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THE EFFECT OF TRACTOR DRIVING SYSTEM TYPE ON ITS SLIP AND ROLLING RESISTANCE AND ITS MODELLING USING ANFIS

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Pulling force required for operations such as tillage is a result of the interaction between the tractor's wheel drive and soil surface limited by various factors, such as the rolling resistance and slip of the wheel drive. In this research, the traction performance of tractors with different driving systems (four-wheel drive, rear wheel drive, and front wheel drive) was investigated. Test parameters included different tractor forward speeds (1.26, 3.96, and 6.78 km·h⁻¹), tire inflation pressures (170, 200, and 230 kPa), ballast weights (0, 150, and 300 kg), and aforementioned driving systems, as well as required drafts (2, 6, and 10 kN). For each experiment, two indices of slip and rolling resistance were measured. The results of this study showed that the four-wheel-driving system indicated a low slip at similar pulling forces. In order to achieve a low slip, the four-wheel driving system did not necessarily need to add the ballast weight or to reduce the inflation pressure. The four-wheel driving system showed lower rolling resistance than the other two systems. Slip and rolling resistance of wheels were predicted using an adaptive neuro-fuzzy inference system (ANFIS). It was found that ANFIS had a high potential for predicting the slip ($R^2 = 0.997$) and rolling resistance ($R^2 = 0.9893$).

Keywords: motion system; ballast weight; tractor performance; inflation pressure

The optimum criterion for evaluating the tractor performance is calculation of the tractor traction performance during ploughing operations on soft soils (Battiatto and Diserens, 2017). The pulling force required for operations such as tillage is a result of the interaction between the tractor's wheel drive and soil surface, which converts the power generated by the engine to the pulling force. Majority of studies have shown that 20 to 55% of tractor power is lost in the process of interaction between tire and soil surface due to the drive wheel slip, tractor's rolling resistance, and tire and soil deformation (Damanauskas and Janulevicius, 2015). The tractive performance is affected by the tractor design parameters, attaching tools, and soil conditions (Moinar and Shahgholi, 2018).

If the wheel drive slip exceeds 15%, it will result in severe soil compaction and reduced performance (Moitzi et al., 2013). Slipping less than 7% during agricultural operations can be achieved by deployment of very heavy tractors. However, in this case, carrying excessive weights leads to increased fuel consumption and soil compaction, which are considered undesirable (Janulevicius et al., 2018).

Main factors affecting the rolling resistance of a pneumatic tire in deformable soils are soil displacement, tire flexibility, and soil friction and adhesion; several other subfactors are wheel diameter, inflation pressure, and axle load. Research shows that the wheel diameter has an indirect relationship, the axle load has a direct relationship, and the inflation pressure has an inverse relationship with the rolling resistance (Elwaleed et al., 2006). When the soil is hard, its cohesion is high, leading to less slipping and lower

rolling resistance (Moitzi et al., 2013), while in plastic state, soil cohesion decreases and adhesion to tire increases. This causes higher tire sinking, making the wheels slip, and high rolling resistance, resulting in greater loss of power and reduced tractor efficiency (Battiatto et al., 2013).

Considering the tillage operation, it has been reported that, depending on the amount of ballast weight and its location, the draft can be increased up to 15% (Muhsin, 2010). However, this method has an adverse effect on soil and causes soil compaction in a depth that is usually deeper than that of conventional tillage operations (Barbosa and Magalhaes, 2015). The excess ballast weight also increases fuel consumption due to increased rolling resistance and higher tire sinkage in the soil. On the other hand, when the ballast weight is lower than optimal value, tractor will waste fuel due to excessive slipping (Lacour et al., 2014). Another way to reduce the slip is to increase the contact surface between the drive wheel and soil surface. By reducing the tire pressure, contact surface can be increased (Battiatto and Diserens, 2013) or it can be used with double wheels (Damanauskas et al., 2015), both of which increase the area of the wheel contact with the soil.

In recent years, artificial intelligence techniques have been developed to model complex and uncertain systems. An efficient example of these techniques is the integration of artificial neural network (ANN) and fuzzy inference system. Fuzzy logic performs the inference mechanism with uncertainty in recognition while the ANN also has the ability to learn, adapt, and process in parallel. The hybrid system is called Adaptive Neuro-Fuzzy Interference System

(ANFIS) (Buckley and Hayashi, 1994). This method can solve complex issues relying on learning capabilities and parallel processing capabilities in ANNs. In terms of fuzzy systems, an approximate decision-making process is based on individual or group human experience. In these systems, the quantitative modelling is performed qualitatively and intuitively (instead of using quantitative values) and thus it is necessary to deal with indeterminants (Wang, 1997). Nevertheless, these systems do not have the ability to learn and, in confrontation with the complex systems, the regulation of membership functions and required rules are time-consuming and difficult. Although the ability of fuzzy systems has been approved in solving of complex problems related to modelling and prediction, control, and artificial intelligence (Wang, 1997), given the complementary (rather competitive) capabilities of these two solutions, it is possible to simultaneously use their advantages by combining them. In a research conducted by Taghavifar and Mardani (2014), authors predicted energy efficiency indicators using ANFIS. Input parameters included wheel load, speed, and slip, each of them at three levels. The results of this study showed a high prediction accuracy ($MSE = 0.0166$ and $R^2 = 0.98$). Ghadernejad et al. (2018) conducted a study to predict soil compaction under tractor wheels, utilizing the ANFIS model with four inputs: manure, number of passes, moisture, and depth. The results of this study showed a higher accuracy in predicting soil density than the regression model.

The objective of this study is to evaluate the tractor performance indices (slip and rolling resistance) in front-wheel-drive, rear-wheel-drive, and four-wheel-drive modes. Furthermore, ANFIS models were designed to predict tractor slip and rolling resistance in different tractor configurations, taking into account ballast weights, tire inflation pressure, various travel speeds of the tractor, and different required drafts.

Material and methods

Field tests were conducted at the Research Farm of Ardabil Agricultural Research Center (38° 12' 46.6" N, 48° 17' 42.2" E, and 1,350 m above sea level). The field was flat and had common barley (*Hordeum vulgare* Linnaeus) stubble residues from the previous season. Soil texture was loamy clay. Moisture and other soil properties were measured in 30 randomly selected points within the whole field at two depths: 0–25 and 25–50 cm. Results are presented in Table 1. Observed parameters included different levels of tractor forward speed (1.26, 3.96, and 6.78 km·h⁻¹), tire inflation pressure (170, 200, and 230 kPa), ballast weights (0, 150, and 300 kg), tractor motion systems (front-wheel-drive, rear-wheel-drive, and four-wheel-drive), and pulling force (2, 6, and 10 kN) for each experiment, on the basis of which two indices of slip and rolling resistance were measured. Type of motion system is not a numerical property, yet the modelling requires numerical values. In this regard, the tractor-implement system slip can represent an appropriate index of driving system type. In order to incorporate the effect of the driving system to the modelling process, the tractor slip value in different motion systems was used.

Table 1 Physical properties of the field soil

Property	Value
Sand (%)	40
Silt (%)	28
Clay (%)	32
Organic matter (g·100 g ⁻¹)	0.29
Plastic limit	25.76
Liquid limit	39.81
Plasticity index	14.05
(%) Field capacity based on dry weight	10.13
Dry bulk density (0–25 cm) (g·cm ⁻³)	1.35
Dry bulk density (25–50 cm) (g·cm ⁻³)	1.46
Moisture content based on dry weight (%) (0–25 cm)	9.3
Moisture content based on dry weight (%) (25–50 cm)	10.4

Technical characteristics of the Goldoni 240 tractor (4WD) used for testing are presented in Table 2. The front and rear tractor differentials related to the driving system were alternately disabled for the experiments, so the tractor could operate either as having front or rear wheel drive system. A subsoiler was used to create draft. Variation in the draft was obtained by changing the depth of subsoiler operation. Drafts of 2, 6 and 10 kN were obtained using a subsoiler tine at a depth of 30 cm, two subsoiler tines at a depth of 30 cm and two subsoiler tines at a depth of 50 cm, respectively. To measure the rolling resistance, the Goldoni 240 tractor in unloaded mode was towed by another tractor and the force required to move the Goldoni 240 tractor was measured using load cell installed between the two tractors. The draft applied to the tractor was measured using a three-point connecting dynamometer (Abbaspour-Gilandeh and Haghighat-Shishvan, 2011). The variation in the measured draft was in the range of ± 0.05 N.

Table 2 Tractor characteristics

Specifications	Unit	Value
Type of tractor engine	–	Diesel (3 Cylinders)
Engine power	(kW)	30.8
Static weight on front tires	(kg)	705
Static weight on rear tires	(kg)	360

The tractor wheel speed was measured utilizing an inductive proximity sensor mounted in line with the outer edge of a 34-tooth sprocket fixed inside the rear wheel (Fig. 1). Inductive proximity sensor is a non-contact device that is set up on a radio frequency field with an oscillator and a coil. Presence of a metal object (tooth) changes the field and the sensor detects the change. The resolution is 0.0003 m·s⁻¹. The sensor detected passing of each tooth during the wheel rotation so that with each full rotation of the gear or rear wheel, digital display of pulse meter attached to a magnetic sensor displayed the number of gear teeth. This number was divided by 34 to calculate the wheel rotation.

Fig. 1 Wheel speed transducer for measuring of tire rotation

Distance travelled was calculated by having a perimeter of the rear wheel. Dynamic rolling radius was determined and considered in computing rear wheel perimeter. The actual speed of the tractor was easily computed by measuring the time required to travel this distance using a stopwatch. The following Eq. (1) was used to calculate the slip:

$$\text{Slip}(\%) = 1 - \frac{v_a}{v_t} \cdot 100 \quad (1)$$

where:

v_a – actual velocity ($\text{m}\cdot\text{s}^{-1}$)
 v_t – theoretical velocity ($\text{m}\cdot\text{s}^{-1}$)

Fig. 2 Basic structure of the Adaptive Neural-Fuzzy Inference System (ANFIS)

Adaptive neuro-fuzzy inference system

ANFIS is a multi-layer adaptive network consisting of main elements and functions of fuzzy logic systems. In general, the ANFIS system consists of a 5-layer structure with a number of input variables, each of which has two or more membership functions. Fig. 2 shows the ANFIS network architecture with two inputs, one output, and two rules.

In this study, two models for predicting slip and rolling resistance were developed in ANFIS. The first model is based on 5 input factors including inflation pressure, ballast weight, pulling force, tractor driving system, and forward speed. The second model is based on four input factors including inflation pressure, ballast weight, tractor driving system, and forward speed. Grid partition structure was used to create the network. Four common types of triangular, trapezoidal,

Table 3 Selected rules in the slip prediction model

Rules	Input variables					Linear output function (% slip)
	D	MS	IP	BW	S	
1	L	L	L	L	L	$\text{Slip} = 1.28D + 1.477MS + 0.02369IP + 0.006237BW + 0.4499S - 2.768$
5	L	L	H	L	L	$\text{Slip} = -0.02834D + 0.1137MS + 0.02552IP - 0.0121BW - 0.271S + 2.046$
17	H	L	L	L	L	$\text{Slip} = 0.4836D + 2.121MS + 0.03794IP + 0.04143BW + 0.4147S + 0.7349$
21	H	L	H	L	L	$\text{Slip} = -1.277D + 4.096MS + 0.1376IP - 0.01722BW + 0.2468S - 0.5424$
25	H	H	L	L	L	$\text{Slip} = 0.03331D - 2.112MS + 0.2052IP + 0.06992BW + 0.3297S - 0.1642$
32	H	H	H	H	H	$\text{Slip} = -0.4357D - 2.77MS + 0.1043IP + 0.03969BW - 0.1946S + 0.0002872$

D – draft; MS – motion system; BW – ballast weight; IP – inflation pressure; S – speed

Table 4 Selected rules in the motion resistance prediction model

Rules	Input variables				Linear output function (rolling resistance)
	MS	IP	BW	S	
1	L	L	L	L	$MR = 0.3103MS + 0.002011IP + 0.00459BW + 0.01378S - 0.005265$
2	L	L	L	H	$MR = 0.2182MS + 0.00149IP + 0.003894BW + 0.02285S + 0.006151$
5	L	H	L	L	$MR = 0.1141MS + 0.003541IP - 0.0004052BW - 0.02053S + 0.003915$
10	H	L	L	H	$MR = -0.1223MS + 0.006777IP + 0.003032BW + 0.04878S + 0.0007311$
14	H	H	L	H	$MR = -0.119MS + 0.008611IP + 0.003029BW - 0.02972S - 0.0004734$
16	H	H	H	H	$MR = -0.08654MS + 0.003808IP + 0.004001BW + 0.02254S + 2.343e-05$

D – draft; MS – motion system; BW – ballast weight; IP – inflation pressure; S – speed

Gaussian, and generalized-bell membership functions were considered for representing inputs. The number of membership functions for each input was considered to be the minimum possible value of 2 to prevent the creation of high rules and excessive system complexity. The input membership function used in this network is the linear type. The hybrid optimization method was used for network learning. The number of rules created by the network for slip and rolling resistance models is 32 and 16, respectively. Since the number of rules created is so high, there are presented only a few of them for a better understanding of ANFIS modelling (Tables 3 and 4). These rules were based on the fuzzy type Takagi-Sugeno-Kang (TSK). In this system, the foreground (if-then) is represented by fuzzy rules, but the resultant part is non-fuzzy and is a linear combination of input variables. The range of all inputs was divided into two parts: the low and the high areas, which were represented by the membership functions L and H, respectively.

According to the weight of each rule, the final output value of the model was calculated by averaging the predicted values by the linear functions of each rule. The weight of each rule was equal to the minimum degree of membership of the inputs of its rule. Finally, the final output of the model was calculated from the following Eq. (2).

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \quad (2)$$

where:

f_1, f_2 – linear functions related to rules 1 and 2, respectively
 w_1, w_2 – weights corresponding with each rule

To evaluate the ability of developed models, two statistical measures of relative error (ε) and coefficient of determination (R^2) were used. These were given by Eqs. (3) and (4) (Carman, 2008):

$$\varepsilon = \frac{100}{N} \sum_{i=1}^N \frac{Y_{measured} - Y_{predicted}}{Y_{measured}} \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^N (Y_{measured} - Y_{predicted})^2}{\sum_{i=1}^N (Y_{measured} - Y_{mean})^2} \quad (4)$$

where:

$Y_{measured}, Y_{predicted}$ – measured and predicted values, respectively

Y_{mean} – average value of all measured data

Furthermore, in this research, several multiple linear regression models were prepared in SPSS software to gain more knowledge on the effect of each input variable on the slip and rolling resistance.

Results and discussion

Tables 5 and 6 present the structural parameters of the models and their statistical measures for evaluating their performance. The results (Tables 5 and 6) show the high predictive power ($R^2 \geq 0.99$ and ε (%) ≤ 4) of all models. The best model for predicting slip uses triangular-shaped membership function (Trimf) with $R^2 = 0.997$ and $\varepsilon = 3.08\%$. The best model for prediction of the rolling resistance is the one that uses the generalized bell-shaped membership function (Gbellmf) with $R^2 = 0.9893$ and $\varepsilon = 1.89\%$.

Tables 7 and 8 present the statistical characteristics of the stepwise regression model for predicting slip and rolling resistance, respectively. The statistical models of slip prediction had $R^2 = 0.867$ and ε (%) = 19, and the rolling resistance prediction had $R^2 = 0.958$ and ε (%) = 5. According to the statistical factors, ANFIS models presented high accuracy in predicting the tractor slip and its rolling resistance. However, in comparison to the ANFIS models,

Table 5 The characteristics of the best structure of developed ANFIS architectures for slip; the bolded values show outperforming models

Model	Type of MF		Number of MF		Optimization method	Test	
	Input	Output	Input	Epoch		ε (%)	R^2
Grid Partition	Trimf	Linear	2 2 2 2 2	20	Hybrid	3.08	0.997
Grid Partition	Gaussmf	Linear	2 2 2 2 2	20	Hybrid	3.31	0.997
Grid Partition	Trapmf	Linear	2 2 2 2 2	20	Hybrid	3.24	0.997
Grid Partition	Gbellmf	Linear	2 2 2 2 2	20	Hybrid	3.67	0.996

Table 6 The characteristics of the best structure of developed ANFIS architectures for rolling resistance; the bolded values show outperforming models

Model	Type of MF		Number of MF		Optimization method	Test	
	Input	Output	Input	Epoch		ε (%)	R^2
Grid Partition	Trimf	Linear	2 2 2 2	20	Hybrid	2.69	0.9808
Grid Partition	Gaussmf	Linear	2 2 2 2	20	Hybrid	2.16	0.9871
Grid Partition	Trapmf	Linear	2 2 2 2	20	Hybrid	2.26	0.9866
Grid Partition	Gbellmf	Linear	2 2 2 2	20	Hybrid	1.89	0.9893

regression models have invaluable benefits. The regression model directly deals with the impact of each factor and it tries to provide a model, in which the importance and impact of each of the factors is clearly evident. In respect to the

standard coefficients listed in Table 7, draft, tractor driving system, inflation pressure, ballast weight, and travel speed showed the greatest effect on the slip, in the presented order. Moreover, in respect to the standard coefficients

Table 7 Statistical characteristics of stepwise regression model for slip

Model	Unstandardized coefficients		Standardized coefficients		
	B	Std. error	Beta	t	sig
(Constant)	-15.474	1.644		-9.413	0.000
D	1.622	0.056	0.689	29.126	0.000
MS	4.330	0.223	0.460	19.436	0.000
IP	0.083	0.007	0.263	11.129	0.000
BW	-0.016	0.001	-0.257	-10.847	0.000
S	-0.734	0.81	-0.215	-9.089	0.000

Table 8 Statistical characteristics of stepwise regression model for rolling resistance

Model	Unstandardized coefficients		Standardized coefficients		
	B	Std. error	Beta	t	sig
(Constant)	-0.545	0.069		-7.909	0.000
MS	0.327	0.010	0.788	34.338	0.000
BW	0.001	0.000	0.451	19.674	0.000
IP	0.005	0.000	0.358	15.604	0.000
S	-0.014	0.003	-0.090	-3.933	0.000

Constant is y-intercept in a linear function

Fig. 3 Comparison of the values predicted by regression and ANFIS models with the observed values for (a) slip, (b) rolling resistance

Fig. 4 Variation of the values predicted by regression and ANFIS models from the observed values for (a) slip, (b) rolling resistance

listed in Table 8, the tractor driving system, ballast weights, inflation pressure, and tractor speed had the greatest impact on the rolling resistance, in the presented order.

Figs. 3a and 3b illustrate the mapping between the experimental and predicted values for slip and rolling resistance by the ANFIS and stepwise regression models. Clearly, in contrast to the regression model, the ANFIS model provides a more accurate mapping of the experimental and predicted values. In addition to this, the deviation between the measured values and predicted values of the models were calculated and plotted. Figs. 4a and 4b show that the standard deviation for the predicted values of the ANFIS model for slip (-0.88 to 0.76) and the rolling resistance (-0.033 to 0.071) are much lower than the deviation of the predicted values of the stepwise regression models for slip (-6.08 to 6.24) and rolling resistance (-0.118 to 0.1186).

Investigation of slip and rolling resistance as a result of the application of experimental factors

The 3D surface curves of slip and rolling resistance as two indicators of the drive wheel performance are shown in Figs. 5 and 6, respectively. As it is clear from Fig. 5a, slip increases with increasing draft, but the use of four-wheel-drive mode makes it possible to achieve the maximum draft of 10 kN at a relatively low slip level of 12.4%, while when in the front-

wheel-drive mode, this pulling force was achieved at a high slip level of 25.5%. Many studies have reported that draft was the most important factor in terms of increasing the slip and optimal and economical slipping is recommended in the range of 10–15% (Battiato and Diserens, 2013; Lacour et al., 2014; Battiato and Diserens, 2017). Fig. 5b illustrates the interaction between the ballast weights and tire inflation pressure. It indicates that the slip decreases with decrease in inflation pressure and increase in the ballast weight. Scrutinizing Fig. 5b reveals that the slip decreases with decreasing inflation pressure and increasing ballast weight so that by applying the inflation pressure of 170 kPa and ballast weight of 300 kg, a slip value of less than 10% can be achieved, while applying the inflation pressure of 230 kPa and without ballast weight, the slip level was higher than 20%. Reducing the slip by raising the ballast weight and decreasing the inflation pressure is because both factors increased the wheel-soil contact area and with the improvement of soil and wheel conflict, the tire slip was reduced (Muhsin, 2010; Battiato and Diserens, 2013; Damanauskas and Janulevicius, 2015).

Fig. 6a shows that the increase of ballast weight leads to an increase in the rolling resistance, since the wheel load plays a major role in increasing the wheel's rolling resistance. Such a process has also been reported by other researchers (Taghavifar and Mardani 2013; Taghavifar and Mardani

Fig. 5 3D surface curves of slip by interactions of input parameters; (a) interaction between MS and draft, (b) interaction IP and BW

Fig. 6 3D surface curves of MR by interactions of input parameters; (a) interaction between MS and BW, (b) interaction IP and speed

2014). In Fig. 6b, increasing travel speed reduced the rolling resistance, which can be attributed to the fact that, at lower speeds, the wheel loading time on the soil increases, resulting in the increased tire sinkage in soil and soil deformation. The energy used to deform the soil increases rolling resistance, so the movement speed can be increased to prevent energy loss in the soil. The type of tractor driving system has a significant effect on the reduction of rolling resistance. As shown in Fig. 6a, the four-wheel-drive mode had a lower rolling resistance in contrast to two the other observed modes. This result can be explained by the fact that drive wheel contact area in four-wheel-drive mode is doubled in comparison to two other modes, and increase in the contact area of wheels with the soil reduced the rolling resistance. The influence of contact area of the wheel with the soil has been investigated by several researchers who reported similar results (Damanauskas et al., 2015). In regards to this, Botta et al. (2012) compared the rolling resistance of a four-wheel drive and two-wheel drive tractor. Although the four-wheel-drive tractor had a higher weight, it had a lower rolling resistance than a two-wheel-drive tractor. As shown in Fig. 6b, reduction of tire inflation pressure reduces the rolling resistance. The influence of inflation pressure on the rolling resistance is explained by the contact area of the tire with the soil.

Conclusion

- In contrast to the stepwise regression model, the ANFIS model showed a higher performance in predicting slip and rolling resistance.
- Applying the four-wheel-drive mode without the use of ballast weights and reduction of the inflation pressure resulted in the lower level of slip and rolling resistance. Therefore, in the four-wheel-drive mode, there is no need for increasing the ballast weights and decreasing the inflation pressure. This solution is superior, since any increase in weight and reduction in pressure cause damage to tires and reduce their lifespan.
- It was found that draft, tractor driving system, inflation pressure, ballast weights, and tractor travel speed have the greatest effect on the slip, in the presented order. Furthermore, the results showed that the tractor driving system, ballast weight, inflation pressure, and tractor travel speed also have a significant impact on the rolling resistance, in the presented order.
- Ballast weight showed both advantages and disadvantages for traction performance, because by increasing the ballast weight, slip decreases and rolling resistance increases. Ballast weight should increase when the tractor slip is high so that the advantages of slip reduction can compensate for the disadvantages of increasing the rolling resistance.

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