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ESTIMATION OF FUEL CONSUMPTION IN AGRICULTURAL MECHANIZED OPERATIONS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: This study aimed to develop artificial neural networks for the estimation of tractor fuel consumption during soil preparation, according to the adopted system. The multilayer perceptron network was chosen. As input data: the soil mechanical penetration resistance, the mobilized area by implements, the working gear and the tractor engine speed. The number of layers and neurons varied to form different architectures. The adjustment was verified based on various statistical criteria. The values estimated by the networks did not differ significantly from those obtained experimentally. The conclusion was that the networks showed adequate reliability and accuracy to predicting the fuel consumption in each tillage system, in function of the input data and this can be a useful tool for planning and management of agricultural operations.

KEYWORDS: machine performance; artificial intelligence; agricultural planning.

INTRODUCTION

The efficient planning of mechanized farming operations is a complex task because it involves multiple factors related to the soil, the machine or implements settings and the man to make decisions. Among these factors, the ones that have a greater direct impact on fuel consumption and therefore deserve special attention are: the type, the coverage and the state of soil compaction, the topography and terrain relief, the technical characteristics of the tractor combination with the machine or implement and the proper selection of gears and the engine speed by the operator, according to the current working conditions.

Among the soil characteristics and properties, its mechanical resistance has gained preference by most of researchers. In this sense, BORGES et al. (2013) modeled this soil property in function of depth and considering its moisture. These dependencies are extremely useful to evaluate and predict the soil mechanical resistance in different layers, according to the time of year and can be practical tools to define the necessary implements in its rational management. However, these models do not allow estimating the fuel consumption required for certain agricultural operation, in order to carry out a proper planning of financial resources.

Also, the soil mechanical resistance to penetration was studied by BORGES et al. (2014). In this study, the authors used this resistance to describe the current state of the land and developed a statistical model to estimate the tensile strength in discs ploughs, spring tillers and planters. The models indicated an increase in tensile strength with the increase of soil mechanical resistance, according to an associated exponential function. Therefore, the fuel would follow a similar trend. Nevertheless, based on these models it was not possible to predict with adequate precision this consumption in agricultural operations.

MACHADO & TREIN (2013) developed mathematical models to predict the tractive effort in rods tools with narrow tips, depending on the soil parameters. The soil indicators used in these models, such as cohesion, internal friction angle, steel grip and friction require experimental samples and their corresponding laboratory analysis, which hamper the practical application. BAIO et al. (2013) developed a computer program for selecting mechanized set by the lowest cost. The

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calculation of fuel consumption is based on trials carried out in Nebraska (United States), which can lead to significant discrepancies to the conditions of Brazilian soils.

The influence of the technical characteristics of the mechanized set, gears and rotations in the tractor engine on fuel consumption is confirmed on the study of MOUNTAIN et al. (2011), VALE et al. (2011), SPAGNOLO et al. (2012), FRANTZ et al. (2014), FEITOSA et al. (2015), FIORESE et al. (2015) and SOUZA et al. (2015). However, in these studies, the functional dependencies to determine this consumption were not established. Moreover, the use of artificial neural networks as an alternative to relate variables and parameters of physical and biological processes is growing daily and its effectiveness confirmed by ALVES SOBRINHO et al. (2011), PANDORFI et al. (2011), CARVALHO et al. (2012), VENTURA et al. (2012), BINOTI et al. (2013, 2014 a, b), GEORGENS et al. (2014), SOARES et al. (2014) and VALENTE et al. (2014).

As a result of this problem, this research was based on the assumption that artificial neural networks are a multidimensional inference model and nonlinear with the ability to generalize or automatically extract rules from complex data sets. Thus, this study aimed to define the appropriate architecture of a neural network to estimate the fuel consumption in agricultural operations, depending on the soil mechanical resistance to penetration, on the technical characteristics of the mechanized set and on operating conditions defined by gears and rotations in the tractor engine.

MATERIAL AND METHODS

The study was carried out for two consecutive years in an experimental area of the Federal University of Viçosa, located in Viçosa-MG, defined by the geographical coordinates 20 °45’14” of South latitude and 42º 52’53” of West longitude and average altitude of 650 m. In the region prevail the hilly terrain (about 85%). The area was intended for direct sowing in the five years preceding the study with corn and beans, alternately.

The average annual temperature ranges between 14.0°C and 26.1°C. The weather was classified as Cwa, temperate humid with hot summers and dry winters (KÖPPEN & GEIGER, 1928) and the soil as red-yellow Latosol of clay loam texture (EMBRAPA, 2006).The soil of the experimental area had a vegetation cover of 5.59 ton ha^{-1} of dry mass, density of 1.53 g cm^{-3} and moisture content of 30.46% (volume basis).

In this study, the tractor used had front-wheel drive (4x2 TDA), MF 265 model, manufactured by MASSEY FERGUSON *, with nominal power of 47.8 kW at 2200 rpm and mass of 3700 kg, including ballast. As implements and machines mounted on hydraulic lift system, we used a reversible plough with 3 discs of 29”, a spring tiller with 6 parabolic rods 30 mm wide provided with common tips without flaps and a planter for direct seeding, PC 2123 model, manufactured by SEED MAX * with three spaced pantograph units in 450 mm, flat cutting discs of 406 mm diameter, seeder and fertilizer doser, furrow openers with double discs and flat compactor wheels in a "V" shape.

Also other equipment and computer tools were necessary such as electronic penetrometer, PNT 2000 * Model, manufactured by DLG Industrial Automation Ltd. *, the load cell, SODMEX * brand and N400 model, with a sensitivity of 2.156 mV V^{-1} and nominal range of 50 kN, the flow meter built in the Agricultural Mechanization Laboratory of UFV, basically consisting of a graduated glass burette with the corresponding log for its handling a profilometer with 200 cm in length, composed of a metal structure provided of a base with bubble level, framework to set graph paper and 80 holes through which slide the rods of 60 cm length arranged vertically and spaced in 2.5 cm, laptop computer, ASPIRE 5920 model, ACER* brand, EXCEL spreadsheet and STATISTICA 8.0 statistical software.

The flow meter was installed in the tractor engine power system, controlling the opening and closing by the log, respectively, at the beginning and end of the course of the experimental plot. Thus, the spent fuel in each transaction was determined by the difference between the initial and final volumes. The fuel consumption was evaluated according to the soil tillage, the mobilized area, the slipping on the drive wheels, the working speed and the tractor engine rotations, taking into account the soil mechanical resistance. Thus, three soil tillage were defined: conventional with disk plough, reduced with tillers and no tillage with planter, set to 25, 35 and 15 cm of depth, respectively.

As the gears for the tractor were selected three reduced, which were: Second reduced A, Second reduced B and Third reduced B. For these three gears, the tractor operated with three rotations included in the range of higher engine torque and nominal power, the minimum speed of 1500 rpm, intermediate of 1700 rpm and maximum of 2000 rpm. Thus, nine combinations of displacement speed for the three agricultural sets were defined. The increase in the number of speed combinations had as main purpose to raise the amount of data to develop artificial neural networks and characterize a wide interval of fuel consumption values in the operation, on the basis of these variables.

The experimental plots measured 20 m of length by 5 m of wide and arranged in the field following a randomized block design with four replications, in a split plot scheme, although the data of soil mechanical resistance to penetration and performance were analyzed by descriptive statistics. Among the blocks, a range of 10 meters wide with surround for maneuvering and equipment stabilization was used. Thus, 108 units were placed at the disposal, coming from three tillage systems, three gears, three engine speeds and four replicates of each variables combination, totaling 216 measurements in two years. The soil mechanical resistance to penetration evaluated with the aid of digital penetrometer whose rod was inserted to a depth of 40 cm in 10 random points of each plot and calculated the corresponding average.

To determine the soil profile mobilized by the implement, before and after each operation, the profilograph backed up and leveled on wooden stakes placed outside the area affected by the tools, guiding the metal frame perpendicular to the direction of the equipment movement. Thus, the rods represent the original or natural profile of the terrain and the internal revolved. The corresponding area to the cross section of the mobilized soil was calculated by numerical method. The slipping of the driving tractor wheels was determined, according to the equation:

$$S = \frac{(S_{SC} - S_{CC}) \cdot 100}{S_{SC}} \tag{1}$$

that,

S - slipping on the drive wheels of the tractor (%);

S_{sc} - displacement speed of the equipment in the transport position (m s^{-1}), and

S_{cc} – displacement speed of the equipment in the operation (m s^{-1}).

Based on the studies of TERRA & PASSADOR (2012), VENTURA et al. (2012), BINOTI et al. (2013, 2014 a, b) and VALENTE et al. (2014), the artificial neural networks with the "Perceptron" structure with multi-layer (MPL) was chosen to determine fuel consumption in agricultural operations according to the performance criteria. The architecture of the networks was set up according to the suggestions of TERRA & PASSADOR (2012) and VENTURA et al. (2012) that is, changing the number of intermediate layers and the number of neurons in the layers. The profile input of the mobilized soil; the mechanical resistance and the slipping on the drive wheels variables as well as the output fuel consumption variable were normalized to reduce the effects of scale. However, the preparation system, the gear and the engine rotation are represented by nine independent binary variables ("*dummy*"), which assume the values 0 and 1.

According to the suggestions of BINOTI et al. (2013, 2014 a, b), CANSIAN et al. (2014), GEORGENS et al. (2014) and VALENTE et al. (2014),for training and validation, the data were randomly divided into two sets, corresponding to 75% and 25%, respectively. In all architectures the logistic function to enable the networks was used, and the initial weights randomly generated between -0.5 and 0.5.The layers are interconnected by complete synapses, each neuron of i layer was connected to all neurons of the next layer (i + 1), the synapse being oriented forward only ("feed forward"). Also, the back propagation error was used as the learning algorithm.

According to SOUSA & MENEZES (2013), BINOTI et al. (2014 a, b) and GEORGENS et al. (2014), to reduce the number of obtained networks and to select the most appropriate, the coefficients and indexes of the corresponding program for training and validation were used, as well as the average error and the root mean square error were determined, given by:

$$AE = \frac{\sum_{i=1}^{N} (FCest_i - FCobs_i)}{N} \tag{2}$$

that,

AE – average error (dimensionless);

N - total number of observations (dimensionless);

$FCobs_i$ - actual fuel consumption measured in observation i (L), and

$FCest_i$ - Estimated fuel consumption corresponding to the observation I (L).

$$RMSE = 100 \cdot \sqrt{\frac{1}{N} \sum_{i=1}^{N} (FCobs_i - FCest_i)^2} \tag{3}$$

that,

RMSE - root mean square error (%);

N - total number of observations (dimensionless);

$FCobs_i$ - actual fuel consumption measured in observation i (L), and

$FCest_i$ - Estimated fuel consumption corresponding to the observation i (L).

The neural networks classified as satisfactory were analyzed more rigorously, applying the t test ("Student") and developing the residues scatter diagrams and the corresponding histogram, as suggested by BORGES et al. (2014). Also, using as reference the studies of BINOTI et al. (2014 a, b), GEORGENS et al. (2014) and SOARES et al. (2014) the correlation coefficients and the Willmott index were calculated, as well as the performance index, which measure the closeness of the values estimated by the networks observed. These statistical criteria are expressed mathematically by:

$$r = \frac{\sum_{i=1}^{N} (FCobs_i - FCMobs) \cdot (FCest_i - FCMest)}{\sqrt{\sum_{i=1}^{N} (FCobs_i - FCMobs)^2 \cdot \sum_{i=1}^{N} (FCest_i - FCMest)^2}} \tag{4}$$

that,

r - correlation coefficient (dimensionless);

N - total number of observations (dimensionless);

$FCobs_i$ - actual fuel consumption measured in observation i (L);

$FCest_i$ - Estimated fuel consumption corresponding to the observation I (L);

FCAobs - average actual fuel consumption (L), and

FCAest – average estimated fuel consumption (L).

$$Iw = 1 - \frac{\sum_{i=1}^{N}(FCobs_i - FCest_i)^2}{\sum_{i=1}^{N}(|FCobs_i - FCAobs| + |FCest_i - FCAest|)^2} \tag{5}$$

that,

Iw - coefficient of Willmott index (dimensionless);

N - total number of observations (dimensionless);

$FCobs_i$ - actual fuel consumption measured in observation i (L);

$FCest_i$ - estimated fuel consumption corresponding to the observation i (L);

FCAobs - average actual fuel consumption (L), and

FCAest – average estimated fuel consumption (L).

$$Pi = r \cdot Iw \tag{6}$$

that,

Pi - performance index (dimensionless);

r - correlation coefficient (dimensionless), and

Iw - coefficient of Willmott index (dimensionless).

*The branding does not mean a recommendation from the authors, but the characterization of the equipment used in this research.

RESULTS AND DISCUSSION

This study did not have as purpose a detailed statistical analysis of soil mechanical resistance to penetration, the main aim was to relate it to the fuel consumption in each plot. So we opted for the general characterization of that variable (Table 1). This table shows the descriptive statistics of soil penetration resistance from 108 measurements. The small difference between the average and the median, as well as the low skewness coefficient, indicate a distribution of data close to normal, however, very elongated because the kurtosis coefficient value is less than 0.263. Also, there was a satisfactory variation coefficient, since the aforementioned resistance often presents large variations around the average.

TABLE 1. Descriptive statistics for soil mechanical resistance to penetration.

Statistic	Value	Unit
Average	1.64	MPa
Median	1.67	MPa
Standard deviation	0.23	MPa
Variance	0.05	MPa
Kurtosis Coefficient	-1.37	Dimensionless
Skewness Coefficient	-0.10	Dimensionless
Variation Coefficient	13.88	%

The variation coefficient for the soil mechanical resistance to penetration obtained in this study was lower than the ones estimated by MARASCA et al. (2011), CAMPOS et al. (2012) and MION et al. (2012), which found high spatial variability of that resistance. The variation coefficient in these studies reached values higher than 40%, indicating much scatter of data. The main causes for these differences may be related to soil textural classification, status and coverage class, management systems and earlier cultures, as well as the water content in the soil at the time of the harvest.

The table 2 contains descriptive statistics of the performance variables of mechanized set, corresponding to 36 measurements for each soil tillage system. In this table, the little difference between the average and the median for all variables, regardless of the soil tillage system, can be seen.

TABLE 2. Descriptive statistics for the performance variables of the mechanized set.

Statistic	Soil tillage system	Performance variables: Mobilized area (m^2).	Slipping (%)	Fuel consumption (L ha^{-1})
Average	Conventional	0.55	12.60	19.60
	Reduced	0.52	11.70	7.89
	No tillage	0.31	3.10	7.12
Median	Conventional	0.55	12.55	19.65
	Reduced	0.52	11.98	7.81
	No tillage	0.31	3.00	7.47
Standard deviation	Conventional	0.04	2.12	1.81
	Reduced	0.02	2.25	1.05
	No tillage	0.04	1.11	1.16
Variance	Conventional	0.01	4.51	3.28
	Reduced	0.00	5.08	1.11
	No tillage	0.01	1.23	1.35
Kurtosis Coefficient (dimensionless)	Conventional	-1.22	0.17	-0.49
	Reduced	-1.55	-0.54	0.24
	No tillage	-1.22	0.76	-1.23
Skewness Coefficient (dimensionless)	Conventional	-0.13	0.31	-0.31
	Reduced	-0.02	0.17	0.61
	No tillage	-0.15	0.43	-0.35
Variation Coefficient (%)	Conventional	7.21	16.86	9.24
	Reduced	3.74	18.25	13.33
	No tillage	11.67	19.73	16.29

However, in Table 2, the Kurtosis and Skewness coefficients are very different from 0.263 and zero, respectively, values which characterize the proximity of the data to a normal distribution. Table 2 shows that the no tillage system showed the highest values of the variation coefficient for all performance variables and the greater oscillation corresponded to the slipping.

The variation coefficients for the slipping on the drive wheels obtained in this study were higher than those estimated by MONTEIRO et al. (2013) and FIORESE et al. (2015) of 3.73% and 5.29%, respectively. These differences are mainly due to the experimental conditions, because this study evaluated the slipping on agricultural land with the implements in operation, depending on the gear and the engine speed, which favored its decrease. However, the variation coefficient for the slipping on the drive wheels corresponding to the conventional and reduced systems of this study are similar to those determined by LEITE et al. (2011) in a range from 7.59 to 16.21%, SPAGNOLO et al. (2012) of 20.05% and CHIODEROLI et al. (2014) of 21.16%. Thus, it appears that the variable analyzed is subject to constant fluctuation, which leads to a greater dispersion of the data.

The fuel consumption measured in this study showed greater variability than the one estimated by LEITE et al. (2011), VALE et al. (2011), SPAGNOLO et al. (2012), CHIODEROLI et al. (2014) and FRANTZ et al. (2014), whose variation coefficients were 3.34; 5.73; 1.31; 5.28 and 3.17%, respectively. However, they approached the ones determined by SOUZA et al. (2015) between 6.05 and 15.12%.These discrepancies agree with the expected because this study used a larger number of operating conditions for agricultural equipment, given by the three gear and three engine speeds in order to increase the range of fuel consumption, which justifies high fluctuations around the average.

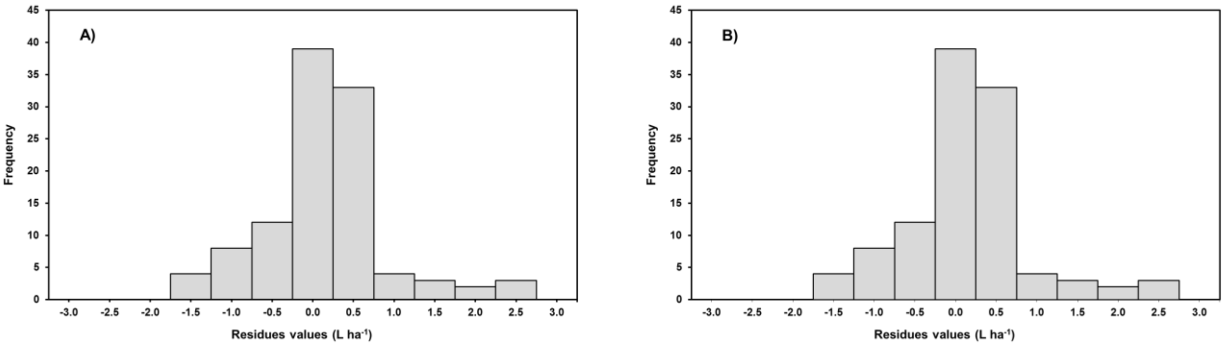
According to the criteria of the consulted literature, different network architectures containing up to two intermediate or hidden layers and each one having at most 24 neurons, a total of 64 combinations, were defined and tested. However, only eight had satisfactory levels, given by the small difference between the selection parameters and program test, the mean error, the squared determination coefficient (R^2) and the root mean square error (Table 3). In this Table, the best results correspond to the artificial neural networks 1, 2, 3, 5, 6 and 7.The networks 4 and 8 showed greater difference in the program parameters and high root mean square error value (Table 3).

TABLE 3. Evaluated index values for each artificial neural network architecture.

ANN	Architecture	Program parameters		Average error	R^2	RMSE
		Selection	Test			
1	MLP 12:12-12-1:1	0.2116	0.2245	-0.0022	0.9875	4.1091
2	MLP 12:12-18-1:1	0.1996	0.1587	0.0013	0.9905	3.5820
3	MLP 12:12-21-1:1	0.1754	0.1937	-0.0010	0.9910	3.5352
4	MLP 12:12-24-1:1	0.2170	0.2685	-0.0061	0.9854	4.4634
5	MLP 12:12-10-3-1:1	0.1743	0.1689	-0.0014	0.9906	3.5467
6	MLP 12:12-18-2-1:1	0.2255	0.1886	0.0064	0.9891	3.9061
7	MLP 12:12-18-3-1:1	0.1788	0.1767	-0.0025	0.9874	4.1942
8	MLP 12:12-21-2-1:1	0.2978	0.2045	-0.0048	0.9808	4.9883

Based on Table 2, the increase in the number of hidden layers and neurons did not affect the accuracy because the best values were obtained with the networks 2, 3, 5 and 6, whose architectures have one or two layers maximum of twenty-one neuron. These results do not agree with the suggestions of TERRA & PASSADOR (2012), about the number of neurons in layers, because none of their proposed criteria was adequate for the data of this study. However, they confirm the recommendations of BINOTI et al. (2013, 2014 a, b) and GEORGENS et al. (2014). These authors state that there is no precise criterion to define the number of neurons in layers, requiring the test and verification of various networks through trial.

Considering that the artificial neural networks 2, 3, 5 and 6 provided the most appropriate indicators, only those networks were object of complementary analysis to check its efficiency and reliability, as graphic as analytical. Thus, the frequency histograms and the residues diagrams were initially developed as a function of the fuel consumption measured for each artificial neural network (Figures 1 and 2).



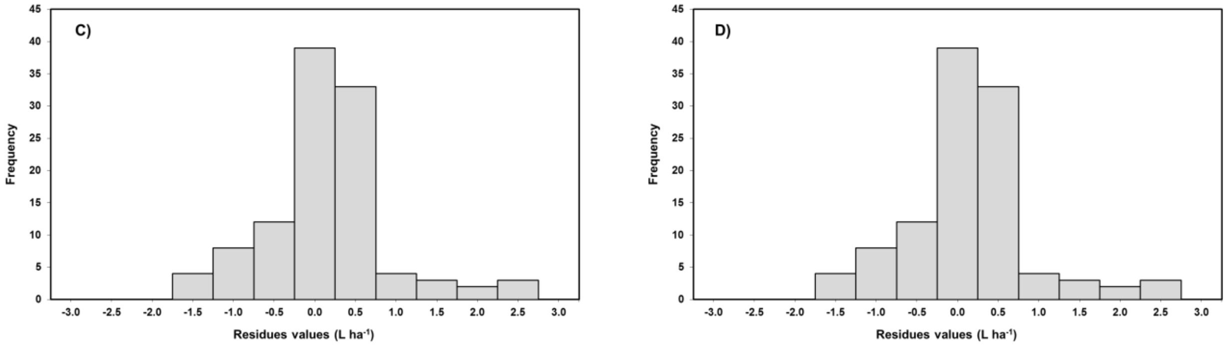


FIGURE 1. Frequency histogram of the residues: a) ANN 2; b) ANN 3; c) ANN 5; d) ANN 6.

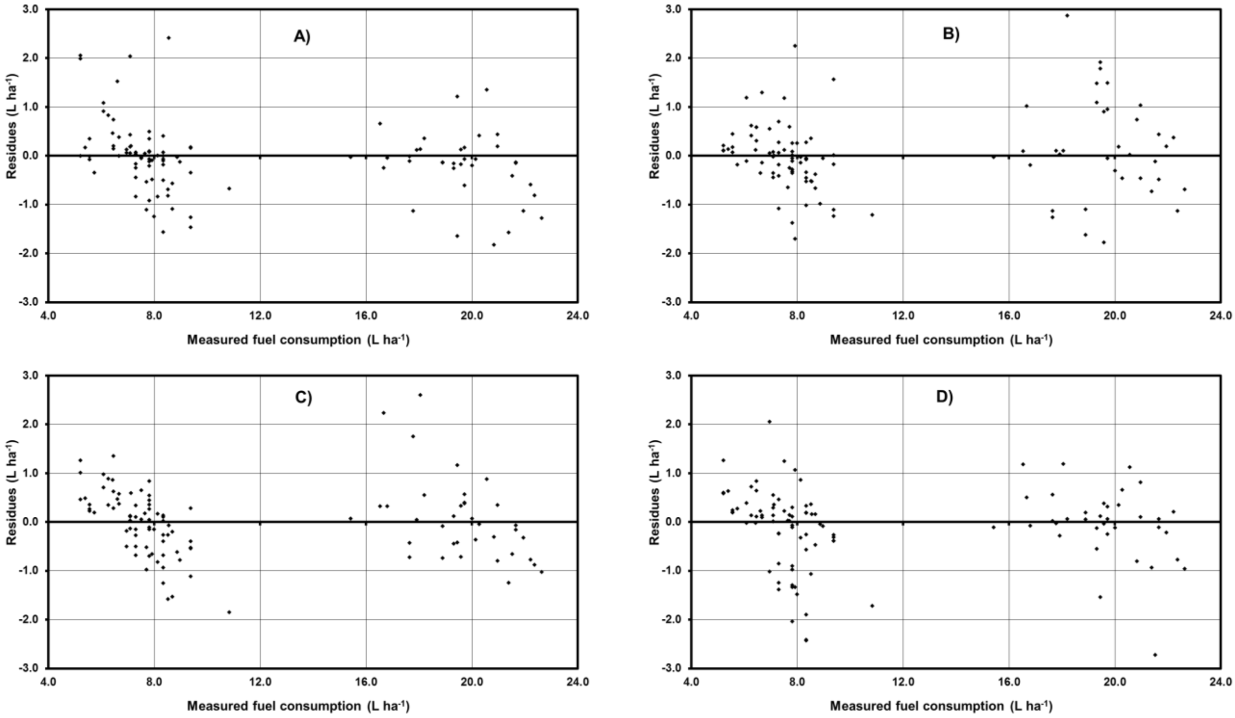


FIGURE 2. Residues values in function of the measured fuel consumption: a) ANN 2; b) ANN 3; c) ANN 5; d) ANN 6.

Based on Figure 2, the differences between the measured and the estimated fuel consumption by the neural network were distributed with appropriate symmetry and near normal curve, meaning that the majority of small magnitude residues concentrated in the center, around zero and the other with higher values in the extremes. This characteristic of the frequency histogram in relation to the normal is a fundamental assumption for defining criteria about the efficiency in the network prediction. Also, according to Figure 2, there is no relation between the residues and the variables considered in the prepared networks, because the dots are located randomly along the horizontal axis, and there are no evidences of a pattern of functional dependence.

Although the distribution of residues showed normal characteristics and no pattern of functional dependence, the graphical analysis is considered a subjective process. Thus, we also decided to verify analytically the normality and efficiency of the networks through the Kolmogorov-Smirnov test, Lilliefors and Shapiro-Wilk, as well as the t (Student) test between the measured and estimated values. The results corresponding to those tests are shown in Tables 4 and 5.

TABLE 4. Results of the normality tests for the four artificial neural networks.

ANN and Architecture	Normality test		
	Kolmogorov-Smirnov (D statistical)	Lilliefors	Shapiro-Wilk (W statistical)
2) MLP12:12-18-1:1	D= 0.1752 p<0.01 **	p<0.01**	W= 0.9045 p=0.0011**
3) MLP12:12-21-1:1	D= 0.1174 p<0.10 ns	P<0.08 ns	W= 0.9598 p=0.0742 ns
5) MLP 12:12-10-3-1:1	D= 0.0959 p<0.05 *	p<0.01**	W= 0.9324 p=0.0351*
6) MLP 12:12-18-2-1:1	D= 0.1662 p<0.01 **	p<0.01**	W= 0.9178 p=0.0005**

Obs. p: Probability value; ns: not significant;* and **: Significant at 5 y 1%.

TABLE 5. Results of the t-Student test for the four artificial neural networks.

ANN and Architecture	t-Student Values			Significance
	Calculated	Tabulated		
		α = 5%	α = 1%	
2) MLP 12:12-18-1:1	0.0387	1.6520	2.3439	ns
3) MLP 12:12-21-1:1	0.0276			ns
5) MLP 12:12-10-3-1:1	0.1810			ns
6) MLP 12:12-18-2-1:1	0.1872			ns

Obs. α: Probability level; ns: not significant

According to Table 4, only the residues of the neural network 3 (MLP 12: 12-21-1: 1) showed normality. Taking as reference the studies of TORMAN et al. (2012) and LOPES et al. (2013), the non-significance in normality tests gives it greater reliability to this network. However, the t-test indicated that there are no differences between the measured fuel consumption values and the estimated by the four networks (Table 5).These results allow to affirm that the four networks are appropriate, although the third formed by a single hidden layer with twenty-one neuron is presented as the most suitable for predicting this consumption, depending on the variables that characterize the soil, the implement type in combination with the tillage system and operating conditions for mechanized set.

In Table 6, the statistical criteria to evaluate the efficiency of the four artificial neural networks are summarized. These results demonstrate that the mentioned networks had excellent performance, characterized by the high coefficients obtained, which exceeded the minimum value of 0.7, suggested by TERRA & PASSADOR (2012), BINOTI et al. (2013, 2014 a, b) and GEORGENS et al. (2014). Therefore, the developed networks showed adequate reliability and accuracy, justifying its application for planning purposes and managing of agricultural operations. Such networks can be implemented with MATLAB, as suggested by FERRO & STURARO (2013) or with JAVA, according to CAMPOS et al. (2010) and MADSEN & ADAMATTI (2011). However, an alternative proposed by DAYS (2008), is the VBA programming language ("Visual Basic for Applications"), available in Microsoft Excel that enables easy interaction with the variables, data and spreadsheets.

TABLE 6. Summary of statistical criteria to evaluate the neural networks efficiency.

ANN and Architecture	Statistical Criterion		
	Correlation coefficient	Willmont Index	Performance Index
2) MLP 12:12-18-1:1	0.9905	0.9951	0.9857
3) MLP 12:12-21-1:1	0.9910	0.9954	0.9865
5) MLP 12:12-10-3-1:1	0.9891	0.9943	0.9835
6) MLP 12:12-18-2-1:1	0.9906	0.9953	0.9859

CONCLUSIONS

The multilayer artificial neural networks of perceptron type are suitable for estimating the fuel consumption in agricultural operations.

It was possible to define and check the architectures to consider the soil mechanical resistance to penetration, the mobilized area, the sliding and engine working conditions.

The use of binary variables to introduce the tillage system and the operating conditions in the architectures raised the generalization of the neural networks.

The developed artificial neural networks showed adequate reliability and accuracy in predictions, which justifies its application.

The obtained artificial neural networks can be a useful tool for planning and management of mechanized farming operations, requiring programming for its implementation.

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