also applied, with the least squares method (10). However, the least squares method can not be regarded as a suitable algorithm for parametric identification of the large-scale gantry crane system, because the nonlinear character of system is too high.

ACKNOWLEDGEMENT

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