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THE MULTI-EQUATIONAL MODELS IN THE ANALYSIS OF RESULTS OF MARINE DIESEL ENGINES RESEARCH

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Abstract

Contemporary empirical researches on the object, which is combustion engine, are proceeded basing on the theory of experiment. Available software applications to analyze the experimental data commonly use the multiple regression model, which enables studying effects and interactions between input values of the model and single output variable. Using multi-equational models gives free hand at analyzing measurement results because it enables analysis of effects and interaction of many output variables. In this paper author presents advantages of using the multidimensional regression model on example of researches conducted on engine test stand.

Keywords: *marine diesel engine, theory of experiment, toxic compounds, emission*

1. Introduction

Contemporary empirical researches on the object, which is combustion engine, are conducted basing on the theory of experiment. Basic purpose of such proceeded scientific researches is to prove the relation between the input signals (introduced by researcher) and output signals (observed by him). The final purpose of statistic analysis of the results of measurements is to determinate functions of the test object and the empirical model of functional engine. Related to this task very wide equations using calculus of probability, theory of stochastic processes and differential calculus are very time-consuming and without computer technique and specialist software are practically impossible. In the process of solving problems concerning interrelationships and complementary approximation issues, statistic correlations, relevancy assessment and inaccuracy of measurements and also adequacy of functions of test object with mathematical issues and graphic defining special points are used available computer programs, among all package STATISTICA PL. Mentioned programs are based on the analysis of variation and they assure:

- defining coefficients of function regression in the test object;
- assessing principal effects and interactions;
- defining correlations of input and output values;
- assessing adequacy of function in the test object (empirical functional model);
- defining mathematical dependences assumed by the operator, which results from the elaborated functional model.

It should be emphasized that the statistic computer analysis could relate to various models which do not concern interactions at various stages of complication, which are accepted in the description of model of input values. Simultaneously there is possibility of rejecting (disregarding) in the statistic analysis both at choice selected input values describing the object and various types of interactions. It means that choice of the appropriate (most adequate) model depends on the operator and his knowledge about the specialist theoretical basis of the researched issue.

At assumed lower accuracy of projecting reality and in practice in case of defining the character of changes (trend) of output values there is possibility of significant simplification of approximating polynomials by concerning only input values and only these of interactions which are statistically significant. Also the stage of approximating polynomials decides about the stage of model complexity and complication of basic values. So it is justifiable pursuing to creating models with the possibly simple form and the most profitable linear models. It is supposed that with regard for making some mistakes it is better to describe researched issue with non-linear character in small linear sections than in single complex non-linear complete section.

Commonly used software securing the experiment planning and its further analysis do not give free hand in analyzing collected material but they use prepared above presented schemes of analysis. So interfering in the program (program package) is impossible. Noticeable in the recent period development of social, medical and economic sciences caused rapid progress in using statistic methods which secure planning the experiment [3,9,10]. Especially econometria has great achievements in this field and new approach to the statistic analysis could be successfully used in technical researches [2]. Among all using the multi-equational models gives possibilities to study the correlations between input and output values and additionally concern feedbacks between output variables and gives possibility of their direct analysis. Such assumption in contrary to commonly used multiple regression is closer to real conditions even if considering the Diesel dilemma i.e. dependence between CO, HC and NO_x. concentration.

Below are presented results of researches on the fuel feeding system of the engine (injection system) using the double-value fractious plan and multi-equational model.

2. Researches on the fuel feeding system of the engine using double-value fractious plan

The object of research was fuel feeding system in the single-cylinder test engine 1SB installed in the Exploitation Laboratory of Shipping Power Stations in the Naval Academy [11].

To identify the influence of technical condition of engine on the energetic parameters of engine, there were defined sets of the input values (given parameters) and output values (observed parameters).

1. Set of the input values X:

- x_1 - rotational engine speed *n [rev/min];*
- x_2 – engine torque T_{tq} *[N·m];*
- x_3 – leak of the cylinder-injection pump piston set S_{pw} $[\mu m^2]$;
- x_4 – leak of the discharge valve of pulverizer needle S_{zt} $[\mu m^2]$;
- x_5 – leak of the skirt of pulverizer needle S_i $[\mu m^2]$;
- x_6 – leak of the needle cone in the pulverizer setting S_r $[\mu m^2]$;
- x_7 – erosive wear of the pulverizer nozzle S_e $[\mu m^2]$;
- x_8 – coking of the pulverizer nozzle S_k $[\mu m^2]$;
- x_9 – strain injector spring ΔP *[MPa].*

2. Set of the output values *Y*:

- y_1 - fuel injection advance angle α_{ww} $[^oOWK]$;
- y_2 – fuel injection angle α_w $[^oOWK]$;

- y_3 – injector opening pressure p_{owtr} *[MPa];*
- y_4 *–maximal fuel injection (forcing) pressure* $p_{wtr(max)}$ *[MPa];*
- y_5 - speed of pressure accumulation in the cylinder $(\Delta p/\Delta\alpha)_s$ $[MPa/^oOWK]$;
- y_6 – speed of pressure accumulation in the injection conduit $(\Delta p/\Delta\alpha)$ $[MPa/^oOWK]$;
- y_7 – fuel consumption per hour B *[g/h]*
- y_8 – outlet exhaust temperature from the cylinder T_{g1} *[K];*
- y_9 – mean indicated pressure p_{mi} *[MPa];*
- y_{10} – compression pressure during the fuel injection p_c *[MPa];*
- y_{11} – highest compression pressure $p_{c(max)}$ *[MPa];*
- y_{12}– maximal combustion pressure p_{max} *[MPa];*
- y_{13} – angle at the moment of maximal combustion pressure α_{pmax} $[^oOWK]$;
- y_{14} – carbon monoxide concentration in the outlet exhaust manifold $C_{CO(k)}$ *[ppm];*
- y_{15} – carbon monoxide concentration in the crankcase $C_{CO(s)}$ *[ppm];*
- y_{16}– hydrocarbon concentration in the outlet exhaust manifold $C_{HC(k)}$ *[ppm];*
- y_{17}- hydrocarbon concentration in the crankcase $C_{HC(s)}$ *[ppm];*
- y_{18}– nitric oxide concentration in the outlet exhaust manifold $C_{NOx(k)}$ *[ppm];*
- y_{19}- nitric oxide concentration in the crankcase $C_{NOx(s)}$ *[ppm];*
- y_{20} – oxygen concentration in the exhausts C_{O2} *[%];*
- y_{21} – air-excess coefficient λ.

For this present paper analysis of the input values were limited to seven values (y_{14}, y_{15}, y_{16}, y_{17}, y_{18}, y_{20}, y_{21}).

As a result of conducted analysis there double-value fractional plan with possibly highest resolution (R = III) and maximal incomplication of interaction of values describing the functional empirical model of fuel feeding system of engine was worked out to realize laboratory artificial tests. Presented in the beginning remarks of general nature and results of analyzed own researches justified linear model [7,11] assumed in the tests of fuel feeding system of engine. Therefore statistic analysis is limited to justification of chosen model, defining approximating polynomials and also characteristic and estimation using possible statistic measures.

As a result of conducted analysis was accepted model considering double-factor interactions, in which the highest values of determination coefficient $R^2 = 1$ and total of rest $MS = 0$ characterize all polynomials approximating output values. Values of these measures indicate that the model is according to the theory of experiment the accepted model is most adequate. Considerably lower values of determination coefficient and significant total of rest are characteristic of the model without interactions, and what is more these differences are depend on defined output values.

Graphic confirmation of rightness of decision can be also exceptional diagrams in Fig. 1.

Determined approximating polynomials allow to define any dependences between individual variables and also to calculate and estimate the influence of introduced (simulated) failures (wear) of the elements in fuel injection equipment on the work and toxicity indicators of engine [3,8]. It is assumed that it is possible to define relations (correlations) between the parameters of structure and exhaust toxicity indicators directly or indirectly using the engine operating indicators. It is assumed that this way it would be possible to select diagnostic parameters of defined elements or sets of engine fuel equipment among the exhaust compounds.

3. Researches on the fuel feeding system of engine using the multi-equation models

As it was mentioned above, commonly available models which were used to test analysis and based on an analysis of the multiple regression have not given possibility of research in the model of input variable (1) connections [2]. Fundamental feature of the models with correlative equations is the fact that they allow the existence of feedback between the input variables, which is certainly a real issue.

Below will be presented theoretic basis of the multi-equational models and its practical use on example of the presented in advance plan of experiment.

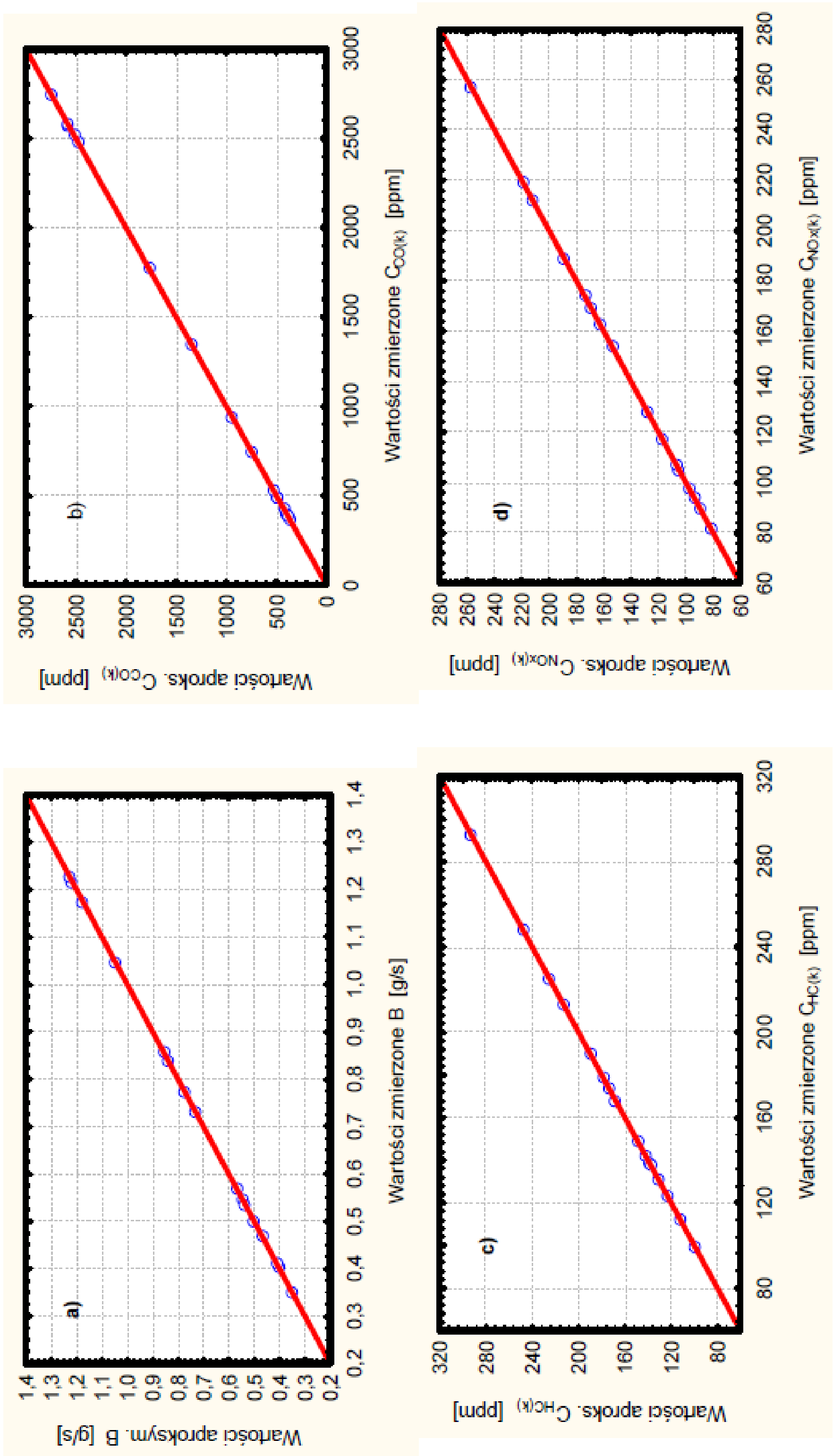

Fig. 1. Dependences between approximated and measured values in the model with interactions fuel consumption, b) concentration of carbon oxides; c) concentration of hydrocarbons; d) concentration of nitric oxides in the outlet exhaust manifold

Dependence between the input signals $x_1, x_2, \cdots, x_N$, and the output signals $y_1, y_2, \cdots, y_M$ could be described by means of the linear system of equations

$$
\begin{aligned}
y_1 &= b_{12}y_2 + b_{13}y_3 + b_{14}y_4 + \cdots + b_{1M}\, y_M \;\; + a_{10} + a_{11}x_1 + a_{12}x_2 + \cdots + a_{1N}x_N + \xi_1 \\
y_2 &= b_{21}y_1 + b_{23}y_3 + b_{24}y_4 + \cdots + b_{2M}\, y_M \;\; + a_{20} + a_{21}x_1 + a_{22}x_2 + \cdots + a_{2N}x_N + \xi_2 \\
y_3 &= b_{31}y_1 + b_{32}y_2 + b_{34}y_4 + \cdots + b_{2M}\, y_M \;\; + a_{30} + a_{31}x_1 + a_{22}x_2 + \cdots + a_{3N}x_N + \xi_3 \\
&\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\
y_M &= b_{M1}y_1 + b_{M2}y_2 + \cdots + b_{MM-1}y_{M-1} + a_{M0} + a_{M1}x_1 + a_{M2}x_2 + \cdots + a_{MN}x_N + \xi_M
\end{aligned} \tag{1}
$$

where:

$y_i, i = 1,2,\ldots,M$ - explained variables (output),

x_j , $j = 1.2,\ldots,N$, - explanatory variables (input),

b_{ij} – is a coefficient appearing in i - this equation at j - this explained (output)variable, $i, j = 1,2,\cdots,M$

a_{ij} - is a coefficient appearing in i - this equation at j - this explanatory (input) variable, $i = 1,2,\cdots,N$, $j = 0,1,\cdots,N$,

ξ_i - is unobserved random element in i -this equation.

System of equations (1) can be described in the matrix form

$$\mathbf{BY} = \mathbf{AX} + \xi \tag{2}$$

where:

$$
\mathrm{B} = \begin{bmatrix} 1 & -b_{12} & \cdots & -b_{1M} \\ -b_{21} & 1 & \cdots & -b_{2M} \\ \cdots & \cdots & \cdots & \cdots \\ -b_{M1} & -b_{M2} & \cdots & 1 \end{bmatrix}, \qquad
\mathrm{A} = \begin{bmatrix} a_{10} & a_{11} & \cdots & a_{1M} \\ a_{20} & a_{21} & \cdots & a_{2M} \\ \cdots & \cdots & \cdots & \cdots \\ a_{M0} & a_{M1} & \cdots & a_{MN} \end{bmatrix},
$$

$$
\mathrm{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ yM \end{bmatrix}, \quad
\mathrm{X} = \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_N \end{bmatrix}, \quad
\xi = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \cdots \\ \xi_K \end{bmatrix} \quad .
$$

Identification of the configuration (1) means the issue of selecting coefficients of the system of equations (1) at values of input signals known from the measurements on the real object of input values $\tilde{y}_{1\nu}, \tilde{y}_{2\nu}, \cdots, \tilde{y}_{M\nu}$, $\nu = 1,2,\cdots,K$.

therefore defined from the measurements $\tilde{x}_{1\nu}, \tilde{x}_{2\nu}, \cdots, \tilde{x}_{N\nu}$, $\nu = 1,2,\cdots,K$ values of input variables $x_1, x_2, \ldots, x_N$ would be presented in the form of matrix of measurements values of input signals

$$
\tilde{\mathrm{X}} = \begin{bmatrix} 1 & \tilde{x}_{11} & \cdots & \tilde{x}_{N1} \\ 1 & \tilde{x}_{12} & \cdots & \tilde{x}_{N2} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \tilde{x}_{1K} & \cdots & \tilde{x}_{NK} \end{bmatrix},
$$

where, similarly to above presented plan of experiment the individual input values are placed in sequence in the columns:

x_0 – indeterminate element,

x_1 – rotational engine speed n,

x_2 – load of engine at torque T_{tq},

x_3 – wear of the cooperative surfaces of cylinder and fuel pump piston S_{pw},

x_4 – loss of leakproofness of the pumping valve S_{zt},

x_5 – wear of the skirt of pulverizer needle S_i,

x_6 – wear of the taper part of sealing needle in the pulverizer setting S_r,
x_7 – wear of the pulverizer nozzle S_e,
x_8 – coking of the pulverizer nozzle S_k,
x_9 –power loss of strain of the pulverizer spring Δp.

However, recorded values $\tilde{y}_{1\nu}, \tilde{y}_{2\nu}, \cdots, \tilde{y}_{M\nu}, \quad \nu = 1,2,\cdots,K$ output signals $y_1, y_2, \cdots, y_M$ were written in the form of matrix of measurement values of output signals

$$\tilde{Y} = \begin{bmatrix} \tilde{y}_{11} & \tilde{y}_{21} & \cdots & \tilde{y}_{M1} \\ \tilde{y}_{12} & \tilde{y}_{22} & \cdots & \tilde{y}_{M2} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{y}_{1K} & \tilde{y}_{2K} & \cdots & \tilde{y}_{MK} \end{bmatrix},$$

where individual output values are placed in sequence in the columns:
y_1 – air-excess coefficient λ,
y_2 –carbon oxide concentration in the outlet manifold C_{COk},
y_3 – carbon oxide concentration in the crankcase C_{COs},
y_4 – hydrocarbon concentration in the outlet manifold C_{HCk},
y_5 – hydrocarbon concentration in the crankcase C_{HCs},
y_6 – nitric oxide concentration in the outlet manifold C_{NOxk},
y_7 – oxygen concentration in the outlet manifold C_{O2k}.

System of equations (1) can be written in the reduced form by multiplying equation (2) by matrix $\mathbf{B}^{-1}$ opposite to matrix $\mathbf{B}$ assuming that its determinant is different from zero, then

$$B^{-1}BY = (B^{-1}AX) + B^{-1}\xi,$$

from this

$$Y = B^{-1}AX + B^{-1}\xi.$$

Marking

$$\Pi := B^{-1}A, \quad \eta := B^{-1}\xi \tag{3}$$

following form of the reduced model is obtained:

$$\mathbf{Y} = \mathbf{\Pi X} + \boldsymbol{\eta} \tag{4}$$

where:

$$\mathbf{\Pi} = \begin{bmatrix} \pi_{10} & \pi_{11} & \cdots & \pi_{1N} \\ \pi_{20} & \pi_{21} & \cdots & \pi_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{M0} & \pi_{M1} & \cdots & \pi_{MN} \end{bmatrix}, \quad \boldsymbol{\eta} = \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_M \end{bmatrix}.$$

Reduced model in the form of system of equation is following:

$$\begin{array}{lll} y_1 & = & \pi_{10} + \pi_{11}x_1 + \cdots + \pi_{1N}x_N + \eta_1 \\ y_2 & = & \pi_{20} + \pi_{21}x_1 + \cdots + \pi_{2N}x_N + \eta_2 \\ \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ y_M & = & \pi_{M0} + \pi_{M1}x_1 + \cdots + \pi_{MN}x_N + \eta_M \end{array} . \tag{5}$$

Coefficients $\pi_{i0}, \pi_{i1}, \ldots, \pi_{iN}, \; i = 1,2,\ldots,M$ from the above system of equation were selected such way to function

$$J_i(\pi_{i0}, \pi_{i1}, \ldots, \pi_{iN}) = \sqrt{\sum_{\nu=1}^{k} (\pi_{i0} + \pi_{i1}\tilde{x}_{1\nu} + \pi_{i2}\tilde{x}_{2\nu} + \ldots + \pi_{iN}\tilde{x}_{N\nu} - \tilde{y}_{i\nu})^2}, \quad i = 1,2,\ldots M \tag{6}$$

reaching the minimum, and problem of selecting best model from the range of equations (5) in sense of minimizing the quality identification indicators (6) was solved using the theorem of orthogonal projection [1], so the optimal coefficients

$$\pi_{ij}^0, \quad i = 1,2,\ldots,M, \quad j = 0,1,\ldots,N$$

reduced form of model (5) can be defined from the identity

$$\hat{\Pi}^T = (\tilde{X}^T \tilde{X})^{-1} \tilde{X}^T \tilde{Y} \tag{7}$$

where matrix of coefficients is following:

$$\hat{\Pi}^T = \begin{bmatrix} \pi_{10}^0 & \pi_{20}^0 & \cdots & \pi_{M0}^0 \\ \pi_{11}^0 & \pi_{21}^0 & \cdots & \pi_{2M}^0 \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{1N}^0 & \pi_{2N}^0 & \cdots & \pi_{MN}^0 \end{bmatrix},$$

The next step of analysis is defining the matrix of variation and co-variation of estimator Π, examining the confidence range for individual coefficient of multiple regression π_{ij}, which is a coefficient of matrix Π, defining the coefficient of multiply correlation R [1,5,6].

All of those variables which possibly could have influence on the forming variable value *Y* should be considered while constructing the regression model. Not every of these variables are significant in the model. To verify which of input variables have not significant influence on the output variables *Y* the relevancy test should be use to every of obtained coefficients of model at individual variables. This test allows to verify the hypothesis that value of regression coefficient is zero. Only after rejecting such hypothesis we can claim that specific variable is significant in the linear regression model. Variables, at which regression coefficients are not significantly different from zero, should be removed from the model and construct model with lower amount of explanatory variables [2].

Final multi-equational model in which all coefficient are significant and it can be used in practice e.g. for diagnostic purposes we obtain only at the second or third stage, what is more at every stage coefficients of multi-equational regression of individual model are estimated, their statistic relevance and removes variables with regression coefficients insignificant from zero [2].

In considered case statistic *t* has arrangement *t* – Student at *K*-*N*-1=20-9-1=10 freedom stages and relevance indicator α = 0,1, and read off the schedule table *t* – Student's crucial value t_α = 3,169 [1]. After conducting the series of test it is seems that the criteria are too severe. It was experimentally certify that lower values t_α significantly approach the model.

After verifying the relevancy of its parameters and rejecting insignificant values as a result, it comes to the considerable simplification of models. The result of analysis is that following dependences occur [11]:

$$\begin{aligned} y_1 &= f(x_1, x_2) \\ y_2 &= f(x_2, x_7) \\ y_3 &= f(x_2, x_8) \\ y_4 &= f(x_2, x_4, x_5, x_6) \\ y_5 &= f(x_2, x_3, x_4, x_5, x_6, x_7) \\ y_6 &= f(x_4, x_5, x_6, x_7) \\ y_7 &= f(x_1, x_2, x_6) \end{aligned}$$

In accordance with (1) an equation y1 describing change of air-excess λ has form:

$$y_1 = b_{12} y_2 + b_{13} y_3 + b_{14} y_4 + b_{15} y_5 + b_{16} y_6 + b_{17} y_7 + a_{10} + a_{11} x_1 + a_{12} x_2 .$$

After reducing (considering relevance of coefficients) the equation was accepted

$$y_1 = b_{12} y_2 + b_{17} y_7 + a_{10} + a_{12} x_2 .$$

Differences between the measured parameters and parameters obtained from the multi-equational model $\tilde{y}_\nu - \hat{y}_\nu, \quad \nu \in \overline{1,20}$ are insignificant. It is confirmed by the courses of dispersion compared in the Fig. 2. The result of their analysis is that adjusting obtained model to values obtained in the experiment are significant.

In case of other models the equations of output variable are following:

$$y_2 = b_{21}y_1 + b_{23}y_3 + b_{24}y_4 + b_{25}y_5 + b_{26}y_6 + b_{27}y_7 + a_{20} + a_{21}x_1 + a_{22}x_2$$
$$y_3 = b_{32}y_2 + b_{35}y_5 + b_{37}y_7 + a_{38}x_8$$
$$y_4 = b_{41}y_1 + b_{45}y_5 + b_{47}y_7 + a_{40} + a_{44}x_4 + a_{45}x_5 + a_{46}x_6$$
$$y_5 = b_{52}y_2 + b_{53}y_3 + b_{54}y_4 + b_{57}y_7 + a_{50}$$
$$y_6 = b_{61}y_1 + b_{67}y_7 + a_{60} + a_{64}x_4 + a_{65}x_5 + a_{67}x_7$$
$$y_7 = b_{71}y_1 + b_{72}y_2 + a_{70} + a_{72}x_2$$

Analyzing equations obtained as a result of model equation researches it should be state that:

- in case of first equation i.e. dependence describing changes of air-excess coefficient λ, it depends on the changes of load of torque T_{tq} and along with them appear changes of carbon oxide concentration in the outlet manifold and changes of nitric oxide concentration. Relation between changes of CO and NO_x is accurate, because in both case amount of oxygen decides about emission of these compound. In case unsupercharged engine of Increase of load also causes the decrease of amount of fresh load in the cylinder.
- in case of carbon oxide concentration in the outlet manifold C_{COk} (y_2) the equation combines dependence between carbon oxide concentration in the crankcase C_{COs}, hydrocarbon concentration in the outlet manifold C_{HCk} and in the crankcase C_{HCs}, nitric oxide concentration C_{NOxk}, oxygen concentration C_{O2} and two input parameters i.e. rotational engine speed n i and load T_{tq}. Analyzing values of the coefficients the most significant are coefficient which are responsible for the amount of oxygen in the combustion chamber. The most insignificant is coefficient which forms value of NO_x.
- carbon oxide concentration in the crankcase C_{Cos} (y_3) is described by the changes of carbon oxide concentration in the outlet manifold C_{COk}, nitric oxide concentration C_{NOxk} and input value i.e.: coking pulverizer nozzle S_k. The greatest influence has variable C_{NOxk}, and it results from the previous researches, because the linear dependence between emission of C_{Cos} and C_{NOxk} is noticeable.
- in case of concentration of hydrocarbons in the outlet manifold C_{HCk} (y_4) the equation combines dependence between air-excess coefficient λ, concentration of hydrocarbon in the crankcase C_{HCs}, concentration of nitric oxides C_{NOxk} and input values, i.e. loss of leakproofness in the pumping valve S_{zt}, wear of the skirt of pulverizer needle S_i and wear of taper sealing part of pulverizer needle in the injector setting S_r. The most significant is air-excess coefficient λ. Also significant is variable C_{NOxk} though it has opposite direction to λ. At the similar level of impact remains input variable S_i, i.e. wear of the skirt of pulverizer needle.
- concentration of hydrocarbons in the crankcase C_{HCs} (y_5) is described by the output variables, first of all concentration of hydrocarbons in the outlet manifold C_{HCk}, which as it was known from the previous researches changes in proportion to concentration of C_{HCs}, at similar level of impact remain C_{COk} and C_{NOxk}., although they are inversely proportional to C_{NOxk}.
- changes of concentration of nitric oxides C_{NOxk} (y_6) describes firt of all the dependence of air-excess coefficient λ, i.e. factor which is directly responsible for forming the nitric oxides. At the lower level is variable C_{O2}. Changes of concentration of nitric oxides C_{NOxk} are also described by input variable S_i, i.e. wear of the skirt of pulverizer needle.
- changes of oxygen concentration in the outlet manifold C_{O2} (y_7) are described, similarly to the changes of λ from the first equation, first of all air-excess coefficient, from he first equation first of all air-excess coefficient, oppositely correlated nitric oxide concentration in the outlet manifold C_{COk}. Similarly correlated is also input variable which comes from engine load by torque T_{tq}.

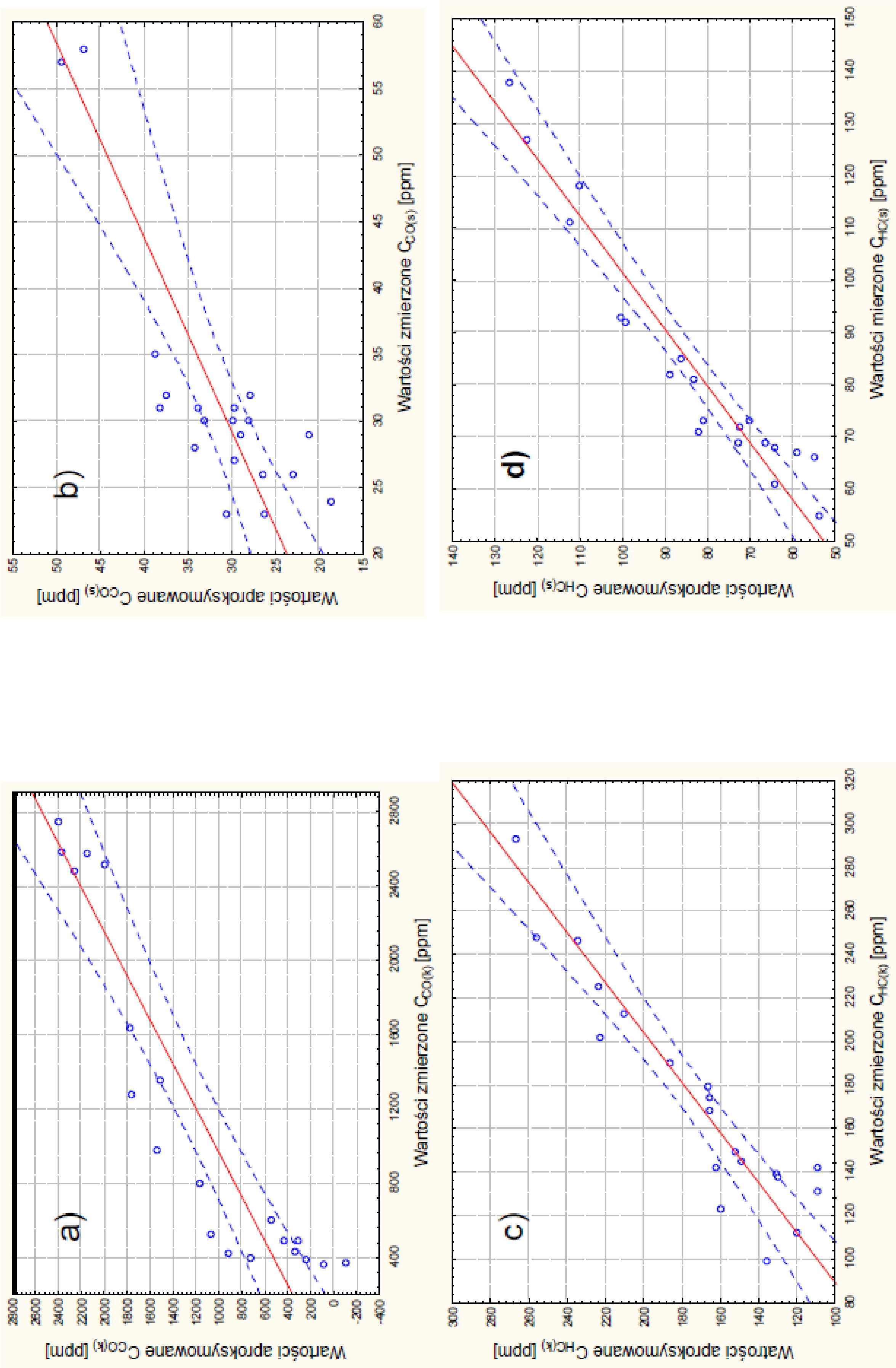

Fig. 2. Dependences between the approximated and measured values in the multi-equational model a) concentration of carbon monoxide in the manifold; b) concentration of carbon monoxide in the crankcase; c) concentration of hydrocarbons in the manifold; d) concentration of hydrocarbon in the crankcase

4. Conclusions

Presented description of the active experiment space by the multidimensional models gives great possibilities in analysis of measurement data and scientific conclusions. Furthermore, assuming that coefficients' matrix Π^T is orthogonal, there is a possibility of fulfilling reverse task, that is assessing, with complex relevance at known input variables, which describe work point i.e. engine rotational speed n and torque load T_{tq}, the other input values. In the nearest future authors will work on this issue.

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