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Mathematical Modelling for Power Requirement of Power Take-Off of Rotary Tiller

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Authors' contributions:

This work was carried out in collaboration among all authors. Author VRK, as a part of M.Tech Thesis work under guidance of author MH and He is also responsible for preparation of the manuscript performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author Dr. Vijaya, Dr. Hemant and Dr. Manoj provided technical guidance and assisted in statistical analysis. All authors read and approved the final manuscript.

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ABSTRACT

For better performance and durability of tractor and machinery during field operations, it is necessary to select a proper matching machine/implement. The purpose of the study was to analyse the effect on parameters affecting to power requirement of power take-off (P.T.O) for rotary tiller, development of mathematical modelling and validation of the model under field conditions. Three different regression models (multiple linear regression, weighted least squares and stepwise regression) were used to predict the P.T.O power requirement. All three developed models were observed significant at 1% level with R^2 value of 0.945, 0.984 and 0.940 for three models respectively. Correlation analysis was performed and all the parameters expressed positive correlation in relation to P.T.O power requirement. Speed of operation, moisture content, depth of

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cut, working width, peripheral velocity, number of blades and weight of rotary tiller were shown linear relation with P.T.O power requirement. L shaped blades consumed more power than the J and C shaped blades. Hard soil consumed more power followed by medium and light soil. The Mean Absolute Percentage Error (MAPE) ranged in reasonable limit for all three models. Based on higher R^2 value, weighted least square regression model was found to be the best fit model for prediction of P.T.O power requirement of rotary tiller.

Keywords: Rotary tiller; mathematical model; regression analysis; multicollinearity; P.T.O power requirement.

1. INTRODUCTION

Agriculture occupies the most vital role in Indian economy. Earlier, Indian farmers mostly relied upon human and animal power. However, with the passage of time, tractor and tractor driven agricultural implements have been introduced. It has been ascertained that the idea of farm mechanization and its importance has been well accepted and consequently new farm implements/equipements have been developed and commercialised [1].

Farm mechanization provides technologies to felicitate agricultural growth through economical utilization of inputs. Testing and evaluation are undertaken to quantify performance of machine for the specified operation [2]. However, testing is defined as an analysis of behaviour of machine when put next with standard codes/norms under ideal and repeatable conditions. On the other hand, evaluation involves a measure of performance under actual field working conditions.

Power take-off (P.T.O), a splined driveshaft installed in tractor to allow mating farm implements and is directly driven by engine. In agriculture system, most of the implements/equipments are driven by P.T.O because of most efficient transmission of (~90%) of net engine power [3]. Implement matching plays a key role in effective utilization of tractor power. An improper matched implement/ equipment results in power loss during field operation which further causes problems, such as a breakdown of prime mower or machinery and economic burden for farmers.

The power requirement is calculated by using torque and speed data, apart from this there are several other factors like implement overall dimensions, weight, depth of cut etc. which are going to affect the power requirement. In the present study, those parameters are studied and a mathematical model is developed, which can reduce the unnecessary field evaluation and laborious work for power measurement. Mathematical modelling is a process in which real-life situations and relations in these situations are expressed by using mathematics [4]. Mathematical modelling of power requirement will help to predict power required to run the agricultural machinery. Mathematical modelling helps in decision-making in a critical situation and also saves time and money. While operating P.T.O driven machinery, a study on P.T.O power requirement is necessary to overcome the problems related to matching of agriculture equipments.

Torque was observed to have linear relation with forward speed [4], rotational speed of the blade and number of blades and also inversely related to pitch of the cut [6,7,8]. While studying the performance of different shaped blades (L, C and J), L shaped blades required more power and more forward thrust was also obtained. C shaped blades required 30% less power than the L shaped blades [9,10]. L type blade required 18.1% more specific work than C type blade due to reduction in surface area of C type blade. When the number of blades per flange increased, due to a reduction in tilling pitch specific work was also significantly increased [3]. Shibusawa [11] reported that retiling of soil is main source of higher energy expenditure and suggested that to reduce the energy and power requirement re-tillage can be avoided. Increase in number of blades caused increased specific work and resulted in increase in P.T.O power requirement [7].

A mathematical model was developed based on the energy required to cut soil, through the cut soil slice by the centrifugal action of the time, to overcome the soil metal friction and to overcome soil-soil sliding friction [12]. Relationship between power required and P.T.O speed in rotary tiller was developed using torque on drive shaft, driven shaft and number of two bevel gears [13] and reported that at fixed P.T.O speed, power requirement of rotary tiller was linearly affected by speed of operation. Rotary tiller blade was designed by calculating specific work method and specific work of rotary tiller was determined by using specific work and dynamic work [14]. Laws of classical mechanics were used to develop torque calculator [15] and the developed model consist of both kinetic and kinematic factors. The developed model was found to determine power requirement of the rotary tiller.

Thus, it can be summarized that though very few works have been carried out for mathematical modelling related to design of rotary tiller and keeping in view of the above facts, the purpose of the study on "Mathematical Modelling of P.T.O Power Requirement of Rotary tiller" is undertaken, to study the parameters affecting the P.T.O power requirement in rotary tiller and development and validation of the mathematical model for prediction of P.T.O power requirement.

2. MATERIALS AND METHODS

2.1 Materials

This study was conducted and secondary data for the study was taken from commercial test reports of rotary tiller tested at Deptt. of Farm Machinery and Power Engineering, COAE&T, CCSHAU, Hisar. P.T.O power requirement was selected as dependent variable. Whereas, soil moisture, speed of operation, depth of cut, working width, number of blades, peripheral velocity of the blade, weight of the rotary tiller, type of soil and type of blade were selected as independent variable.

2.2 Methodology

Data for the modelling of P.T.O power requirement of rotary tiller is based on commercial test reports collected from CCS HAU, Hisar. Effect of parameters on P.T.O power requirement was performed by person bivariate correlation analysis. To develop mathematical model regression analysis was performed on 80% of the total data. Regression analysis is a set of statistical processes for estimating the relationships among variables. It includes several techniques for modelling and analysis of several variables. Three different regression analysis such as multiple linear regression, weighted least square and stepwise regression analysis were adopted and performed using SPSS software.

Stepwise regression is a way to build a model by adding or removing predictor variables, usually via a series of F-tests or T-tests. A variable selection method is a way of selecting a particular set of independent variables (IVs) for use in a regression model. This selection might be an attempt to find a 'best' model, or it might be an attempt to limit the number of IVs when there are too many potential IVs. The variables to be added or removed are chosen based on the test statistics of the estimated coefficients.

Weighted least squaresis estimation technique which weights the independent variable proportional to the reciprocal of the error variance for that observation & overcomes the issue of non-constant variance. Mosteller and Tukey [16] suggested the action of assigning "different weights to different observations, either for objective reasons or as a matter of judgement" in order to recognize "some observations as 'better' or 'stronger' than others". Weighted least squares regression analysis minimizes the sum of squared residuals (and therefore maximizes the coefficient of determination) with respect to transformed variables. SPSS programme script to perform weighted least squares is as follows [17].

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Soil moisture Speed of operation dry kmph Depthofcutcm Working widthm Peripheral speed of bladems Noofblades Weight of implement Kg Typeofblade Type of soil.

Multicollinearity is a state of very high inter-correlations or inter-associations among the independent variables. It is therefore a type of disturbance in the data, and if present in the data the statistical inferences made about the data may not be reliable. In the presence of high multicollinearity, the confidence intervals of the coefficients tend to become very wide and the statistics tend to be very small. It becomes difficult to reject the null hypothesis of any study when multicollinearity is present in the data under study. The presence of multicollinearity affects the R^2 value of the regression analysis causing in errors in results.

A variance inflation factor (VIF) detects multicollinearity in regression analysis and it estimates how much the variance of a regression coefficient is inflated due to multicollinearity in the model. If the VIF value is >10 then the multicollinearity is problematic.

$$VIF = \frac{1}{1 - R_i^2}$$

Tolerance is associated with each independent variable and ranges from 0 to 1. Multicollinearity can also be detected with the help of tolerance. If the value of tolerance is less than 0.2 or 0.1 then the multicollinearity is problematic.

$$\text{Tolerance} = 1 - R_i^2$$

The mathematial model was developed by using 80 % of the collected observations and the model was validated by using remaining 20% observations. The predicted P.T.O power requirement was again validated with observed P.T.O power requirement at the field. The Mean Absolute Percentage Error (MAPE) is a statistical measure of the accuracy of a prediction system. As a percentage, it measures this accuracy and can be calculated as

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P - A}{P}\right|$$

P – Predicted value

A – Actual value

The mean absolute percentage error (MAPE) is the most common measure used to forecast error, and works best if there are no extremes to the data (and no zeros).

3. RESULTS AND DISCUSSIONS

3.1 Effect of Parameters Affecting on P.T.O Power Requirement of Rotary Tiller

Pearson bivariate correlation was performed to understand the relationship of independent variables with dependent variable. The results were tabulated in Table 1. and it is clear that independent variables such as soil moisture, speed of operation, depth of cut, working width, peripheral speed of the blade, number of blades and weight of implement were expressed positive correlations in relation to P.T.O power requirement which are at 1% level of significance.

Table 1 shows high positive correlation in between soil moisture and P.T.O power requirement. Hence, it is evident that P.T.O power requirement linearly increased with an increase in soil moisture content. Table 4 shows that, an increase in soil moisture by 1% P.T.O power requirement was observed to increase by 0.232 kW to 0.271 kW. This effects was at 1% level of significance for all three models.

Speed of operation expressed high positive correlation of 0.838 which is significant at 1% level (Table 1.) and it is obvious that the P.T.O power requirement was linearly increased with an increase in speed of operation. From Table 4. if speed of operation is increases by 1 km h^{-1} resulted in an increase of P.T.O power requirement by 0.525 kW to 0.651 kW and this effect was observed significant at 1% level for multiple linear regression and weighted least squares model. Speed of operation was excluded in stepwise regression. Hence, the effect of speed of operation on P.T.O power requirement by stepwise regression model was neglected. Similar results are also evident from study reported by Niyampa et al. [18].

P.T.O power requirement was linearly affected by depth of cut i.e., from Table 1. it is evident that depth of cut was observed to have very high positive correlation of 0.963 in relation to P.T.O power requirement. Increase in depth of cut by 1 cm resulted in an increase of P.T.O power requirement by 1.51 kW to 1.56 kW. The effect of depth of cut on P.T.O power requirement was observed significant at 1% level for all developed model. Increase in depth of cut resulted in higher cutting force. Hence, P.T.O power requirement was due to increase in depth of cut. Similar results were also evident from Hendrik and Gill [19] and Ahmad [20].

Working width of the rotary tiller was observed to have a very high positive correlation of 0.915 significant at 1% level (Table 1) and it is obvious that, P.T.O power requirement was linearly increased with an increase in working width of the rotary tiller. Table 4 shows, an increase in working width by 1 m resulted increase in P.T.O

Table 1. Correlation between parameters in relation to P.T.O power requirement of rotary tiller

Independent variables	Correlation coefficient
Soil moisture (%)	0.730**
Speed of operation (km h^{-1})	0.838**
Depth of cut (cm)	0.963**
Working width (m)	0.915**
Peripheral speed of blade (m s^{-1})	0.842**
Number of blades	0.934**
Weight of implement (kg)	0.931**
Type of blade	0.636
Type of soil	0.597

*** significant at 1% level*

power requirement by 2.3 kW to 2.416 kW. This effect was observed at 1% level of significance for all developed model. As working width of rotary tiller increases volume of soil disturbed also increases this further demanded extra energy and resulted in increase in P.T.O power requirement. Ahmad [20] reported similar results.

Table 1 shows that peripheral velocity and P.T.O power requirement are linerarly related as there is high positive correlation of 0.842 was observed which is significant at 1% level of significance. From Table 4 it is obvious that, an increase in peripheral velocity by 1 m s^{-1} resulted in an increase of P.T.O power requirement by 0.16 kW to 0.30 kW and this effects were observed significant at 1% level for multiple linear regression and weighted least squares models. Peripheral velocity of the blade was excluded variable in stepwise regression model. Hence its effect is not considered on P.T.O power requirement. Toriyama et al. [8] suggested that peripheral velocity should not exceed 6 m s^{-1} for better power consumption and peripheral velocity collected are less than 6 m s^{-1} during the study.

In rotary tiller, number of blades was wide-ranging from 36 to 60. Number of blades of rotary tiller was observed to have a very high positive correlation of 0.934 at 1% level significance which is evident that the number of blades and P.T.O power requirement is linearly related. P.T.O power requirement was increased by 0.22 kW to 0.236 kW with an increase in one number of blade (Table 4). The effects were observed significant at 1% level of significance for all the developed models. As number of blades increases in rotary tiller specific work increases which further demands more energy. Asl and Singh [3] stated similar results and also reported that number of blades affected length of soil slice due to which P.T.O power requirement was increased.

A very high positive correlation of 0.931 was observed in weight of rotary tiller in relation with P.T.O power requirement (Table 1) and it is obvious that weight of the rotary tiller and P.T.O power requirement are linearly related to each other. An increase in P.T.O power requirement of 0.006 kW to 0.007 kW was detected with an increase in weight of the implement by 1 kg. The effects were observed significant at 1% level for all developed model.

In rotary tiller, blades of ‘L’, ‘J’ and ‘C’ shaped are commonly used. During modelling, blades were assigned a rank of 1, 2 and 3 for L, J and C shaped blades respectively. Pearson bivariate correlation was found non-significant for type of blade in relation with P.T.O power requirement (Table 1). ‘L’ shaped blade consumed more P.T.O power compared to ‘J’ and ‘C’ shaped blades (Fig. 1). Adams and Furlong [21] determined that “L” and “C” shaped blades had a significant influence on P.T.O power requirement. Chamen et al. [10] reported that “C” shaped blade consumed 30% less power compared to “L” shaped blade as “C” shape blades had ability to carry out several operations.

During testing of rotary tiller, soil was classified as light, medium and hard soil. Type of soil was assigned a rank of 1, 2 and 3 for hard, medium and light soil respectively. Pearson bivariate correlation was found non-significant for type of soil in relation with P.T.O power requirement (Table 1). Hard soil consumed more power followed by medium and light soil (Fig. 2). Tupakari et al. [22] observed that soil layer physical properties affected P.T.O power requirement of rotary tiller.

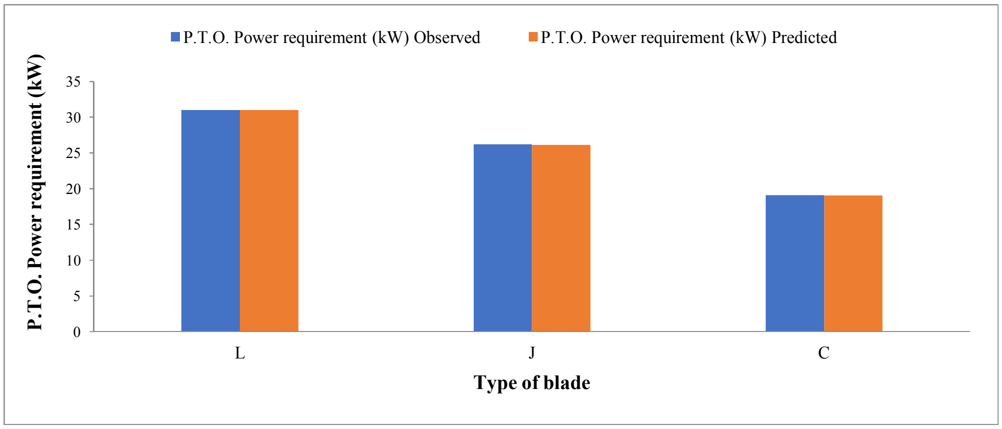

Fig. 1. Effect of type of blade on P.T.O power requirement of rotary tiller

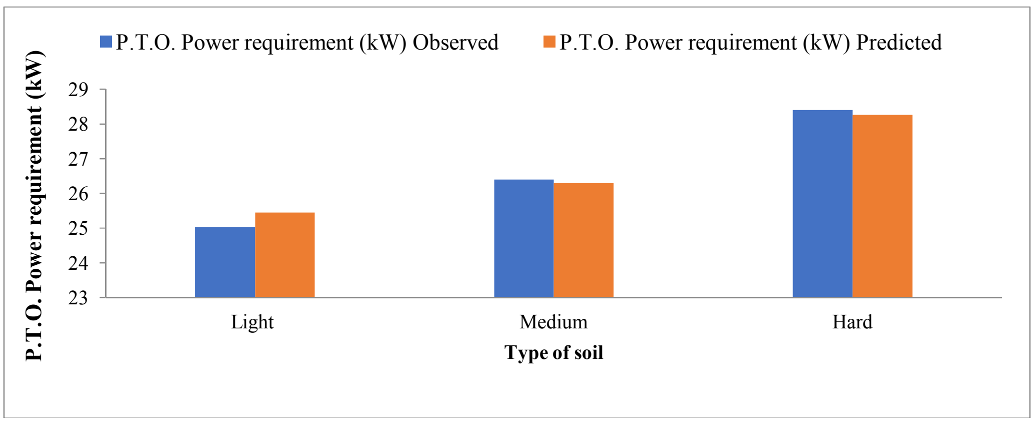

Fig. 2. Effect of type of soil on P.T.O power requirement of rotary tiller

3.2 Mathematical Model for Prediction of P.T.O Power Requirement for Rotary Tiller

Multicollinearity among variables in relation to P.T.O power requirement was checked using tolerance and VIF values. Tolerance and VIF values were illustrated in Table 2. The VIF values obtained to all independent variables in relation to dependent variable were <10 and also tolerance values were >0.2. Three different regression analysis such as multiple linear regression, weighted least square regression and stepwise regression analysis were performed.

The R^2 values obtained for different models were illustrated in Table 3. Weighted least squares model showed the highest R^2 value followed by multiple linear regression and stepwise regression models.

Table 4. shows the regression coefficient values for multiple linear regression, weighted least squares and stepwise regression models.

From Table 4, regression coefficients (β) obtained from multiple linear regression, weighted least squares and stepwise regression models the mathematical model developed for prediction of P.T.O power requirement are as follows:

P.T.O Power Requirement$_{\text{(Multiple Linear Regression)}}$ = 0.269 × Soil moisture (%) + 0.525 × Speed of operation (km h^{-1}) + 1.56 × Depth of cut (cm)+ 2.3 × Working width (m) + 0.306 × Peripheral speed of blade (m s^{-1}) + 0.229 × Number of blades + 0.006 × Weight of implement (Kg) – k_1 - k_2 -15.009 (1)

P.T.O Power Requirement$_{\text{(Weighted Least Squares)}}$ = 0.271× Soil moisture (%) + 0.651 × Speed of operation (km h^{-1}) + 1.561 × Depth of cut (cm)+

2.322 × Working width (m)+0.16 × Peripheral speed of blade (m s^{-1}) + 0.236 × Number of blades + 0.006 × Weight of implement (Kg) – k_1 - k_2 -15.103 (2)

P.T.O Power $Requirement_{(Stepwise\ Regression)}$ = 0.232× Soil moisture (%) + 1.515 × Depth of cut (cm) + 2.416 × Working width (m)+0.16 × Peripheral speed of blade (m s^{-1}) + 0.22 × Number of blades + 0.007 × Weight of implement (Kg) - 11.665 (3)

$k_1$and k_2 are the regression coefficients for the qualitative variables which are type of blade and type of soil. The k_1 and $k_2$values for multiple linear regression and weighted least squares are illustrated in Table 5. The qualitative variables were excluded from the stepwise regression model as they did not exhibit significant correlation in relation to P.T.O power requirement.

All three developed models were observed significant at 1% level. The regression coefficients soil moisture, depth of cut, working width, number of blades and weight of implements were detected at 1 level of significance.

Multiple linear regression, weighted least squares and stepwise regression models were developed by using SPSS V23 software and from ANOVA table obtained for multiple linear regression (Table 6), weighted least squares (Table 7) and stepwise regression (Table 8) were presented and observed significant at 1% level.

Table 2. Collinearity statistics table of rotary tiller

Independent variables	Tolerance	VIF
Soil moisture (%)	0.564	1.773
Speed of operation (km h^{-1})	0.516	1.939
Depth of cut (cm)	0.739	1.353
Working width (m)	0.519	1.925
Peripheral speed of blade (m s^{-1})	0.691	1.448
Number of blades	0.471	2.123
Weight of implement (kg)	0.542	1.844
Type of blade	0.867	1.153
Type of soil	0.373	2.679

Table 3. Model summary and R2 value for three models of rotary tiller

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
MLR	0.972	0.945**	0.938	1.41077
WLS	0.992	0.984**	0.982	1.23242
SR	0.97	0.94**	0.936	1.42754

*** significance at 1% level*

Table 4. Regression coefficient for multiple linear regression, weighted least squares and stepwise regression

Independent variables	MLR	WLS	SR
(Constant)	-15.009	-15.103	-11.665
Soil moisture (%)	0.269**	0.271**	0.232**
Speed of operation (km h^{-1})	0.525	0.651	--
Depth of cut (cm)	1.56**	1.561**	1.515**
Working width (m)	2.3**	2.322**	2.416**
Peripheral speed of blade (m s^{-1})	0.306	0.16	--
Number of blades	0.229**	0.236**	0.22**
Weight of implement (kg)	0.006**	0.006**	0.007**
Type of blade	-0.151	-0.206	--
Type of soil	-0.14	-0.096	--

The multiple linear regression model was significant, F (9, 70) = 133.173, p < 0.001 (Table 6) and R^2= 0.945 (Table 3). The weighted least square model was significant, F (9, 70) = 483.91, p < 0.001 (Table 7) and R^2= 0.984 (Table 3). The stepwise regression model was significant, F (5, 74) = 232.983, p < 0.001 (Table 8) and R^2= 0.940 (Table 3).

The R^2 value was observed greater in weighted least squares model followed by multiple linear regression and stepwise regression (Table 3). To reduce error and better prediction of P.T.O power requirement weighted least squares model is selected as P.T.O power prediction equation.

3.3 Validation and Refinement of the Developed Model under Field Condition

Validation of the developed model was performed on 20% data. Validation was measured by a graphical representation of actual and predicted values. Similarly, MAPE value was calculated and checking the range of the MAPE.

From Fig. 3, graphical representation of actual P.T.O power requirement and predicted P.T.O power requirement, values obtained by multiple linear regression, weighted least squares and stepwise regression model showing errors in reasonable limit i.e., predicted values from all

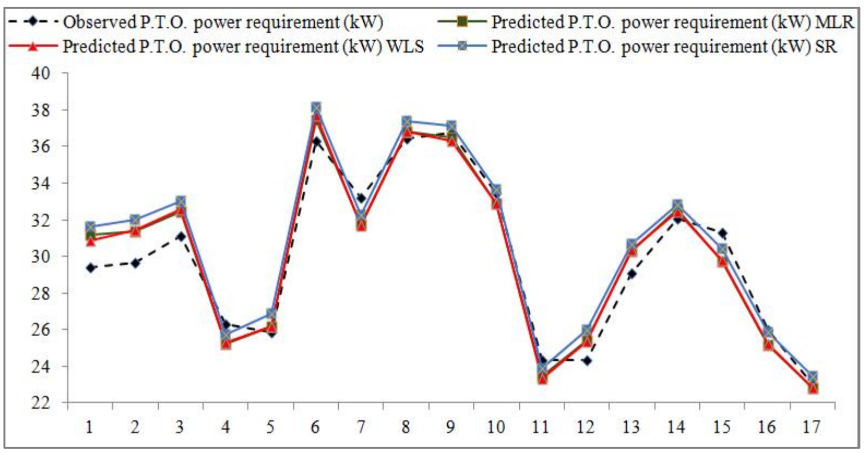

Fig. 3. Observed and predicted P.T.O power requirement for multiple linear regression, weighted least squares and stepwise regression model

Table 5. Regression constants ($k_1$and k_2) of qualitavive variables

	k_1			k_2		
	Type of Blade			Type of Soil		
	L	J	C	Light	Medium	Hard
Multiple Linear Regression	0.15	0.30	0.45	0.14	0.28	0.42
Weighted Least Squares	0.206	0.412	0618	0.096	0.192	0.288

Table 6. ANOVA of multiple linear regression model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2385.447	9	265.05	133.173	<0.001**
Residual	139.318	70	1.99		
Total	2524.765	79			

Table 7. ANOVA of weighted least squares model

	Sum of squares	df	Mean Square	F	Sig.
Regression	6614.956	9	734.995	483.91	<0.001**
Residual	106.321	70	1.519		
Total	6721.277	79			

Table 8. ANOVA of stepwise regression model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2373.962	5	474.792	232.983	<0.001**
Residual	150.803	74	2.038		
Total	2524.765	79			

Table 9. Observed and predicted P.T.O power requirement and MAPE of multiple linear regression, weighted least squares and stepwise regression

Observed P.T.O. power requirement (kW)	Predicted P.T.O. power requirement (kW)			MAPE (%)		
	MLR	WLS	SR	MLR	WLS	SR
29.39	31.16	30.87	31.62	6.03	5.04	7.58
29.66	31.36	31.44	31.99	5.72	5.99	7.86
31.11	32.47	32.55	33.04	4.39	4.63	6.21
26.32	25.20	25.27	25.76	4.25	3.99	2.13
25.85	26.16	26.19	26.86	1.21	1.31	3.92
36.28	37.48	37.73	38.18	3.30	4.01	5.23
33.22	31.73	31.70	32.23	4.49	4.58	2.97
36.44	36.79	36.84	37.39	0.96	1.09	2.61
36.78	36.48	36.30	37.12	0.81	1.29	0.93
33.44	32.90	32.86	33.65	1.62	1.74	0.62
24.34	23.43	23.31	23.90	3.73	4.23	1.81
24.36	25.39	25.34	26.01	4.21	4.02	6.79
29.10	30.30	30.38	30.68	4.12	4.40	5.44
32.04	32.59	32.46	32.80	1.73	1.33	2.37
31.33	29.72	29.77	30.40	5.13	4.98	2.96
26.01	25.18	25.21	25.86	3.18	3.07	0.59
22.98	22.82	22.80	23.48	0.72	0.76	2.18

three models underestimated observed values. MAPE values for all three models were within prescribed limit i.e., <10% (Table 9). Hence, all the developed models fit well.

4. CONCLUSION

In rotary tiller, the independent parameters such as, soil moisture, speed of operation, depth of cut, working width, peripheral speed of the blade, number of the blade, and weight of the rotary tiller, expressed a positive correlation in relation to P.T.O power requirement at 1% level of significance. All the independent parameters resulted linear relation with P.T.O power requirement except type of soil and type of blade. The qualitative parameters (type of soil and type of blade) L type of blade consumed more power than the J & C shaped similarly hard soil consumed more power than the light and medium soil. The independent parameters did not exhibit multicollinearity among themselves in relation to P.T.O power requirement. The R^2 values obtained for all three model was in order of weighted least squares>multiple linear regression>stepwise regression. Weighted least square model was selected as P.T.O power requirement prediction. The developed models were observed to be significant at 1% level. The regression coefficients such as soil moisture, depth of cut, working width, number of blades and weight of implements were found to be significant at 1% level. Speed of operation, peripheral velocity of the blade, type of blade and type of soil were excluded variables in stepwise regression model. The developed models were validated and it was found that all models fit well to predict P.T.O power requirement with minimum error.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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