SUPERIOR INFERENTIAL STATISTICS OF THE EXPERIMENTAL DATA OF A COMPLEX EXPERIMENTAL CULTIVATOR
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STATISTICA INFERENȚIALĂ SUPERIOARĂ A DATELOR EXPERIMENTALE ALE UNUI CULTIVATOR EXPERIMENTAL COMPLEX

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ABSTRACT
The aim of the research is to highlight some statistical tools that favour extracting the components of the dynamic process that are dependent on the forward speed of some agricultural aggregates. The main objectives are: (I) identification of a minimum number of components in a multitude of random variables, with the help of which the other random variables can be calculated, and the application of this result to the strain gauge measurements; (II) establishing the connection between the synthetic results that partially solve the first objective and the forward speed of the agricultural aggregate. The second objective is used to obtain indications in search of the parameters' dependencies on the forward speed of the aggregate. The first objective seeks to determine a group of three signals from the twelve, with the help of which the best multivariate linear interpolation is obtained for the other nine signals, which in physical terms means the reduction to a quarter of the measurement points and of the strain sensors used. A result associated with the first objective refers to the estimation of information loss due to the limited number of deformation sensors mounted on the tested structure. The article also presents attempts to use the results of the theory of neural networks and statistical interaction. In order to capitalise on the experimental data in this complex statistical framework, it is necessary to monitor at least the working speed (not only the average speed per experiment), fuel consumption, working depth (continuously monitored), soil moisture etc.

REZUMAT
Scopul cercetării este de a evidenția unele instrumente statistice care favorizează extragerea componentelor procesului dinamic care sunt dependente de viteza de avans a unor agregate agricole. Principalele obiective sunt: (I) identificarea unui număr minim de componente într-o multitudine de variabile aleatoare, cu ajutorul cărora pot fi calculate celelalte variabile aleatoare și aplicarea acestui rezultat la măsurătorile extensometrice; (II) stabilirea legăturii dintre rezultatele sintetice care rezolvă parțial primul obiectiv și viteza de avans a agregatului agricol. Al doilea obiectiv este utilizat pentru a obține indicații în căutarea dependențelor parametrilor de viteza de avans a agregatului. Primul obiectiv urmărește determinarea unui grup de trei semnale din cele douăsprezece, cu ajutorul cărora se obține cea mai bună interpolare liniară multivariată pentru celelalte nouă semnale, ceea ce în termeni fizici înseamnă reducerea la un sfert a punctelor de măsurare și a senzorilor de deformare utilizați. Un rezultat asociat primului obiectiv se referă la estimarea pierderii de informații din cauza numărului limitat de senzori de deformare montați pe structura testată. Articolul prezintă, de asemenea, încercări de utilizare a rezultatelor teoriei rețelelor neuronale și a interacțiunii statistice. Pentru a valorifica datele experimentale din acest cadru statistic complex, este necesar să se monitorizeze cel puțin viteza de lucru (nu doar viteza medie pe experiment), consumul de combustibil, adâncimea de lucru (monitorizată continuu), umiditatea solului etc.

INTRODUCTION
The results presented in this article are the last of the series of those presented by *Cardei and collaborators* (*Cardei et al., 2023a*; *Cardei et al., 2023b*; *Cardei et al., 2023c*) regarding the numerical data obtained in the field with a complex structure of experimental cultivator MCLS.

The dependence of some parameters of the dynamics of agricultural aggregates on the forward speed has been studied for many decades, with various solutions appearing in many publications (*Letosnev, 1959; Moenifa et al., 2014; Cardei et al., 2019; Cardei et al., 2020; Ranjbar et al., 2013; Naderloo et al., 2009; ASAE, 2003 and 2017; McKyes, 1985; Owen 1989; Larson, 1964; Fechete-Tutunaru et al., 2019; Cardei et al., 2023b; Shafei et al., 2018; Damanauskas, Janulevicius, 2022; Dizaji, 2022; Karmarkar, Gilke, 2021; Askari et al., 2017; Al-Suhaibani, Ghaly, 2010; Elsheika et al., 2021; Deshpande, Shirwal, 2017; Saleh et al., 2021; Rashidi et al., 2013*), for example. In general, the draft force depending on the main parameters that define the soil, the geometry of the working bodies, the mass of the machine, the forward speed, the working depth, and the working width was studied and modelled. At first, simple models were proposed, for example *Letosnev* (*1959*), then the models were gradually complicated with geometric components, for example (*McKyes, 1985; Owen 1989; Al-Neama, Hertzilius, 2017*). Later, generalisations appeared relative to the components that contain work speed, in *ASAE* (*2003*) or *Moenifar et al.* (*2014*). In search of more precise approximations of the draft force, the research became theoretical-experimental. The experimental data were directly transformed into formulas through various interpolation procedures. Since experimental research has taken place on a large scale, statistics have been increasingly used for the processing of experimental data, as shown in *Da Silva et al.* (*2020*) or *Gomez and Gomez* (*1984*), referring to modern agriculture. Having as an objective the rationalisation of fuel consumption, the authors *Mamkagh*(*2018*) and *Singh et al.* (*2018*) carried out some review of the main influencing factors: forward speed, tractor ballast, and tyre pressure. Finally, the authors *Sadek et al*. (*2021*) determine, using experimental data, a linear regression equation in which the forward speed, gang angle, inclination angle, working depth, and disc diameter appear. The authors *Ahmed and Al_Sayed* (*2022*) obtained results regarding the influence of forward speed and soil type on the performance of the Massey Ferguson tractor (model 290). Analysis of variance, or ANOVA tests, are used, for example in *Deshpande and Shirwal*(*2017*), to determine the influence of the forward speed and the shape of the working bodies on the draft force. Statistical modelling has become a tool often used to make predictions of draft force. For this purpose, speed and working depth are used as predictors, as are others (*Afify et al.,2020; Kim et al., 2020; Rashidi, 2013a and 2013b; Saleh et al., 2021*). Artificial neural networks have started to be used in the last decades to obtain predictions of the parameters targeted in the field of agricultural soil processing (*Shafei et al., 2018; Çarman et al., 2021; El Wahed, Aboukarima, 2007; Al-Dosary et al., 2020; Carman et al., 2019; Askari, Abbaspour-Gilandeh, 2020*). Also, nonlinear regression formulas for the problem of predicting the draft tillage force are used in *Shafei et al.* (*2018*) and *Almaliki et al*. (*2019*), in the case of a disc plough. The use of neural networks in the case of measuring several parameters, including fuel consumption, allowed highlighting the decrease in this consumption with the increase in forward speed (*Çarman et al., 2019*).

Proceeding in this way, the generality of the solution is deeply affected due to the dependence on the soil and the environmental conditions in which the experiments were made. Not only the generality was affected, but also the cost of research. Experimental research, however satisfactory, is expensive and beyond the reach of any research team.

The research whose results are described in this work also uses experimental data in the statistical framework, both descriptive and inferential. Within the descriptive statistics, it was sought to highlight some estimators that are well correlated with the forward speed. Inferential statistics were used to investigate the possibilities of reducing the number of measurements or measurement points with minimal loss of information. For this purpose, linear multivariate analysis techniques were used, which are also used in PCA analyses or in neural networks. Due to the small data structure, the statistical analysis of the networks, which can provide very important results, could not be applied in these studies (*Brinkmeier, Schank, 2005; Avrachenkov, Dreveton, 2022*). Instead, it was possible to estimate some of the structural data needed for modelling, which must be collected in future experiments to effectively use such statistical tools.

Regarding the first objective of our research, namely that of studying the relationships between the randomvariables that describe each recording within an experiment, modern statistics provides a specific notion calledinteraction (statistics), defined in *Dodge* (*2003*); *Cox* (*1984*); *https://en.wikipedia.org/wiki/Interaction_(statistics)*. According to these sources, in statistics, an interaction can occur when considering the relationship between three or more variables and describing a situation where the effect of one causal variable on an outcome depends on the state of a second causal variable (i.e., when the effects of the two causes are not additive). Interactions are often considered in regression analyses or factorial experiments. Non-linear relationships with interaction have been proposed since the beginning of modelling the phenomenon of soil processing in agriculture (*Cardei et al., 2019*).

Also, in a research done by *Dodge* (*2003*), it was stated that the presence of interactions can have important implications for the interpretation of statistical models. If two variables of interest interact, the relationship between each of the interacting variables and a third "dependent variable" depends on the value of the other interacting variable. In practice, this makes it more difficult to predict the consequences of changing the value of a variable, especially if the variables it interacts with are difficult to measure or control.

The notion of interaction is closely related to that of moderation, which is common in social and health science research. The interaction between an explanatory variable and an environmental variable suggests that the effect of the explanatory variable was moderated or modified by the environmental variable (*Dodge, 2003*). This framework of statistical interaction is probably the best description of our research framework for achieving, the first goal. The link between the notions of interaction and influence is strong, as the dictionary also shows (*https://dexonline.ro/definitie/interacțiune;https://dictionary.cambridge.org/dictionary/english/interaction*).

The efficiency of some modern scientific tools is evaluated in the problem of forecasting traction parameters in soil works, such as the neuro-fuzzy strategy (*Shafei et al., 2018*). The method of optimising the combination of channels that, through multivariate analysis, can generate the best linear approximations of the other channels considered unmonitored, presented in subchapter 2.3 and whose results are summarised in table 3, is part of the working techniques of inferential statistical analysis described in the last paragraphs. The method is simple and logical, and it only needs knowledge of the definitions of the notions to be worked with. Calculation algorithms can be easily developed without the need for software specialists. The calculation volume increases a lot with the number of basic channels (monitored and unmonitored) and with the number of experiments. The dependence on the working speed of the optimal predictor channel combinations is insignificant, remaining in the field of randomness.

MATERIALS AND METHODS

The working material of the research whose results are presented in this article is made up of the strain gauge measurement recordings made in experiments carried out in 2022, presented in detail in *Cardei et al.* (*2023a and 2023b*).

The research, the results of which are described in this article, proposed the analysis of experimental recordings as sets of parametrized random variables. Concretely, the sets of random variables are the experimental records (converted into draft force) grouped into 12 numerical strings each, with different lengths between 2000 and 4000 samples (real numbers). Seven such groups of random variables were examined and parameterized according to the timed average speed corresponding to each experiment.

Our investigations tried to highlight the characterization efficiency of some statistical tools, the detection of possible links between the random variables of each group or the non-existence of these links, the correlation of some characteristics with the values of the characterization parameters of the groups (forwarded speed), or the non-correlation. Therefore, the investigations are open to any conclusions and do not follow a fixed orientation, such as, for example, the optimisation of some work regimes. The aim is only to obtain information that can be used in the research activities that will be developed.

Fig. 1 - The tractor unit (45 HP)-MCLS, the version with a working width of 1 m (left), and the locations of the deformation sensors on the supports of the working bodies of the MCLS (right)

2.1. The average signal

In this chapter, the average signal of the twelve signals collected from the supports of the working bodies of the MCLS, the version with a working width of 1 m, will be defined according to equation (2). Definition (1) was considered.

$$A = \{x_{i,j}, i = 0, \dots n, j = 0, \dots, 11\} \tag{1}$$

Where: A is the matrix of numerical recordings converted into forces obtained from the twelve deformation sensors (fig. 1, right). An average signal will be defined according to the natural definition given in (2).

$$xm_i = \frac{\sum_{k=0}^{11} x_{i,k}}{12} \tag{2}$$

For each moment of time (sample), the average signal represents the arithmetic mean of the values of the twelve signals at that moment (sample).

For the study of the dependence of the force on the traction resistance, a quantity dependent on the variation compared to the average of the signals that form the columns of the matrix A namely the matrix of standardized signals, is defined:

$$AS = \{xs_{i,j}, i = 0 \dots n, j = 0, \dots, 11\} \tag{3}$$

where:

$$xs_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \tag{4}$$

and:

$$\mu_j = \frac{\sum_{k=0}^{n} x_{k,j}}{n}, \sigma_j = \sqrt{\frac{\sum_{k=0}^{n} (x_{k,j} - \mu_j)^2}{n-1}}, j = 0, \dots 11. \tag{5}$$

are the mean and standard deviation of the signal j. To give a measure of the representativeness of the average signal, (2), for the signals collected during an experiment, it was used the formula of a given distance as in (6).

$$dmed_j = \sqrt{\sum_{k=0}^{n-1} ((A^{\langle j \rangle})_k - xm_k)^2} \tag{6}$$

The coding of the recording channels, according to the notations in Fig. 1 (right), is listed in Table 1.

Table 1

Coding of signals stored in matrix A

$ch4$	$A^{\langle 0 \rangle}$	$x_{i,3}, i = 0, \dots, n$	$ch23$	$A^{\langle 10 \rangle}$	$x_{i,10}, i = 0, \dots, n$	$ch24$	$A^{\langle 11 \rangle}$	$x_{i,11}, i = 0, \dots, n$
$ch21$	$A^{\langle 8 \rangle}$	$x_{i,8}, i = 0, \dots, n$	$ch3$	$A^{\langle 2 \rangle}$	$x_{i,2}, i = 0, \dots, n$	$ch22$	$A^{\langle 9 \rangle}$	$x_{i,9}, i = 0, \dots, n$
$ch19$	$A^{\langle 6 \rangle}$	$x_{i,6}, i = 0, \dots, n$	$ch20$	$A^{\langle 7 \rangle}$	$x_{i,7}, i = 0, \dots, n$	$ch2$	$A^{\langle 1 \rangle}$	$x_{i,1}, i = 0, \dots, n$
$ch1$	$A^{\langle 0 \rangle}$	$x_{i,0}, i = 0, \dots, n$	$ch17$	$A^{\langle 4 \rangle}$	$x_{i,4}, i = 0, \dots, n$	$ch18$	$A^{\langle 5 \rangle}$	$x_{i,5}, i = 0, \dots, n$

In Table 1, by $A^{\langle j \rangle}$, was symbolised the column j of the data matrix A, which contains the signal $j = 0,\dots,11$. Table 1 contains notations valid for each of the seven experiments, corresponding to six different values of the average forward speed (two experiments were carried out with the same speed). The experiment codes, corresponding average forward speed, and data file sizes are listed in Table 2.

Table 2

The codes, the average speeds, and the sizes of the data files corresponding to the experiments

Experiment code	Rows	Cols	Forward speed, m/s
T2_R2_1500rpmtxt	4001	13	0.781
T1_R2_2400rpmtxt	4001	13	0.789
T1_R3_1500rpmtxt	2501	13	1.095
T2_R2_2700rpmtxt	1501	13	1.613
T2_R3_1500rpmtxt	2501	13	1.613
T3_R2_1500rpmtxt	2201	13	2.158
T2_R3_2000rpmtxt	1701	13	2.256

2.2. The statistical estimators calculated for the evaluation of the link with the forward speed

To evaluate the link between the draft force and the forward speed of the aggregate, the most frequently used descriptive statistical estimators were used: the average value, the median, the variance, the standard deviation, the asymmetry coefficient, and the vaulting for all the signals of each experiment and for the average experiment of each experiment, both for the original signals (1) and for the standardised signals (3). The results are given in Table 3.

2.3. Determination of essential components for signal interpolation

The estimators whose method of calculation is explained in this chapter are not part of the category of descriptive statistics but are elements of inferential statistical analysis. These estimators are developed for the purpose of finding the "best channel combinations" (of channel recordings). The optimal meaning of this combination of random variables (experimental records) is that, with their help, a linear multivariate interpolation formula can be obtained, which produces a matrix of the coefficients of determination with the largest sum of elements or produces signals of interpolation with the smallest variation compared to the original signals.

To achieve this goal, several channels are conventionally used. Any number of channels between 1 and the maximum number of registered channels can be taken. Obviously, the interest is to reproduce as much information as possible (see 2.4) with as few physical records as possible. If the interests of the experimenter and the operator who processes the data are considered, then the smallest possible number of sensors that generate a quantity of information that can be generalised to the entire studied structure would be taken into account. In the case of the version with a working width of 1 m of the MCLS (fig. 1), the maximum number of recorded channels is 12. For the optimisation analysis of the linear multivariate interpolation, the number of three basic channels was taken inspired by the number of channels on a line of working body perpendicular to the forward axis of the aggregate. Obviously, one, two, four, or more channels could be used. Increasing the number of channels makes the operation more expensive (when processing only for calculation but when experimenting with all sensor mounting operations, calibration, and recording, in addition to the optimal selections for eliminating transient areas or recording accidents). If fewer basic channels are taken, then obviously the precision decreases and the loss of information becomes important (see 2.4).

If three basic channels are taken, the number of possible combinations between the 12 channels is 220 (for a number N of basic channels, $C_{12}^{N}, N = 1, \ldots, 12$ possible combinations of channels that each generate a linear multivariate interpolation must be estimated for N variables). In this case, N=3 was taken, and for each of the seven experiments, 220 interpolations were made. Then, for each interpolation, the coefficient of determination and the variance were selected. There were two objectives. The first was the global coefficient of determination (the sum of the coefficients of determination corresponding to the interpolation with the combination of channels used, including the basic channels, so the maximum value would be 12). The second objective function was the sum of variances achieved with each interpolation over all signals in an experiment (global variance). The optimisation consisted of maximising the global coefficient of determination objective function and minimising the global variance objective function. The results for each experiment are listed in Table 3.

The calculations presented in subsection 2.3 are related to the notion of *statistical interaction*, to which references were made in the introduction of the article.

2.4. Loss of information due to survey measurement

In general, in practise, strain sensors are mounted on a small number of measurement points. In this way, information loss occurs. In this subchapter, it was intended to give the reader an idea of the size of the information loss.

First, the term "information loss" must be rigorously defined because the calculation depends on the definition. For simplicity, an information loss will be defined relative to the arithmetic mean of the random variables (the twelve numerical strings collected on the measurement channels, fig. 1, right), because it is simpler to calculate. Therefore, the information loss is defined relative to the average value of the random variables by formula (7).

$$I_l = \min_{k=0,\ldots,219} \sum_{j=0}^{11} \frac{\left|\mu 3_k - \mu_j\right|}{12 \cdot \mu_j} \tag{7}$$

In Eq.7, $\mu 3_k$ is the arithmetic mean of the basic channel signals, μ_j is the arithmetic mean of the recording on channel j. The minimum value is taken after all 220 combinations of three channels out of the 12 possible.

Practically, for each of the combinations of channels (random variables) generated by the combinations of twelve taken in threes (see 2.3), the arithmetic mean of the three channels is calculated. From this, the mean corresponding to each channel is subtracted in absolute value, after which it is summed up, averaged over the number of channels, and relativized to the true average (measured in this experiment). After this, the combination with the minimum value of information loss from the 220 results is taken. The third set of channels realises the minimum loss of information and retains the amount of this loss. With these specifications, the combinations and values of the minimum information loss are obtained for each of the seven experiments listed in Table 2. These combinations and the corresponding information loss values are listed in Table 3.

Obviously, instead of three basic channels, any number between 1 and the number of channels (random variables) contained in the data file can be used. With the increase in the number of basic channels considered for the calculation of the average value (or other comparison criteria), the precision increases, but the measurements with a larger number of basic channels are more expensive.

Instead of the average value criterion for choosing a satisfactory base combination of the measurement channels, the global option can be chosen for the optimisation criterion, as defined in 2.3. The calculation becomes much more complex. Also, the calculation becomes more complex, and when we choose a larger number of basic channels, for example, taking the number of combinations for four basic channels, 495 combinationsthat must be evaluated are obtained.

RESULTS

The numerical results obtained using the methods described above are given in this chapter. For a better understanding, fig. 2 gives the graphic representation of the signals of a data file recorded in one of the seven experiments, namely the one with the code T3_R2_1500rpmtxt, corresponding to the average forward speed of the aggregate with a value of 2.158 m/s. In order to make the discrete curves and the average curve more easily observable, only 1000 samples were represented from 2201 of the selected recording (to eliminate transient passages). In Fig. 3, the same type of graphs is given but for standardised signals, according to formulas (3), (4), and (5).

Graphic representations like those in Figs. 2 and 3 are obtained for each of the seven data files recorded in the seven experiments. The channels in the legends of Figs. 2 and 3 correspond to the labels of the deformation sensors mounted on the structure according to Fig. 1 (right). Using formulas 2, 3, 4, and 5, it is observed that the average value of the standardised signal and the average value of the average standardised signal are zero. For this reason, they were not included in Table 3 because their correlation with the speed of travel is meaningless. In the same situation are the variance of all the signals and the standard deviation for the standardised signals, which give a constant value of 1.1.

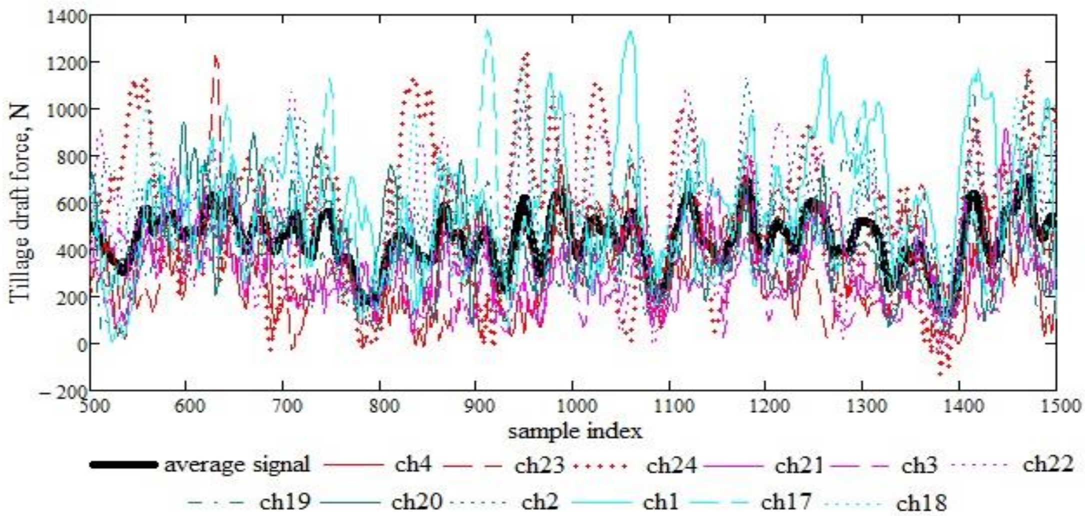

Fig. 2 - Graphic representation of the recorded signals and the average signal for the experiment, working at a forward speed of 2.158 m/s

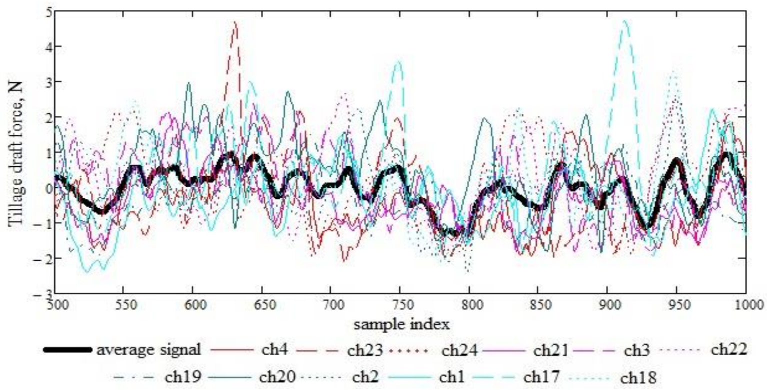

Fig. 3 - Graphic representation of the recorded signals and the average signal for the experiment (detail), working at a forward speed of 2.158 m/s

The values of the statistical estimators calculated for each signal and experimental recording and their correlations with the forward speed

The values of the main statistical estimators of the signals, in the original and standardised versions, as well as the optimal interpolation performances using as a basis three signals from each experimental data file, are listed in Table 3.

Table 3

Descriptive statistics estimators of the data recorded in the experiments carried out with the 1 m working width variant of MCLS and estimators of the optimal channels for generating the other recordings

Experiment code	T2_R2_ 1500rpmtxt	T1_R2_ 2400rpmtxt	T1_R3_ 1500rpmtxt	T2_R2_ 2700rpmtxt	T2_R3_ 1500rpmtxt	T3_R2_ 1500rpmtxt	T2_R3_ 2000rpmtxt	Correlation with speed
Speed, m/s	**0.781**	**0.789**	**1.095**	**1.613**	**1.613**	**2.158**	**2.256**	1
Minimum value, N	16.342	23.03	30.952	-51.566	28.041	-130.612	-65.466	-0.805
Maximum value, N	1110.303	1086.078	1432.804	1345.208	1250.377	1343.686	1468.57	0.715
Mean value, N	478.413	518.448	491.532	508.53	495.54	448.719	452.695	-0.6842359
Mean value of the mean signal, N	478.413	518.448	491.532	508.53	495.54	448.719	452.695	-0.6842359
Median, N	474.97	517.684	480.54	494.14	474.473	423.896	441.37	-0.7870628
Median of the mean signal, N	484.086	520.204	495.332	502.667	492.819	453.272	461.094	-0.7554842
Variance of all signals	30764.988	24291.887	27717.492	38210.409	31887.955	49279.026	46055.503	0.9188198
Average signal variance	5318.869	4600.255	6822.551	9501.582	5120.232	13059.114	12081.83	0.8738812
Standard deviation (A)	175.4	155.859	166.486	195.475	178.572	221.989	214.605	0.9197003
Standard deviation (xm)	72.931	67.825	82.599	97.476	71.556	114.276	109.917	0.8679225
Skew (A)	0.126	0.127	0.39	0.405	0.503	0.572	0.399	0.8141647
Skew (xm)	-0.699	-0.192	-0.127	0.112	0.26	-0.334	-0.146	0.329507
Kurt (A)	-0.223	-0.187	0.377	0.364	-0.026	0.166	0.222	0.5266001
Kurt (xm)	0.864	-0.03	-0.015	-0.417	0.255	-0.069	-0.338	-0.5818835
Median*, N	-0.017	-0.004	-0.053	-0.11	-0.069	-0.079	-0.068	-0.7393499
Medium signal median*, N	0.036	0.019	0.029	-0.028	-0.017	0.017	0.043	-0.1001057
Medium signal variance*	0.252	0.253	0.297	0.309	0.299	0.314	0.321	0.9077523
Standard deviation (xm)*	0.502	0.503	0.545	0.556	0.547	0.56	0.567	0.9031289
Skew (A)*	0.091	0.076	0.353	0.46	0.46	0.481	0.43	0.8496965
Skew (xm)*	-0.7	-0.201	-0.08	0.082	0.243	-0.295	-0.165	0.3347382
Kurt (A)*	0.022	-0.198	0.467	0.291	0.529	0.147	0.239	0.3787685
Kurt (xm)*	0.959	-0.056	0.007	-0.391	0.282	-0.14	-0.298	-0.5859633

Experiment code	T2_R2_ 1500rpmtxt	T1_R2_ 2400rpmtxt	T1_R3_ 1500rpmtxt	T2_R2_ 2700rpmtxt	T2_R3_ 1500rpmtxt	T3_R2_ 1500rpmtxt	T2_R3_ 2000rpmtxt	Correlation with speed
Maximum component of the correlation Matrix of the original signals	0.645	0.645	0.585	0.749	0.653	0.586	0.628	-0.0767691
Maximum component of the correlation of the original signals with the average signal	0.7	0.683	0.709	0.754	0.636	0.658	0.733	0.0258697
Minimum component of the correlation matrix of the original signals	-0.207	-0.157	-0.042	-0.115	-0.11	-0.105	-0.319	-0.267858
Minimum value of the correlation of the original signals with the average signal	0.289	0.354	0.389	0.272	0.357	0.429	0.395	0.501923
Sum of the distances between the signals and the average signal	20.534	16.801	14.57	12.7	15.786	19.55	16.545	-0.0783404
Optimal combination of channels for maximum R	ch2 ch3 ch19	ch3 ch22 ch23	ch1 ch3 ch18	ch19 ch20 ch22	ch2 ch21 ch24	ch3 ch18 ch19	ch1 ch4 ch22	-
Maximum total R	0.4072	0.4041	0.4408	0.5526	0.4658	0.4714	0.4919	0.6835293
Optimal combination of channels for minimum variance	ch18 ch20 ch22	ch3 ch22 ch23	ch1 ch3 ch18	ch19 ch21 ch24	ch2 ch21 ch24	ch3 ch18 ch19	ch1 ch4 ch22	-
Minimum total variance	4.536	42.13	32.35	22.32	31.57	29.49	25.39	0.0849382
Combination of channels that gives the minimum information loss	ch4 ch18 ch23	ch2 ch19 ch22	ch19 ch20 ch211	ch4 ch18 ch21	ch4 ch19 ch20	ch1 ch3 ch23	ch4 ch20 ch22	-
I_l minimum, %	19.35	12.163	11.454	15.229	18.997	14.021	15.354	0.042
SMD minimum, %	6.061	13.636	9.091	6.061	7.576	9.091	7.576	-0.299

**For standardised signals.*

Also, Table 3 lists the combinations of channels that achieve the minimum information loss relative to the average of the random variables and the value of this loss in percentages. The value of the Pearson correlation coefficient corresponding to the series of information losses and average forward speeds for the seven analysed experiments is also given.

The main observations from Table 3 are:

- the most intensively correlated statistical estimators with the forward speed of the aggregate are: standard deviation and variance (slightly higher for the original signals than for the average signal);
- an intense descriptive statistical estimator related to the forward speed is, according to the results in Table 2, asymmetry (skew);
- remarkable for future tests are the inverse correlations with the forward speed of the averages and medians of the original signals and the average signal;
- remarkable is also the correlation of the series of the best interpolations made with three channels each if the determination coefficient is taken as a performance criterion; the variance, as a performance criterion of the interpolation, is not correlated with the forward speed.

The last statements are also supported by the linear regression tests, which indicate, for example, a value of 0.92 for the dependence between the standard deviation of the draft force and the work speed and a value of 0.846 for the adjusted coefficient of determination, according to https://jasp-stats.org/. The probability of rejecting the linear model with zero free terms is p=0.003, so the hypothesis of linear dependence is accepted. The proposed linear model is given by relation (8).

$$\sigma_F = 131.871 + 37.388v \tag{8}$$

In (8), σ_F is the standard deviation of the average resistance force per experiment, and v is the average forward speed in the same experiment.

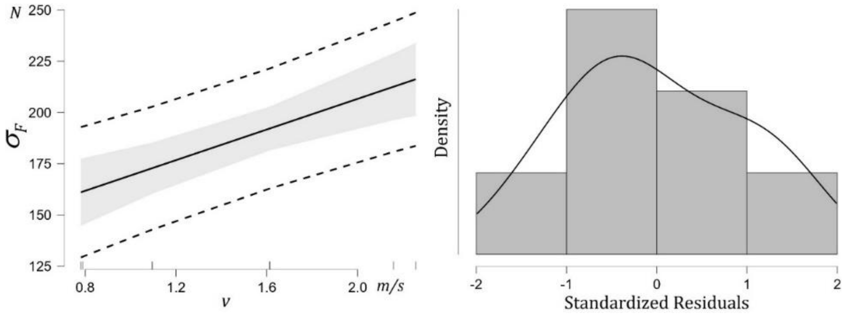

Fig. 4 - Edge effects of forward speed on the standard deviation of the draft force (left) and histogram of standardised residuals (right)

Connection tests between random variables and relationships with work speed values

A PCA analysis, carried out with the help of the JASP programme (*https://jasp-stats.org*), shows that the principal components detected for each of the twelve random variables obtained in each of the seven physical experiments are different in each of the seven experiments both in structure and in number. The main components detected for each work speed differ in number and structure between the seven sets of twelve random variables, and there is no parameter that links the number and structure of the main components to the average forward speed of the experiment. On the other hand, the number and structure of the main components depend on a series of parameters of the programme and the choice of some work options.

Another test on the link between the signals (random variables) of a data file and between their synthetic indicators and the series of forward speeds was obtained using the standardised mean differences (SMD)(*https://cran.rproject.org/web/packages/TOSTER/vignettes/SMD_calcs.html;https://towardsdatascience.com /how-tocompare-two-or-more-distributions-9b06ee4d30bf; https://statisticaloddsandends.wordpress.com/2021/ 10/31/standardized-mean-difference-smd-in-causal-inference*).

An absolute value of SMD below the threshold of 0.1 is conventionally considered the small one between two random variables (*https://towardsdatascience.com/how-to-compare-two-or-more-distributions-9b06ee4d30bf*; *https://statisticaloddsandends.wordpress.com/2021/10/31/standardized-mean-difference-smd-in-causal-inference*). Discussions on the threshold value for separating small differences between random variables and the effects on percentage overlap can be found in *https://www.psychiatrist.com/jcp/psychiatry/mean-difference-standardized-mean-difference-smd-and-their-use-in-meta-analysis*, for example. The online calculation of SMD can be checked at: *https://www.campbellcollaboration.org/escalc/html/EffectSizeCalculator-SMD1.php*. For the seven data sets corresponding to the working speeds realised in our experiments, the percentages of SMDs below the 0.1 threshold (so with small differences between random variables) are listed in Table 3. The maximum percentage of signal pairs with small differences between them is 13,636% in the case of the experiment with an average working speed of 0.789 m/s. This means that most pairs of signals in all seven experiments differ greatly from each other, which is an argument in favour of the random character of the draft force.

Structuring data files with the help of statistical network techniques

In search of the expression or representation of some of the measured channels, depending on the base of channels used as independent variables in the multiple regression calculation, the neural network technique was also used, according to the programme from: *https://jasp-stats.org/*. As dependent variables, three random variables out of the twelve were used, corresponding to the deformation sensors mounted on the supports of the first line of bodies behind the tractor: ch4, ch23, and ch24. For the experiment with the code T2_R2_1500rpmtxt, carried out with an average speed of 0.781 m/s, the network is shown in Fig. 5.

On this network, one can read the weights of the relationships between the dependent variables (the other nine channels, whose labels are written on the network). The programme also provides many other tabulated or graphical data sources. For more information *https://ro.wikipedia.org/wiki/Re%C8%9Bea_neural%C4%83* and the literature included in this source are recommended. The network from Fig. 5 shows the links between the random variables (recordings on each of the twelve channels) and the intensity of these links. The model introduced in the programme data tried to obtain a forecast of the approximation of the signals from the nine channels in the diagram given in Fig. 5, using only the data from the channels on the first line of bodies after the tractor, respectively ch4, ch23, and ch24 (see Fig. 1, right). As it was seen from the analysis in 2.4, the three channels do not give the best result in the interpolation of the other nine channels.

According to the reasoning in 2.4, a neural network analysis should be done for each of the 220 cases highlighted for the three-channel model used for interpolation. For a larger number of interpolation channels (the non-economic case), the number of analyses increases. Practically, this neural network is the precursor of an e-learning network, with three nodes as input, nine nodes consisting of the interpolated channels, and several nodes for validation, as well as many estimators of the interpolation performance that are used. After covering all possible cases, the most favourable case or cases are selected.

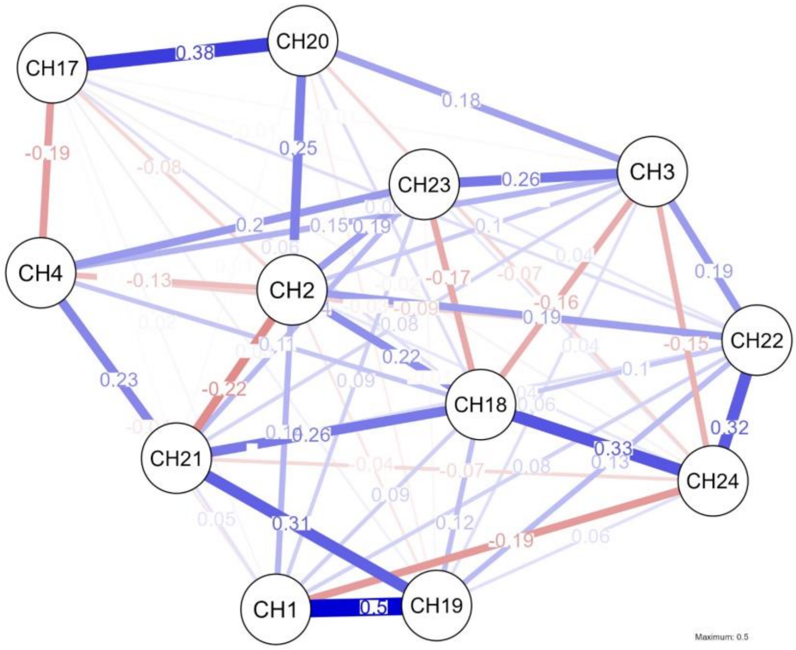

Fig. 5 - The neural network corresponding to the R2_T2_1500rpmtxt experiment, carried out with the average speed having a value of 0.781 m/s, considering all channels as dependent variables

Figs. 6 and 7 show the structure of the network of random variables formed by the data files of the experiments with the codes T2_R2_1500rpmtxt and T2_R2_2700rpmtxt. The network structures of the other five experiments are not given because it is established that there are no constant groupings and a fixed number of main components (it can be seen in Figs. 6 and 7, experiments with four and three main components, under similar setting conditions of the calculation programme) to help us choose the supports for mounting a small number of deformation sensors so that the loss of information during interpolation is minimal. It is possible to force a constant number of main components with special settings in the calculation, but these have hard-to-appreciate consequences on the interpolation errors (under conditions of the uniform set of the calculation programme, the number of main components has no significant relationship with the value of the forward speed of the aggregate). As a result, principal component analysis is not appropriate for our purposes. Similarly, the use of neural networks or machine learning techniques is not beneficial for our purposes since there is little physical data, which does not allow us to formulate calculation models in which to impose inputs and outputs.

Working techniques with PCA analysis, neural networks, or machine learning would have made sense if there was a complete monitoring of working depth, speed, fuel consumption, etc. Among the parameters listed previously, the dependent variables could have been chosen, while the forward speed and the forces would have become predictors, for example.

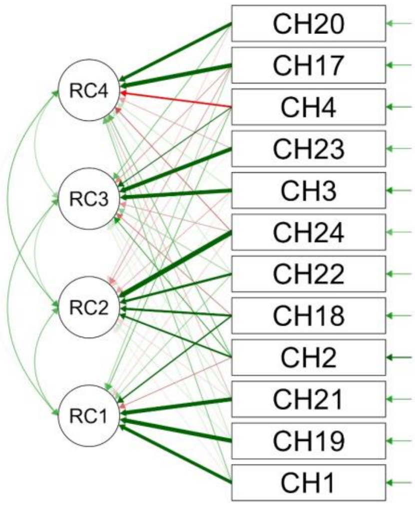

Fig. 6 - Diagram of the main components highlighted in the data file of the experiment T2_R2_1500rpmtxt

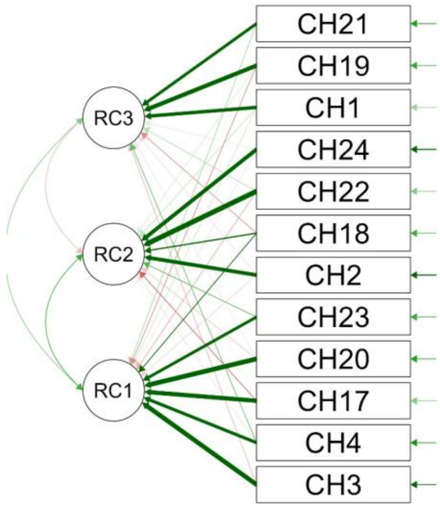

Fig. 7 - Diagram of the main components highlighted in the data file of the experiment T2_R2_2700rpmtxt

COMMENTS

The physical structure whose characteristics were analysed in the research described in this article and in the related precedents (*Cardei et al., 2023a, 2023b, 2023c*) is a working variant of a cultivator, equipped with working bodies whose supports allow vibrations of an appreciable amplitude of assemblies formed by bodies and supports. Moreover, the vibrations are transmitted to the supporting structure, leading to errors in the working depth. For this reason, such soil processing tools are not intended for work that requires high precision in the working depth. Tools of this type have other advantages, as shown, for example, in *Gheorghita et al.* (*2017*) and *Abbaspour-Gilandeh et al.* (*2020*): reducing energy consumption in the execution of agricultural works; improving the quality of agricultural technological processes; increasing the productivity of agricultural machines; and universalizing certain assemblies or subassemblies of agricultural machines.

Complex mathematical models confirm the operation in the vibration mode of cultivators equipped with working bodies used in the experiments of the MCLS variant analysed in this article (*Cardei et al., 2015a and 2015b*). According to some previous works, the search for optimal working speeds is related to crossing certain speed thresholds (*Cardei et al., 2019; Cardei et al., 2021*), which cannot always be reached. One of the observed effects is that, in the absence of rigorous control of the working depth, the increase in the forward speed implies a decrease in the working depth (*Cardei et al., 2023b; Chehaibi et al., 2008*). The authors *Singh et al*. (*2018*) confirmed two clear phenomena: increasing draft force with working speed and with working depth. It is also important to note that the increase in draft force due to the increase in working depth is much more significant than the increase in the same force due to the increase in work speed, which is also shown in *Dizaji et al.* (*2022*); *Karmarkar and Gilke* (*2021*). However, the authors *Singh et al.* (*2018*) do not specify whether increasing the working speed affects the precision of the working depth. *Kim et al.* (*2022*) finds the well-known conclusions also noted by the authors *Singh et al.* (*2018*), but, in addition, they also find a decrease in the working depth with the increase of the working speed (for each of the three types of soil they worked on). The attempt to maintain or increase the working depth results in an increase in the slippage of the tractor, a phenomenon noticed by *Chenarbon* (*2022*), and implicitly affects the increase in the working speed. Experimental research with statistical processing of the results regarding the skidding (or sliding) of traction wheels and the effect of loading these wheels is published in *Taghavifar and Mrdani* (*2015*). For more in-depth studies on the traction performance of tractors, one can consult the work of *Zoz and Grisso* (*2003*). For electric tractors, the results of similar research, also using inferential statistical analysis techniques, are published in *Baek et al.* (*2022*). Similar conclusions are obtained by the authors *Al-Suhaibani and Ghaly* (*2010*), who make additional specifications on the vertical component of traction and on the unit of horizontal and vertical draft. The authors *Al-Suhaibani and Ghaly* (*2010*) also do not refer to the influence of the forward speed on the precision of the working depth. Monitoring the working depth is a difficult problem; this may be the reason why it is rarely performed. A solution for monitoring the working depth is presented by the authors *Kim et al.* (*2020*).

The authors *Damanauskas and Janulevicius* (*2022*) find the same conclusions relative to the dependence of the traction resistance force on the forward speed and on the working depth, their work focusing on other very important and less common aspects, namely the dependence of the quality of soil processing on the speed and depth of work in two types of soil. The authors *Askari et al.* (*2017*) also find an increasing dependence of the draft force on working depth and speed. In *Askari et al.* (*2017*), it is also shown that, under the specified experimental conditions, the increase in draft force decreases, in general (with some exceptions), depending on the working speed; that is, the force increases, but its derivative in relation to the speed decreases. Similar conclusions are reached by the authors *Becker et al.* (*2019*) for operations of cutting plant residues in cultivation systems without ploughing (no-tillage systems). The authors *Becker et al.* (*2019*) use the tools of experimental research and statistical processing of the results, including inferential analysis (box-plot representations, statistical tests, interpolations, etc.). According to the results of *Becker et al.* (*2019*), the traction force increases non-linearly with the working speed, which leads to the same type of increase in the hourly fuel consumption.

Descriptive and inferential statistical tools and the technique of random functions are not new techniques; they have been frequently used in the field of motor vehicle research since the second half of the 20th century (*Sireteanu, 1981; Harris and Crede, 1969; Negrus et al., 1983*). Moreover, in *Myalo et al.* (*2019*), Marius Iosifescu drew attention to the delay in the introduction of these tools into education: "However, we cannot overlook the fact that, in a striking discrepancy with the role they play today, the theory of probabilities and mathematical statistics have not find their place and the appropriate weight in the study programmes of technical and economic influence on the ability of our technical and economic specialists to successfully solve the complex problems of tomorrow's world". This is what it was found in *Cardei et al.* (*2023b*). In addition, these appreciations also refer today to the research activity, where the limits of purely theoretical models are becoming more and more visible.

Regarding the objective of finding possible relationships between the random variables that are part of the recordings of some experiments, the literature is poor in such attempts, if not completely devoid of examples. Somewhat more complex statistical tools, such as ANOVA-type analyses, were used to highlight the effect of soil moisture, working depth, and forward speed on the forward resistance force (*Deshpande, Shirwal S., 2017; Saleh et al., 2021; Rashidi et al., 2013; Shafei et al., 2018*), for example. Multivariate regression analysis is used by the authors *Sadek et al*. (*2021*) to estimate the effects of forward speed and working depth on the longitudinal and vertical components of the draft force. Regression analysis is used by the authors *Sadek et al.* (*2021*) together with DEM (discrete element method, available at https://en.wikipedia.org/wiki/Discrete_element_method) analysis of the working process of a disc in soil. The authors *Sadek et al.* (*2021*) show that increasing the forward speed and/or the working depth contributes to the increase of the longitudinal component (soil draft force) and to the decrease of the vertical component. In *Myalo et al.* (*2019*), it is shown that the elastic systems of some cultivators increase the traction resistance force, but the whole of the working bodies is not studied, but only an individual working body. The authors *Babitsky et al*. (*2021*) use the shape of the scarab as a source of inspiration for the design of the working bodies of a cultivator, but they still limit themselves to an individual working body; they do not address the whole, the relationships between the bodies, or the degree of randomness of their movements. Only at the theoretical level (mathematical modelling) was an initial approach to the problem of the interaction of the working bodies of cultivators made (*Cardei et al., 2015b*). Modern experiments are done on problems that interact deeply with the problem of the effect of the interaction of the working bodies of the cultivators (*Fanigliulo et al., 2023*). Multiple regression prediction models are used by the authors *Askari et al.* (*2017*) for the prediction of the traction resistance force depending on the forward speed, working depth, and working width of a working body wing for three types of bodies: subsoiler, paraplow, and bentleg. The conclusions are like those in the published literature and those found in this paper. The authors *Saleh et al.* (*2021*) proceed in the same way, relative to a characteristic soil for an area of Nigeria. Again, the same conclusions apply: the increase in draft force is associated both with the increase in forward speed and with the working depth. From the results presented in graphic form, the non-linear trend of these relationships can be observed. For the study of the non-linear aspect of the dependence of the draft force on the forward speed and working depth (but also on other parameters such as soil moisture, working width, etc.), more data (and therefore more experiences) are needed to satisfy the calculation needs of the nonlinear multivariate analysis programmes, at least of the second degree. Similar results (increasing draft force with forward speed and working depth, as well as the non-linear aspect) are obtained by more complicated statistical methods in the paper of *Shafei et al.* (*2018*), together with the evaluation of the prediction procedure that uses the neuro-fuzzy modelling method.

CONCLUSIONS

The obtained results allow drawing some conclusions linked to their possible practical application. As for example, the triplets of strain sensors that perform the interpolation of all the signals in the processed experiments do not at the same time maximise the coefficient of determination *R*, minimise the variance, and minimise the loss of information relative to the average value of the signal. As a result, the statistical results show that working with only three deformation sensors, all three optimisation objectives cannot be simultaneously achieved. Optimal compromise criteria can be developed. The correlation of the synthetic characteristics of the experiments with the forward speeds has high values for the variance over all signals (0.9188), the standard deviation (0.9197), the variance of the average signal (0.87388), and the standard deviation of the average signal (0.8679). Also interesting are the values of 0.739 for the median of the average signal, 0.68 for the coefficient of determination, and -0.68 for the average value of the signal and the average signal. As a result, the influence of feed (or work) speed on draft force is most easily found using the standard deviation or variance. Also, it appears that the minimum and maximum values of the force on the set of the twelve channels of each recording correlate well with the forward speed: the maximum value is in direct correlation with the value 0.715, and the minimum in inverse correlation with the value -0.805. The twelve signals corresponding to each of the seven experiments with different forward speeds (yet two with the same speed value) do not show connections between them and do not show signs of influence, which provides an additional reason to characterise the vibrations in the work of the cultivator's bodies as predominantly random. The use in the analysis of some complex inferential statistical tools (non-linear multivariate analysis, factor analyses, variance analyses, statistical interaction analyses, etc.) can bring new data and knowledge only for data collections containing the monitoring of many parameters of the experienced and modelled system (input, output, control, and adjustment parameters). The data collections analysed in this article and in the previous ones contain only one continuously monitored parameter (soil tillage draft force, measured indirectly through strain gauge measurement), the forward speed is estimated as an average per experiment, and the working depth is estimated only through a few surveys as a number and is ineffective. That is why complete statistical analyses are useless and even impossible in this case. Practically, in common experiments and in exploitation, the forward speed, and the working depth (even the working width) are random parameters obtained from the interaction of the soil processing machine and the entire aggregate with the soil and vegetation. These parameters must be permanently monitored and recorded at the values they take; their exact programming has no meaning in such a random framework as that of the soil processing phenomenon. It is sufficient to maintain these parameters within the desired limits.

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