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Potential assessment of neuro-fuzzy strategy in prognostication of draft parameters of primary tillage implement

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ABSTRACT

This study investigates potential of neuro-fuzzy strategy in prognostication of draft parameters of primary tillage implement. To this aim, computer simulation environment of adaptive neuro-fuzzy inference system (ANFIS) was employed to simulate field data of tillage operations with moldboard plow implement. The field trials were conducted at three levels of forward speed (2, 4 and 6 km/h) and three levels of plowing depth (10, 20 and 30 cm). The plowing depth and forward speed were marked as independent input variables and the draft parameters (draft force and specific draft force) were labeled as dependent output variables in the ANFIS simulation environment. The ANFIS results were compared to those obtained by the equation standardized by American Society of Agricultural and Biological Engineers (ASABE) based on statistical descriptor parameters. Results revealed that the outperforming ANFIS model with acceptable statistical descriptor parameters was more accurate than the ASABE model for prognostication of the draft parameters. The ANFIS modeling results presented that simultaneous increment of forward speed and plowing depth resulted in nonlinear increment of draft force from the lowest bound (< 4 kN) to the highest bound (> 20 kN). Meanwhile, forward speed increment along with plowing depth decrement resulted in nonlinear increment of specific draft force from the lowest bound (< 32 kN/m^2) to the highest bound (> 120 kN/m^2). Furthermore, interaction of forward speed and plowing depth on draft force was congruent. However, it was incongruent in case of specific draft force. According to potential of the ANFIS model assessed in this study, the proposed model can be served as an efficient alternative modeling tool for direct prognostication of the draft parameters of an implement during tillage operations associated with concurrent changes of forward speed and plowing depth.

Introduction

One of important performance parameters of tractor-implement in tillage operations is draft force. Draft force is horizontal component of pulling force generated by tractor to pull, penetrate and keep implement within soil. Availability of draft force data is useful to select proper tractor for pulling a particular implement in the most efficient manner. This scheme for suitable selection of tractor and implement combination leads to enhancement of tractor tractive efficiency as well as tractor overall energy efficacy.

To compare required draft force of the same implement in various soils and experimental field conditions, specific draft force parameter is defined as draft force per unit cross-sectional area of tilled zone. Tilled zone is corresponding to rectangular area which is confined by cutting width and plowing depth of implement. Specific draft force data can be applied to modify cutting width or the number of tools of implement in order to reach the highest field efficiency.

According to the explanations given in the previous paragraphs, over the past decades, researchers focused their studies on behavior determination of the draft parameters (draft force and specific draft force) of various tillage implements to better understand the effect of field operational variables on this phenomenon. They found that the draft parameters changed as influenced by plowing depth, forward speed, soil texture, type and geometry of tillage implement. Therefore, researchers attempted to model the effect of these operational variables on the draft parameters. Hence, applying different modeling strategies was aimed by researchers to extend limited observations towards vast interpretable results.

Abbreviations: ASABE, American Society of Agricultural and Biological Engineers; ANN, artificial neural network; ANFIS, adaptive neuro-fuzzy inference system; ANOVA, analysis of variance; MVAPRE, mean value of absolute prognostication residual errors; RMSE, root mean square error; MRDM, mean relative deviation modulus; FIS, fuzzy inference system; RNAM, Regional Network for Agricultural Machinery

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Nomenclature

W	implement width (m)
FS	forward speed (km/h)
N	number of used data
M	mean of used data
SD	standard deviation
CV	coefficient of variation (%)
CNU	coefficient of non-uniformity (%)
R^2	coefficient of determination
W_w	mass of initial soil (g)
W_d	mass of dried soil (g)
MC	moisture content of sampled soil (d. b. %)
DF	draft force (kN)
H	gross traction force (kN)
R	rolling resistance force (kN)
SDF	specific draft force (kN/m^2)
PD	plowing depth (m)
DP_i	ith sampled draft parameter
DP_{max}	maximum of draft parameter
DP_{min}	minimum of draft parameter
F_i	dimensionless soil texture adjustment parameter
A	machine-specific parameter
B	machine-specific parameter
C	machine-specific parameter
RMSE	root mean square error
MRDM	mean relative deviation modulus (%)
$DP_{act,i}$	ith actual draft parameter
$DP_{mod,i}$	ith modeled draft parameter
DP_{actave}	average of actual draft parameter

In modeling domain of the draft parameters as affected by forward speed and plowing depth, general modeling strategies employed by researchers are chronologically summarized in tabular form in Table 1. The modeling strategies listed in Table 1 can be categorized as mathematical and nonmathematical models. Although, the mathematical models (the ASABE equation, simple linear regression, multiple linear regression, one variable nonlinear regression, two-variable nonlinear regression and dimensional analysis) might provide reliable results with acceptable accuracy, coefficients and constants, and assumptions of the models change by variation of input variables. Therefore, care must be taken to use these coefficients and constants, and assumptions in other conditions. Hence, development of several mathematical equations with different assumptions limits general applications of mathematical modeling strategy in this context. Accordingly, authors intended to employ nonmathematical models. Nonmathematical models are offered based on aptitudes of computer simulation environments.

The ANN computer simulation is soft computing strategy on the basis of artificial neural features. Meanwhile, the FIS computer simulation is soft computing strategy based on expert knowledge and fuzzy rules. Combination of the ANN and FIS strategies is recently recommended in neuro-fuzzy based computer simulation environment. This modeling strategy is known as the ANFIS. The ANFIS strategy is an intelligent computer simulation which is commonly used to prognosticate uncertain and nonlinear relationships between multiple input

Table 1
Modeling strategies developed to prognosticate the draft parameters of various implements during tillage operations.

Authors	Year	draft force	specific draft force
Harrison and Reed [1]	1962	Multiple linear regression	
Dwyer et al. [2]	1974	One variable nonlinear regression	
Upadhyaya et al. [3]	1984	Two-variable nonlinear regression	
Summers et al. [4]	1986		One variable nonlinear regression
Bashford et al. [5]	1991		Multiple linear regression
Ismail and Burkhardt [6]	1993	ASABE equation	
Smith [7]	1993	One variable nonlinear regression	
Glancey and Upadhyaya [8]	1995	Two-variable nonlinear regression	
Harrigan and Rotz [9]	1995	ASABE equation	
Glancey et al. [10]	1996	Two-variable nonlinear regression	
Grisso et al. [11]	1996	Two-variable nonlinear regression	
Kushwaha and Linke [12]	1996	Simple linear regression	
Al-Janobi and Al-Suhaibani [13]	1998		Two-variable nonlinear regression
Choi et al. [14]	2000	ANN	
Al-Janobi et al. [15]	2001		ANN
Thomas and Singh [16]	2002	Two-variable nonlinear regression	
Mamman and Oni [17]	2005	Multiple linear regression	
Aboukarima and Saad [18]	2006	ANN	
Aboukarima [19]	2007	ANN	
Godwin et al. [20]	2007	One variable nonlinear regression	
Serrano and Peca [21]	2008		Simple linear regression
Alimardani et al. [22]	2009	ANN	
Roul et al. [23]	2009	ANN	
Marakoglu and Carman [24]	2010		FIS
Mohammadi et al. [25]	2012	FIS	
Nkakini and Akor [26]	2012	Dimensional analysis	
Al-Hamed et al. [27]	2013		ANN
Askari and Khalifahamzehghasem [28]	2013	ASABE equation	
Ranjbar et al. [29]	2013	Two-variable nonlinear regression	
Moeenifar et al. [30]	2013	Dimensional analysis	
Akbarnia et al. [31]	2014	ANN	
Moeenifar et al. [32]	2014	Dimensional analysis	
Nkakini [33]	2015	Simple linear regression	
Nkakini [34]	2015	Dimensional analysis	
Al-Suhaibani et al. [35]	2015	Multiple linear regression	
Ranjbarian et al. [36]	2017	ASABE equation	
Shafaei et al. [37]	2017	ANFIS	

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