Computers and Electronics in Agriculture 142 (2017) 406–415

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Appraisal of Takagi-Sugeno-Kang type of adaptive neuro-fuzzy inference system for draft force prediction of chisel plow implement

S.M. Shafaei, M. Loghavi, S. Kamgar*

Department of Biosystems Engineering, School of Agriculture, Shiraz University, Shiraz 71441-65186, Iran

ARTICLE INFO

Keywords:
Soft computing method
Forward speed
Plowing depth
Single effect
Dual interaction effect

ABSTRACT

Required draft force of chisel plow implement during tillage operations was comprehensively apprised. Field experiments were carried out at three levels of plowing depth (PD) (10, 20 and 30 (cm)) and three levels of forward speed (FS) (2, 4 and 6 (km/h)) in a clay loam soil. An intelligent model based on soft computing technique, adaptive neuro-fuzzy inference system (ANFIS), was used to integrally predict draft force. The FS and PD were chosen as input variables and the draft force was considered as output parameter in the first order Takagi-Sugeno-Kang type of ANFIS model. A comparison was also performed between results of the best developed ANFIS model and those of the well-known mathematical model suggested by American Society of Agricultural and Biological Engineers (ASABE). To select the best model with the highest predictive ability, some statistical performance criteria (SPC) (coefficient of determination (R^2), root mean square error (RMSE), mean relative deviation modulus (MRDM), mean of absolute values of prediction residual errors (MAVPRE) and prediction error mean (PEM)) were used. The results demonstrated that the best ANFIS model with acceptable SPC values of $R^2 = 0.994$, RMSE = 0.722 (kN), MRDM = 3.172%, MAVPRE = 0.561 (kN) and PEM = −0.071% was more accurate than the ASABE model. The ANFIS modeling results also showed that the simultaneous or individual increment of FS and PD resulted in nonlinear increment of draft force. Additionally, the interaction of FS and PD on draft force was congruent. Application of physical perception obtained from developed ANFIS model results led to exposition of a new scientific window towards deep root understanding of draft force behavior. Thus, it is practically proposed to employ the ANFIS model for proper selection of tractor type for pulling chisel plow implement in the most efficient manner.

1. Introduction

In tillage operations, the major part of power produced by tractor is consumed to provide required pulling force of tillage implement. In case of mounted and semi-mounted type of tillage implement, this pulling force is devoted to pull, keep and penetrate the implement into the soil. Draft force is the horizontal component of the pulling force which is generally known as the most important factor for matching tractor-implement combination. The proper match of tractor and implement results in achievement of maximum tractive efficiency of tractor and consequently, optimization of fuel and energy consumption in tillage system. Awareness of this fact has led to the attempts to be made by researchers in this regard.

The results of the attempts in field of determination of required draft force of various tillage implements have been summarized in the ASABE agricultural machinery management standard. According to the standard, the draft force changes as affected by soil texture, type and geometry of tillage implement, the PD and FS. Hence, Eq. (1) is generally proposed to predict draft force in different conditions (ASABE, 2015).

$$DF = F_i[\ A + B(FS) + C(FS)^2]\ W \times PD \tag{1}$$

The draft force of tillage implements was mathematically predicted by means of Eq. (1) in previous works (Ismail and Burkhardt, 1993; Harrigan and Rotz, 1995; Askari and Khalifahamzehghasem, 2013; Ranjbarian et al., 2017). In some cases, comparison between predicted and measured draft force data indicated that the ASABE equation was

Abbreviations: FS, forward speed; PD, plowing depth; ANN, artificial neural network; ANFIS, adaptive neuro-fuzzy inference system; SPC, statistical performance criteria; ANOVA, analyses of variance; DIE, dual interaction effect; DMRT, Duncan's multiple range test; MAVPRE, mean of absolute values of prediction residual errors; RMSE, root mean square error; MRDM, mean relative deviation modulus; SE, single effect; 2WD, two-wheel drive; 4WD, four-wheel drive; PRE, prediction residual error; SDP, statistical descriptor parameter; FIS, fuzzy inference system; ASABE, American Society of Agricultural and Biological Engineers; SLR, simple linear regression; MLR, multiple linear regression; NR, nonlinear regression; RNAM, Regional Network for Agricultural Machinery; PEM, prediction error mean

* Corresponding author.
E-mail address: kamgar@shirazu.ac.ir (S. Kamgar).

http://dx.doi.org/10.1016/j.compag.2017.09.023
Received 29 April 2017; Received in revised form 14 September 2017; Accepted 17 September 2017
Available online 11 October 2017
0168-1699/ © 2017 Elsevier B.V. All rights reserved.

Nomenclature

Y	percentage of wheat stubble cover (%)
X	dry weight of wheat stubble per unit surface area (Lb/acre)
N	number of used data
M	mean of used data
SD	standard deviation
CV	coefficient of variation (%)
CNU	coefficient of non-uniformity (%)
CT	contribution of variation (%)
SS_t	total sum of square
SS_v	sum of square of variation
R^2	coefficient of determination
DF	draft force (kN)
F_i	dimensionless soil texture adjustment parameter
A	machine-specific parameter
B	machine-specific parameter
C	machine-specific parameter
FS	forward speed (km/h)
W	machine width (m)
PD	plowing depth (cm)
H	gross traction force (kN)
R	rolling resistance force (kN)
DF_i	ith sampled draft force (kN)
DF_{max}	maximum value of draft force (kN)
DF_{min}	minimum value of draft force (kN)
$DF_{act,i}$	ith actual draft force (kN)
DF_{actave}	average of draft force (kN)
$DF_{pre,i}$	ith predicted draft force (kN)
RMSE	root mean square error (kN)
MRDM	mean relative deviation modulus (%)

not suitable for the tested conditions. The draft force was also predicted by SLR model based on one variable (FS or PD) rather than ASABE equation (Kushwaha and Linke, 1996; Nkakini, 2015a). Therefore, a unique model was developed for each experimental condition of FS or PD. To predict draft force on the basis of both FS and PD, the comprehensive MLR model was applied by some researchers (Harrison and Reed, 1962; Mamman and Oni, 2005; Al-Suhaibani et al., 2015). Because the draft force changes nonlinearly as affected by FS and PD, the SLR and MLR model could not be typically used for draft force prediction. Thus, application of the NR models was proposed to nonlinearly predict the draft force. The one variable NR model (Dwyer et al., 1974; Smith, 1993; Godwin et al., 2007) and two-variable NR model (Upadhyaya et al., 1984; Glancey and Upadhyaya, 1995; Grisso et al., 1996; Glancey et al., 1996; Thomas and Singh, 2002; Ranjbar et al., 2013) were developed to directly predict draft force. Although high predictive ability of the NR models was reported, due to the changes of coefficients of the models in other conditions, they are incoherence models. Hence, the modeling method is not reliable enough for continuous prediction of required draft force of tillage implement in actual conditions.

One of the numerical modeling methods that has been recently used in many agricultural studies is dimensional analysis. This method is commonly applied for prediction of desired parameters based on multiple input variables. Many researchers concentrated their attempts to develop several equations for draft force prediction of tillage implements (Nkakini and Akor, 2012; Moeenifar et al., 2013, 2014; Nkakini, 2015b). Development of several mathematical equations with different assumptions, based on the method, limited the universal applications of the modeling method in this context.

Soft computing methods are capable modeling techniques which are used widely to predict uncertain and nonlinear relationships between multiple input and output variables. The ANN soft computing technique principally works regarding the artificial intelligence capabilities. This dominant ability led to special interest dedication of researchers on ANN prediction of implement draft force based on field conditions (Aboukarima and Saad, 2006; Aboukarima, 2007; Alimardani et al., 2009). The predictive ability of ANN soft computing technique was also investigated for draft force prediction of tillage tools in controlled soil bin environment (Choi et al., 2000; Roul et al., 2009; Akbarnia et al., 2014). The results of cited works demonstrated that the ANN soft computing technique is a powerful modeling method for accurate prediction of required draft force of implement/tool based on simultaneous changes of FS and PD in a specific soil condition.

The FIS soft computing technique uses expert knowledge between input and output data of the system. The relative knowledge is determined among desired parameters corresponding to the defined fuzzy rules of the system. Similar to ANN, the FIS is capable of modeling multiple input and output variables. In a recent study, Mohammadi et al. (2012) experimentally assessed the FIS predictive ability for draft force prediction of a winged share tillage tool in a well-equipped soil bin facility. According to the study results, performance of the developed FIS model was found to be acceptable.

The advantages of both ANN and FIS soft computing techniques are presently conjoined in an intelligent system, ANFIS. The ANFIS performs based on the explicit knowledge of the FIS combined with the learning power of the ANN. Therefore, this intelligent modeling method does not require expertise knowledge and trained system. The simplest type of ANFIS soft computing technique is the first order Takagi-Sugeno-Kang type which is principally used for modeling of one output parameter based on two input variables (Jang, 1993). This simple fuzzy modeling method was initially proposed regarding two fuzzy If-Then rules (Takagi and Sugeno, 1985). To avoid prolongation of the paper, descriptions of the ANFIS type details are referred to the literature.

ANFIS soft computing technique has been widely used in many fields of agricultural and biosystems engineering due to its capability of nonlinear modeling with multiple input variables. A probe into some papers showed the applications of the first order Takagi-Sugeno-Kang type of ANFIS in prediction of agricultural and biosystems engineering parameters (Karaman and Kayacier, 2011; Sefeedpari et al., 2014; Shafaei et al., 2015, 2016b).

The chisel plow implement is commonly used for primary tillage operations with minimum soil dispersion, specially, for farms having crop residue on the soil surface. Literature review demonstrated that draft force prediction using aforementioned modeling methods has added to the information about chisel plow implement behavior within different field conditions over the years (Upadhyaya et al., 1984; Ismail and Burkhardt, 1993; Harrigan and Rotz, 1995; Grisso et al., 1996; Glancey et al., 1996; Aboukarima and Saad, 2006; Aboukarima, 2007; Askari and Khalifahamzehghasem, 2013; Moeenifar et al., 2014; Ranjbarian et al., 2017). But there is a no information about application of ANFIS soft computing technique in draft force prediction of chisel plow implement. Hence, this study was carried out to validate the efficiency of ANFIS soft computing technique for integrated prediction of draft force behavior of chisel plow implement as function of FS and PD. The results were also compared with those obtained from ASABE equation. Additionally, the effect of FS and PD on draft force behavior of chisel plow implement was comprehensively investigated with the adaption of statistical analysis.

2. Materials and methods

2.1. Tillage site

The test farmland with uniform wheat stubble coverage was

Download English Version:

https://daneshyari.com/en/article/6458715

Download Persian Version:

https://daneshyari.com/article/6458715

Daneshyari.com