

Article

Validity of Nebraska Tractor Test Laboratory (NTTL) Data for Estimating Drawbar Pull and Fuel Consumption of a Massey Ferguson Tractor Under Field Operating Conditions

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Abstract

The most critical aspect of farm mechanization management is determining the optimal capacity, including the size and type of implements, to efficiently perform agricultural operations within the available time frames while minimizing the operating costs of farming mechanisms. In this study, 30 test reports yielded 353 data points as each test had different values of drawbar pull, forward speed and fuel consumption for Massey Ferguson tractors were obtained from the Nebraska Tractor Test Laboratory (NTTL), USA. The tractors chassis type was front wheel assist tractor. These test reports were reviewed for the period from 1997 to 2016, except for 2002. Stepwise regression was applied, and two mathematical models were derived to predict drawbar pull (kN) ($R^2 = 0.907$) and fuel consumption (lit/h) ($R^2 = 0.911$). Through a field test on an asphalt track, data were obtained on the drawbar pull, forward speed, and fuel consumption of a Massey Ferguson tractor, model 440. The values of drawbar pull and fuel consumption were compared with those from the developed mathematical models after incorporating the appropriate independent variables. The average relative error for drawbar pull was found to be approximately 21.25%, and the average relative error for fuel consumption was approximately 12.38%. Therefore, the two developed models can be used in agricultural mechanization management.

Keywords: agricultural tractor; draft force; farm mechanization; fuel consumption; regression; farm management



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1. Introduction

In most farming systems, tractors remain the primary source of mechanical power. Tractors are the energy source for farming operations [1]. Scientists in the past few decades have cited ongoing improvements in tractor technology and where most work remains ahead. One review by Lanças et al. [2] examined more than fifty years of tractor testing, covering the period from 1969 to 2023, with particular focus on energy use, efficiency, and overall performance.

Tractor tests are not limited to reporting the maximum engine output. They also provide farm managers with practical indicators, including drawbar power, traction, and fuel consumption. At the same time, they offer manufacturers structured data on engine systems, transmission, and tractor design. The Nebraska Tractor Test Laboratory (NTTL) in the United States is widely regarded as one of the leading facilities in this area. Standardized

tests conducted on a concrete test track enable reliable comparisons of tractors from different brands and varieties [3,4].

Effective testing should reflect several performance attributes, including rated power, traction efficiency, and fuel economy. These results help verify that the official specifications are realistic and guide managers when matching tractors with field conditions. Nevertheless, values obtained under test settings are often affected by external influences. Temperature, atmospheric pressure, and altitude all play a role in changing tractor performance. Rao et al. [5] found that as altitude rises, power and torque of diesel engines both decrease, especially at altitude above 2000 m. Farmers often notice these effects during field operations, especially in highland areas. For this reason, standardized tests remain an essential reference, but their accuracy is not always guaranteed under different climatic and environmental situations.

Several testing options are available to match the various countries where tractors are sold and fulfill manufacturers' promotional objectives. A tractor's official test report should contain primary performance parameters such as engine power and fuel consumption. Results should be equivalent to or better than the manufacturer's claims, particularly regarding rated power and fuel efficiency. Standard conditions' measured performance value is definitive and objective for mechanization managers. However, deviations should be expected if environments vary from conditions within the testing area. For example, reductions or increases in air temperature and pressure can alter tractor output. Specific weather conditions, such as high pressure accompanied by low temperatures or low pressure accompanied by high temperatures, can increase or reduce a tractor's ability by up to 8%. Additionally, a reduction in air pressure resulting from an increase in elevation can reduce tractor power by about 3% with respect to every addition of 300 m to altitude, with higher losses above 1.61 km [6].

Selecting a perfect tractor to pair with a prescribed implement is one of the critical decisions for managers of mechanized farms. Efficient management and scheduling of tractors and machines are crucial in influencing agricultural production level, operational schedules, and production scale. Of particular concern is identifying a prescribed tractor power comparable to available implements to enable the timely completion of tasks within a prescribed field and improve operational costs [7,8]. Of particular relevance here is drawbar power and fuel usage because they directly influence machine selection and cost estimation [9,10].

Designing a mathematical equation that includes variables affecting tractor performance to predict drawbar power and fuel consumption is therefore beneficial to managers of mechanized farms [11]. According to Harrigan and Rotz [12], a drawbar power measurement is paramount to selecting an adequate implement because managers can match tractors with machines, they can pull efficiently with such a measure, and they can estimate fuel consumption beforehand to guide field operations.

Fuel itself contributes about 16% to tractor operating costs and, under some circumstances, contributes about 45% [13]. Thus, various studies were conducted to estimate tractor drawbar power and fuel consumption from different independent variables. A few of such studies were carried out with the help of field measurements [14–16], while some were created with data obtained from tests conducted by the Nebraska Tractor Test Laboratory (NTTL). For instance, Özbayer and Özbayer [17] collected data from 418 tractors whose tests were conducted by NTTL between 2004 and 2017. These researchers attempted to gather standard data about PTO power, engine speed, specific fuel consumption, forward speed, drawbar power, and tractor weight. Mathematical formulas were developed using linear and nonlinear regression analysis to estimate fuel consumption and drawbar power. Evans et al. [18] developed an equation to estimate drawbar pull using tractor design pa-

rameters together with the soil cone index. Their results indicated a strong and satisfactory correlation between the measured drawbar pull and the values predicted by the proposed model for a class of two-wheel drive tractors. In a follow-up study, Rahimi-Ajdadi and Abbaspour-Gilandeh [19] employed NTTL data to predict fuel consumption as a function of engine speed, load condition, throttle setting, tractor frame type, weight of tractor, PTO power, and drawbar power. They used artificial neural networks (ANN) and multiple regression with coefficients of determination of 0.986 and 0.973, respectively. Harris [20] employed NTTL data to predict tractor engine performance parameters such as torque and fuel consumption by creating prediction models where the predictor parameters were engine speed and throttle setting. Other approaches extrapolated the prediction to the overall tractor–implement system. For example, Nagar et al. [21] presumed that a function for fuel usage and drawbar power could be formulated to explain a host of parameters influencing fuel usage and distinguish consumption patterns across tillage tasks.

Predicting tractor performance is a primary study area because tractor functioning is governed by many parameters, including ground conditions and implement type [22]. Several additional parameters have been proposed in previous studies. Şeflek et al. [23] demonstrated that the height of the drawbar above the ground has a regulating effect on drawbar power and fuel consumption. Moinfar et al. [24] showed that tire pressure, wheel weight, and drive type strongly affect fuel use. Alhassan et al. [25] added that tire pressure, speed, tractor power, and soil factors together shape how well a tractor performs.

A variety of modeling approaches have been explored in the literature to estimate drawbar power and fuel consumption. Some relied on linear regression [25]. Others used neural networks to capture nonlinear effects [26]. Additionally, several researchers employed statistical or numerical techniques to achieve comparable predictive objectives [27–30]. It can be possible to refer to their advantages and disadvantages, but most studies confirm that regression-based and ANN-based approaches hold reasonable error levels. Frequently used prediction equations to estimate drawbar power and fuel consumption include those formulated per ASABE Standards [31], D497, by the American Society of Agricultural and Biological Engineers. These equations would then be modified to be suitably aligned with local surroundings [32]. Kheir [33], for example, assessed the prospect of using ASABE criteria to assess machinery operating costs under Sudanese conditions. Plugging locally observed parameters into equations and comparing measured results with actual operating costs revealed that sizeable deviations emerged between predicted costs and real agricultural operations costs. Additionally, Ahmed [34] assessed a few ASABE standards [31] for various soils, tractors, and implements in actual operating conditions before comparing the values determined on the ground with those determined using the ASABE D497 equations. The calculated values using ASABE standards [31] and the measured drawbar pull values were found to agree. The error ranges for the rotovator, disk plow, and ridger were 22 to 66%, 38 to 55%, and 7.5 to 30%, respectively. Numerous techniques have been employed to forecast fuel consumption; some of these techniques are primarily based on power, while others are specific to individual engines and necessitate extensive engine testing for verification [35]. Grisso et al. [36] examined the most recent ASABE Standards fuel consumption data and contrasted it with 20 years of data from NTTL. A generalized model that forecasted fuel consumption during full and partial load conditions, as well as when engine speeds were lowered from full throttle, was also created by them.

This review highlights the need for locally adapted equations to predict tractor drawbar power and fuel consumption. Therefore, the primary aim of the present study is to derive mathematical models for estimating drawbar pull and fuel consumption rate based on NTTL test results for Massey Ferguson tractors, in particular for front wheel assist (FWA)

tractors (sometimes called mechanical front-wheel drive, MFWD) using multiple linear regression. A secondary aim is to compare the predicted values with field measurements taken under local conditions for the same tractor type, thereby quantifying prediction errors. The unique advantages of this study compared to existing prediction models are relied on using actual data for developing the regression models and the impact of independent variables in the regression model of drawbar pull and fuel consumption are not considered before to develop such models in the mechanization field. The algorithm, however, specifies how the chosen parameters should be employed and is effective even in the absence of comprehensive tractor and implement information [37]. Moreover, the derived regression models in this study can be applied in farm mechanization management to estimate drawbar pull and power and fuel consumption, and similar regression models may also be developed for other tractor types. Furthermore, the findings would make it possible to choose the ideal combination of factors, namely those pertaining to operating conditions for a specific drawbar load and fuel consumption, in order to enhance a tractor's performance under various field circumstances.

2. Materials and Methods

2.1. Collecting the Required Tractor Test Data

Nebraska Tractor Test Laboratory (NTTL), USA, has an online database with tractor test reports accessible through the NTTL website [38]. It has a database with a summarized report about tests on performance with different tractor models. A complete set of datasets is also available through the same portal.

For the present study, Massey Ferguson tractors were selected because of their widespread use on farms in Saudi Arabia, particularly for operating agricultural machinery. A total of 30 test reports of this tractor type were considered without any specifying of screening criteria, and the relevant performance variables were recorded. The investigated 30 test reports yielded 353 data points as each test had different values of drawbar pull, forward speed, and fuel consumption.

2.2. Procedure of the Research Work

All available test reports on the NTTL website for Massey Ferguson tractors conducted over several years were reviewed. These data were then loaded into a Microsoft Excel worksheet. The independent and dependent selected variables, including their symbols and units from the NTTL test reports for FWA Massey Ferguson tractors are presented in Table 1. All tractors work with diesel fuel and tested on standard concrete track according to official tractor test method. Twenty independent variables and two dependent variables were considered in this research.

Table 1. The selected independent and dependent variables, along with their symbols and units as listed in the NTTL test reports for FWA Massey Ferguson tractors.

Independent Variables	Symbols of the Variables	Measurement Unit
Fuel density	X1	(kg/lit)
Number of engine cylinders	X2	(Dimensionless)
Rated engine speed	X3	(rpm)
Cylinder diameter	X4	(mm)
Stroke length	X5	(mm)

Table 1. Cont.

Independent Variables	Symbols of the Variables	Measurement Unit
Compression ratio	X6	(Dimensionless)
Engine displacement	X7	(ml)
Wheelbase	X8	(mm)
Forward speed	X9	(km/h)
Engine speed	X10	(rpm)
Cooling medium temperature	X11	(°C)
Ambient air temperature	X12	(°C)
Barometer	X13	(kPa)
Diameter of the rear wheel rim	X14	(in)
Inflation air inside rear tires	X15	(kPa)
Diameter of the front wheel rim	X16	(in)
Inflation air inside front tires	X17	(kPa)
Height of the drawbar above the ground	X18	(mm)
Static weight on rear tires	X19	(kg)
Static weight on front tires	X20	(kg)
Dependent Variables		
Drawbar pull	Y1	(kN)
Fuel consumption	Y2	(lit/h)

2.3. Development of Multiple Linear Regression Models

The collected data were entered into the Statistical Package for Social Sciences (SPSS) software package Version 29 [39*] to undergo statistical analysis involving stepwise linear regression. Statistical software [39] carries out the selection process automatically in stepwise regression using different criteria for variable selection [40–42]. In SPSS Package [39], the criteria used for variables entered/removed stepwise is defined as Probability-of-F-to-enter ≤ 0.050 , Probability-of-F-to-remove ≥ 0.100 .

The statistical analysis identifies the strongest independent variables in the regression equation by gradually including or excluding predictor variables based on statistical rules. Typically, two forms of stepwise regression are employed: forward selection and backward elimination. In this present study, forward stepwise regression was used. The regression model looked as follows:

$$Y = B_0 + B_1X1 + B_2X2 + B_3X3 + B_4X4 + B_5X5 + B_6X6 + B_7X7 + B_8X8 + B_9X9 + B_{10}X10 + B_{11}X11 + B_{12}X12 + B_{13}X13 + B_{14}X14 + B_{15}X15 + B_{16}X16 + B_{17}X17 + B_{18}X18 + B_{19}X19 + B_{20}X20 \quad (1)$$

where Y is the variable to be predicted (dependent variable), $X1$ to $X20$ are independent variables, and B_0 to B_{20} are unstandardized regression coefficients. However, all independent ($X1$ to $X20$) and dependent variables ($Y1$ and $Y2$), along with their symbols and units are shown in Table 1 as listed in the NTTL test reports for Massey Ferguson tractors. However, unstandardized regression coefficients (are often estimates of model variables derived from raw data analysis). Standardized regression coefficients, on the other hand, are estimates of model variables that are derived from the analysis of standardized data;

that is, all variables are assumed to have unit variance. The relative importance of variables that are incommensurable—that is, assessed in different units on the same or separate scales—can be compared using standardized data, which are less impacted by the scales of measurement [43]. For instance, while performing multiple regression analysis, researchers are recommended to compare the relative significance of several incommensurable independent variables for the outcome using beta weights, also known as normalized regression coefficients [44]. However, standardized regression coefficients (β_i) can be calculated as follows [45]:

$$\beta_i = B_i \times (SD_{X_i} / SD_Y) \quad (2)$$

where SD_{X_i} is the standard deviation of predictor i , SD_Y is the standard deviation of the outcome variable, β_i is standardized regression coefficients of predictor i , and B_i is unstandardized regression coefficients of predictor i .

The coefficient of determination (R^2) was applied to measure model performance. R^2 is a statistical value that indicates the proportion of the variation among the dependent variable explained by the variable(s) within the model. It has a value ranging from 0 to 1, where a higher value is better to indicate a good variable relationship. Nonetheless, R^2 is sensitive to such things as sample size and outliers. Additionally, mean relative error (MRE) was also applied to measure model accuracy, where MRE was quantified using Sadek et al. [46] as:

$$\text{MRE (\%)} = \frac{1}{N} \times \frac{(\text{Measure value} - \text{Predicted value})}{\text{Measured value}} \times 100 \quad (3)$$

where N is number of data points.

2.4. Field Measurements

The field experiments measured drawbar pull, forward speed, and fuel consumption for a Massey Ferguson 440 tractor (MF 440). The tractor's technical details are listed in Table 2. The experimental work was conducted on an asphalt track at the experimental farm of the College of Food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia. However, from the tire size, we can obtain diameter of the front and rear wheel rims.

Table 2. Technical details of the Massey Ferguson 440 (MF 440) tractor.

Technical Items	Measurement Unit	Value
Cylinder diameter	(mm)	100
Stroke length	(mm)	127
Rated engine speed	(rpm)	2200
Rated power	(kW)	61.1
Chassis type	Front wheel assist	FWA
Number of engine cylinders	(Dimensionless)	4
Wheelbase	(mm)	2140
Tractor weight	(kg)	2619
Front tire size	(in)	7.5–16
Rear tire size	(in)	18.4–30
Engine displacement	(ml)	4000

Table 2. *Cont.*

Technical Items	Measurement Unit	Value
Manufacture		Brazil
Compression ratio	(Dimensionless)	17.3
Height of the drawbar above the ground	(mm)	550

For drawbar pull measurement, two tractors were used in the tests with a load cell connected between them. The tractor in the front was Massey Ferguson 440 tractor and, another tractor (Volvo BM tractor) hitched behind it using an iron chain. The chain was placed horizontally tightly by tightening the chain [47]. However, a load cell (Omega, 0–10,000 lb capacity) between the two tractors registered the Massey Ferguson tractor’s drawbar pull. The measurements were conducted according to RNAM [48] on 20 February 2020.

During operation, the front tractor (Massey Ferguson 440) ran at a specific forward speed as the gear lever of the forward tractor was set to the second gear position. Different loading conditions were applied using the brake pedal of the rear tractor. The Massey Ferguson tractor was also driven for a constant distance, with time and distance measured to find the forward speed. The calculated forward speeds were 2.25, 3.10, and 3.60 km/h.

The tank refill approach was used to calculate fuel consumption [49]. The fuel tank was filled to a specified initial level before each experimental run. The tank was replenished to the same level when the field operation was finished, and the amount of fuel added was noted as the amount used during the test. Under a variety of operating circumstances, this technique offers a clear and accurate assessment of real fuel use. The fuel consumption rate was then calculated from the consumed fuel volume and the required time. Other parameters monitored, like tire air pressure; however, the front tire air pressure was adjusted to 10 bar, and the rear tire air pressure was adjusted to 5 bar. Rim diameter and engine speed were considered. Cooling water temperature after loading was taken with a thermometer, alongside atmospheric conditions, which were monitored from a weather site on an Android phone; however, the ambient air temperature was 20 °C, relative humidity 41%, and atmospheric pressure was 1.017 bar. Cooling water temperature was approximately 30 °C, with an assumed 70% of the tractor’s weight supported by the rear axle of the tractor, so the for the MF 440, static weight on the rear tires is 1518.3 kg.

3. Results and Discussion

3.1. Massey Ferguson Tractor Test Data Analysis

Analysis of the compiled Massey Ferguson tractor test data (using NTTL data from 1997 to 2016) showed that the records covered 1997 to 2016, except for 2002, where no testing data was available. Figure 1 illustrates the distribution of tested Massey Ferguson tractors at NTTL during these years, while Figure 2 shows the annual percentage of tested tractors. The curves in Figures 1 and 2 demonstrate that the highest number of tractors tested was in 2016, with 32 tractors, representing 18% of the total tractors tested in the selected period. The data were grouped by tractor drive type (tractor chassis type): two-wheel drive (2WD), four-wheel drive (4WD), and front-wheel assist (FWA). Figures 3 and 4 illustrate the distribution of chassis type for Massey Ferguson tractors tested from 1997 to 2016. The results show a clear trend: FWA tractors comprised about 88% of the tests, while no 4WD models were included. Data was recorded and analyzed for the front-wheel assist (FWA) tractors only. Summary of descriptive statistics of the independent and dependent variables is given in Table 3. For FWA tractors, the minimum drawbar pull was 7.3 kN,

while the maximum reached 120.57 kN, with a mean of 42.7 kN. These tests were conducted on a standard concrete track. For FWA tractors, fuel consumption ranged from a minimum of 13.23 lit/h to a maximum of 68.7 lit/h, with an average of 32.37 lit/h.

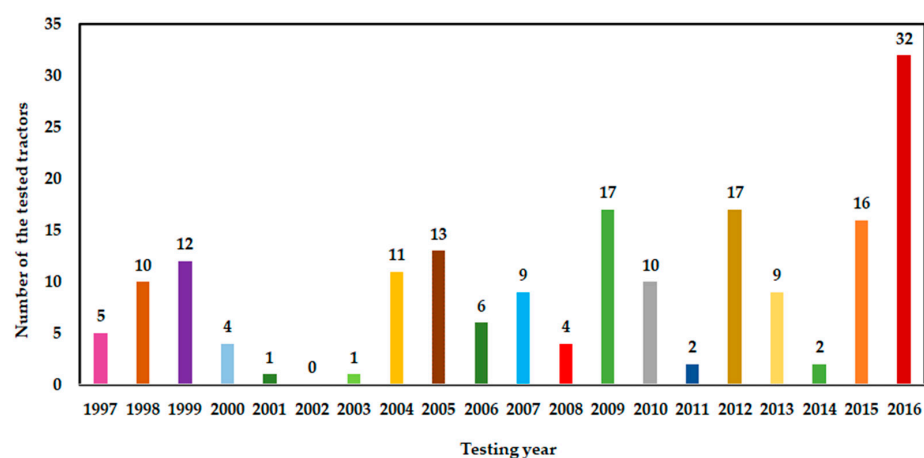


Figure 1. The distribution of the tested Massey Ferguson tractors using NTTL data from 1997 to 2016.

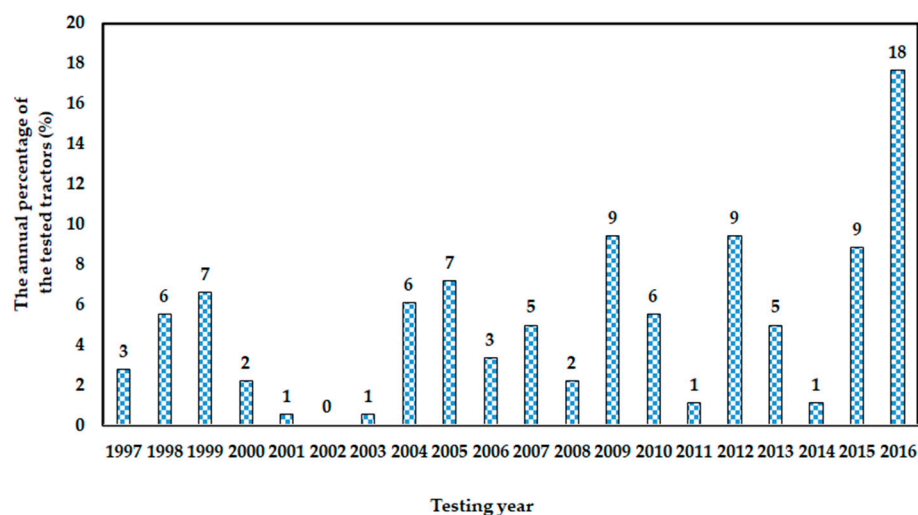


Figure 2. The annual percentage of the tested Massey Ferguson tractors using NTTL data from 1997 to 2016.

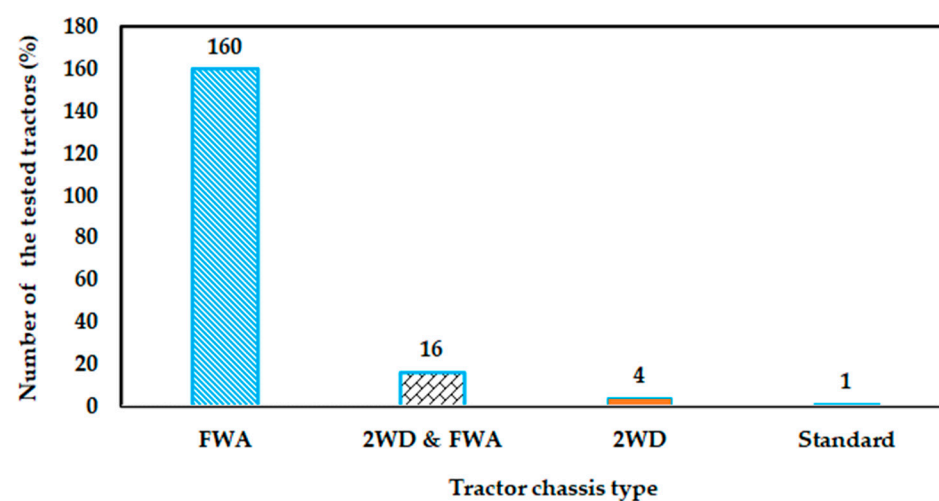


Figure 3. The tractor chassis type of the tested Massey Ferguson tractors using NTTL data from 1997 to 2016.

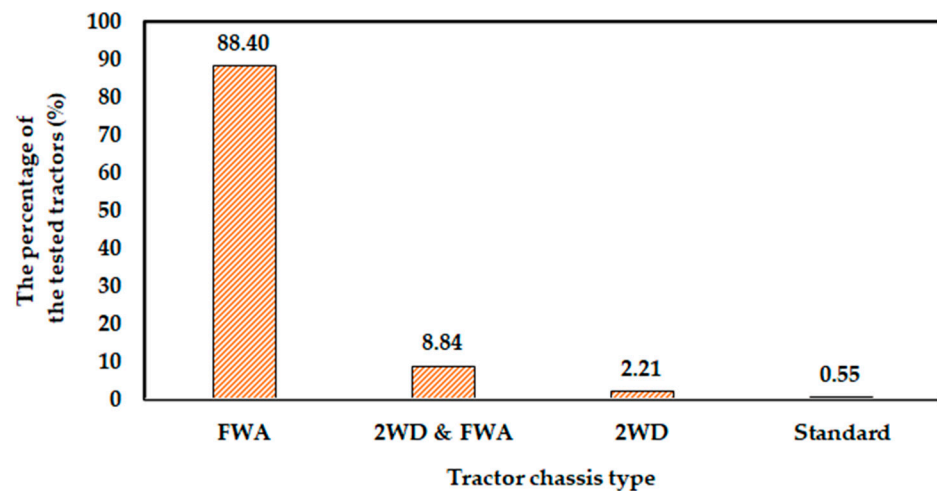


Figure 4. The percentage of tractor chassis type of the tested Massey Ferguson tractors using NTTL data from 1997 to 2016.

Table 3. Descriptive statistics of the independent and dependent variables for FWA Massey Ferguson tractors tested using NTTL data from 1997 to 2016.

Variable	Unit	Minimum	Maximum	Mean	Standard Deviation
X1	(kg/lit)	0.84	0.85	0.85	± 0.01
X2	(Dimensionless)	4.00	6.00	5.57	± 0.82
X3	(rpm)	2100.00	2200.00	2180.74	± 39.49
X4	(mm)	100.00	111.00	104.66	± 4.32
X5	(mm)	120.00	145.00	128.83	± 7.57
X6	Dimensionless)	16.00	19.30	17.24	± 0.72
X7	(ml)	3990.00	8419.00	6221.41	± 1320.72
X8	(mm)	2093.00	3105.00	2759.88	± 251.33
X9	(km/h)	2.14	20.06	8.47	± 3.55
X10	(rpm)	1793.00	2282.00	2023.35	± 138.99
X11	(°C)	64.00	95.00	85.21	± 4.24
X12	(°C)	0.00	27.00	16.71	± 6.95
X13	(kPa)	95.73	103.20	100.90	± 1.52
X14	(in)	34.00	46.00	40.07	± 3.26
X15	(kPa)	65.00	110.00	94.35	± 11.33
X16	(in)	24.00	34.00	28.68	± 1.76
X17	(kPa)	60.00	130.00	102.40	± 15.53
X18	(mm)	500.00	640.00	554.77	± 37.86
X19	(kg)	2478.00	6930.00	4022.88	± 1304.85
X20	(kg)	1605.00	5090.00	2803.95	± 1038.50
Drawbar pull	(kN)	7.30	120.57	42.70	± 20.04
Fuel consumption	(lit/h)	13.23	68.70	32.37	± 12.75

3.2. Interrelationships Among Some Dependent and Independent Variables

Some interrelationships among dependent and independent variables were explored using NTTL data. Figure 5 expresses the relationship between fuel consumption and static weight on the rear tires for FWA Massey Ferguson tractors. It was a positive inter-

relationship with a coefficient of determination (R^2) value of 0.8211. Similarly, Figure 6 illustrates the positive interrelationship between static weight on the rear tires and drawbar pull, with an R^2 value of 0.46. Figure 5 shows that with a rise in static weight on the rear tires, fuel consumption also rises due to an increase in the higher drawbar force required by the tractor, as seen from Figure 6. The findings are consistent with previous studies. Adam et al. [50] reported that increasing tractor weight increases drawbar pull and slippage, though the rise in slippage is relatively small. Likewise, Ghalehjoghi and Loghavi [51] found that adding weight to the rear tires increase drawbar pull and fuel consumption. Figure 7 further illustrates the relationship between static weight on the rear tires and drawbar power, with an R^2 value of 0.8324. As static weight on the rear tires increases, the tractor generates a higher pulling force, generating higher drawbar power at constant speed.

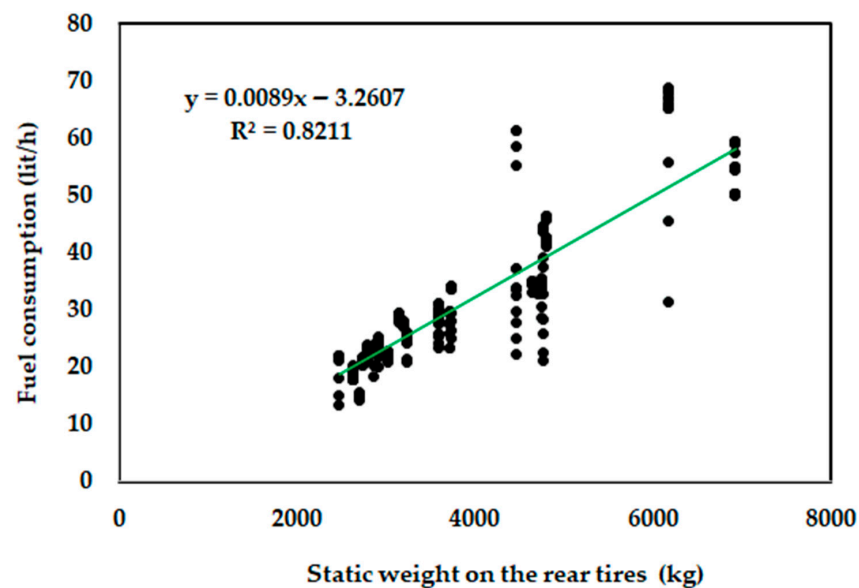


Figure 5. Relationship between fuel consumption and static weight on the rear tires for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016.

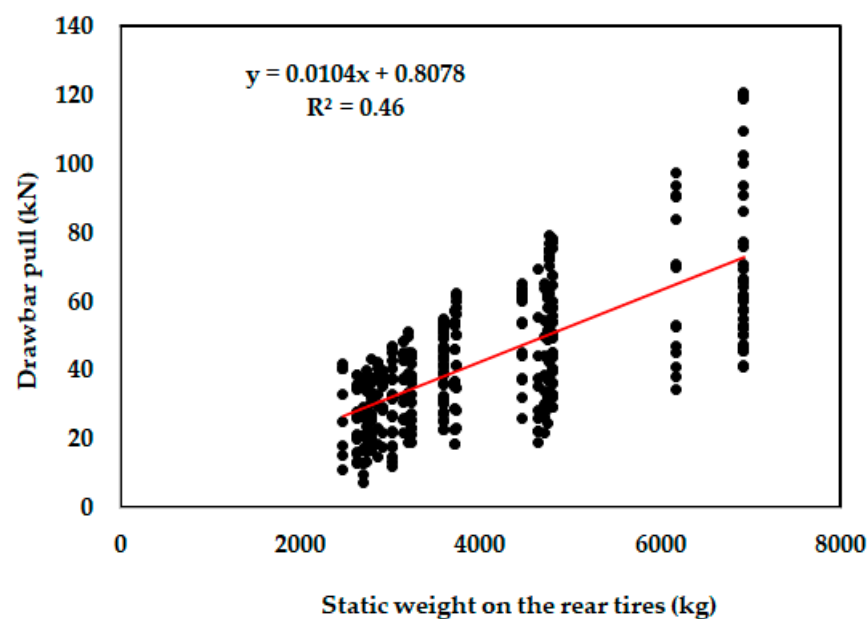


Figure 6. Relationship between drawbar pull and static weight on the rear tires for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016.

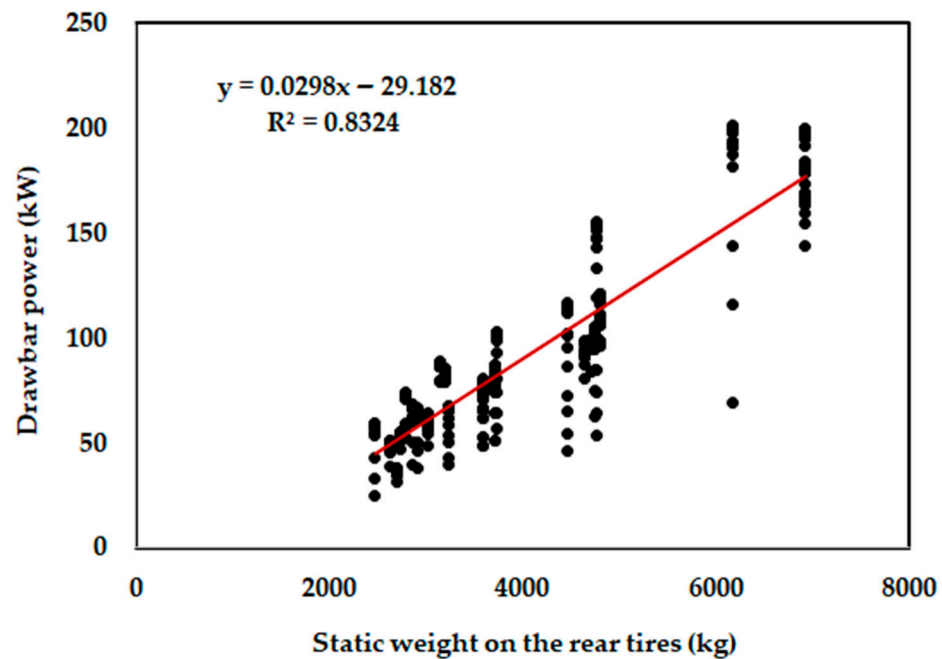


Figure 7. Relationship between drawbar power and static weight on the rear tires for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016.

3.3. Regression Analysis of Drawbar Pull and Fuel Consumption Parameters

Using stepwise regression, a forward scheme in SPSS software was applied [39]. The software program was employed for analysis on a personal computer. Two mathematical models were derived. For drawbar pull, eight models were delivered for the highest R^2 , as shown in Table 4, and for fuel consumption, twelve models were brought for the highest R^2 , as shown in Table 5. The unstandardized regression coefficients (B), which looked in Equation (1) are presented in Table 6 for drawbar pull and fuel consumption. However, the calculated standardized regression coefficients (β) were presented in Table 7 to identify the most important independent variables, which impact on the outcome. Additionally, Table 8 shows the values of independent variables for MF 440 tractor used to forecast drawbar pull and fuel consumption using the two established mathematical models.

Table 4. Eight regression models were tested for the highest R^2 for drawbar pull prediction (data for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016).

Model *	Correlation Coefficient	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.687 ^a	0.472	0.471	14.57
2	0.936 ^b	0.876	0.875	7.09
3	0.944 ^c	0.891	0.890	6.64
4	0.949 ^d	0.900	0.899	6.36
5	0.950 ^e	0.903	0.902	6.28
6	0.952 ^f	0.906	0.904	6.20
7	0.952 ^g	0.906	0.904	6.20
8	0.952 ^h	0.907	0.905	6.17

* All symbols refer to predictors in the model, however, the symbol h refers to (Constant), X20, X9, X6, X18, X19, and X2.

Table 5. Twelve regression models were tested for the highest R^2 for fuel consumption prediction (data for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016).

Model *	Correlation Coefficient	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.906 ^a	0.821	0.821	5.40
2	0.930 ^b	0.864	0.864	4.71
3	0.937 ^c	0.878	0.877	4.47
4	0.942 ^d	0.887	0.886	4.31
5	0.946 ^e	0.894	0.893	4.18
6	0.948 ^f	0.899	0.897	4.09
7	0.949 ^g	0.901	0.899	4.05
8	0.951 ^h	0.904	0.902	4.00
9	0.952 ⁱ	0.906	0.903	3.96
10	0.955 ^j	0.911	0.909	3.85
11	0.954 ^k	0.911	0.909	3.85
12	0.954 ^l	0.911	0.909	3.86

* All symbols refer to predictors in the model, however, the symbol j refers to (Constant), X19, X11, X7, X9, X16, X5, X6, X12, X3, and X15.

Table 6. Unstandardized regression coefficients (B) for drawbar pull (model 8) and for fuel consumption (model 10) (training data for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016).

Independent Variables	B (Unstandardized Regression Coefficients) for Drawbar Pull	Independent Variables	B (Unstandardized Regression Coefficients) for Fuel Consumption
B_0 (Constant)	54.138	B_0 (Constant)	−194.973
B_{20} (X20)	0.012	B_{19} (X19)	0.003
B_9 (X9)	3.784	B_{11} (X11)	0.484
B_6 (X6)	−2.934	B_7 (X7)	0.003
B_{18} (X18)	−0.051	B_9 (X9)	0.394
B_{19} (X19)	0.004	B_{16} (X16)	2.087
B_2 (X2)	2.046	B_5 (X5)	0.056
		B_6 (X6)	1.864
		B_{12} (X12)	0.057
		B_3 (X3)	0.033
		B_{15} (X15)	0.229

Table 7. The calculated standardized regression coefficients (β) for drawbar pull (model 8) and for fuel consumption (model 10) (training data for FWA Massey Ferguson tractors using NTTL data from 1997 to 2016).

Independent Variables	β (The Calculated Standardized Regression Coefficients) for Drawbar Pull	Independent Variables	β (The Calculated Standardized Regression Coefficients) for Fuel Consumption
β_0 (Constant)		β_0 (Constant)	
β_{20} (X20)	0.622	β_{19} (X19)	0.307
β_9 (X9)	0.671	β_{11} (X11)	0.161
β_6 (X6)	−0.105	β_7 (X7)	0.311
β_{18} (X18)	−0.096	β_9 (X9)	0.110
β_{19} (X19)	0.261	β_{16} (X16)	0.287
β_2 (X2)	0.084	β_5 (X5)	0.033
		β_6 (X6)	0.105
		β_{12} (X12)	0.031
		β_3 (X3)	0.102
		β_{15} (X15)	0.203

Table 8. The values of independent variables for MF 440 tractor used to forecast drawbar pull and fuel consumption using the two established mathematical models.

Independent Variables	Symbols of the Independent Variables	Value
Static weight on front tires (kg)	X20	650.7
Forward speed (km/h)	X9	Changeable
Compression ratio (Dimensionless)	X6	17.3
Height of the drawbar above the ground (mm)	X18	550
Static weight on rear tires (kg)	X19	1518.3
Number of engine cylinders ((Dimensionless)	X2	4
Rated engine speed (rpm)	X3	2200
Stroke length (mm)	X5	127
Engine displacement (ml)	X7	4000
Cooling medium (water) temperature (°C)	X11	30
Ambient air temperature (°C)	X12	20
Inflation air inside rear tires (kPa)	X15	70
Diameter of the front wheel rim (in)	X16	24

The developed mathematical model for drawbar pull is as follows:

$$Y1 = 54.138 + 0.012 X20 + 3.784 X9 - 2.934 X6 - 0.051 X18 + 0.004 X19 + 2.046 X2 \quad R^2 = 0.907 \quad (4)$$

The developed mathematical model for fuel consumption is as follows:

$$Y2 = -194.973 + 0.003 X19 + 0.484 X11 + 0.003 X7 + 0.394 X9 + 2.087 X16 + 0.056 X5 + 1.864 X6 + 0.057 X12 + 0.033 X3 + 0.229 X15 \quad R^2 = 0.911 \quad (5)$$

Overall, the outcomes specified that the selected input variables using SPSS [39] enhanced approximation accuracy. Model 8 for drawbar pull prediction and Model 10 for fuel consumption estimation accomplished the highest assessment accuracy, with R^2 values ranging from 0.907 to 0.911. In general, an R^2 value larger than 0.70 is measured to specify satisfactory performance [52], while values in the range of 0.80–0.90 or higher are viewed as indication of strong predictive capacity in agricultural and engineering sciences [53]. However, the cooling medium (water) temperature (X11) and ambient air temperature (X12) were selected to be significant variables in fuel consumption model (Equation (5)). However, repeated experiments after experiment day (20 February 2020), it will likely give similar results as no big differences in weather parameters were detected.

Figure 8 illustrates the relationship between drawbar pull values estimated by Equation (4) and the actual drawbar pull measured when the tractor operated on an asphalt track. Figure 9 presents the relationship between predicted fuel consumption, obtained from Equation (5), and the actual fuel consumption recorded during tractor operation on the asphalt track. The curves presented in Figure 8 show that the measured drawbar pull values followed a similar trend to those predicted by Equation (4) across different forward speeds. Likewise, Figure 9 demonstrates that the measured fuel consumption values showed a similar trend to those predicted by Equation (5). The variations observed between measured and predicted values may be attributed to differences in the conditions under which the predictive models were developed and the specific conditions of the field test, which was conducted in this study on an asphalt track.

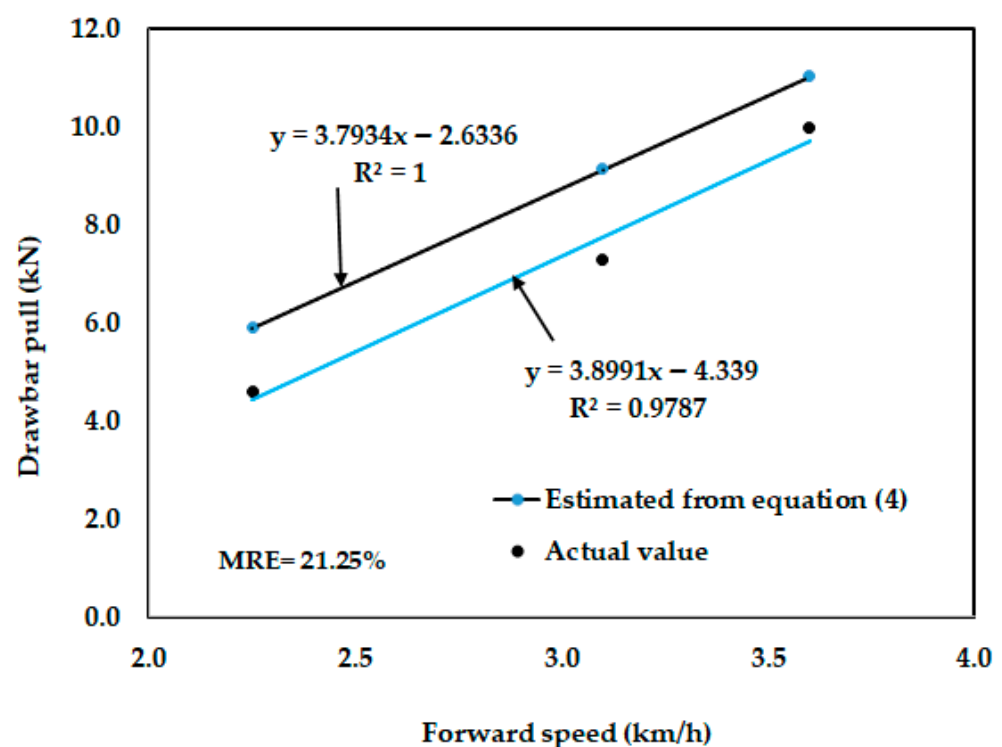


Figure 8. The relationship between drawbar pull values estimated by Equation (4) and the actual drawbar pull measured when the tractor operated on an asphalt track.

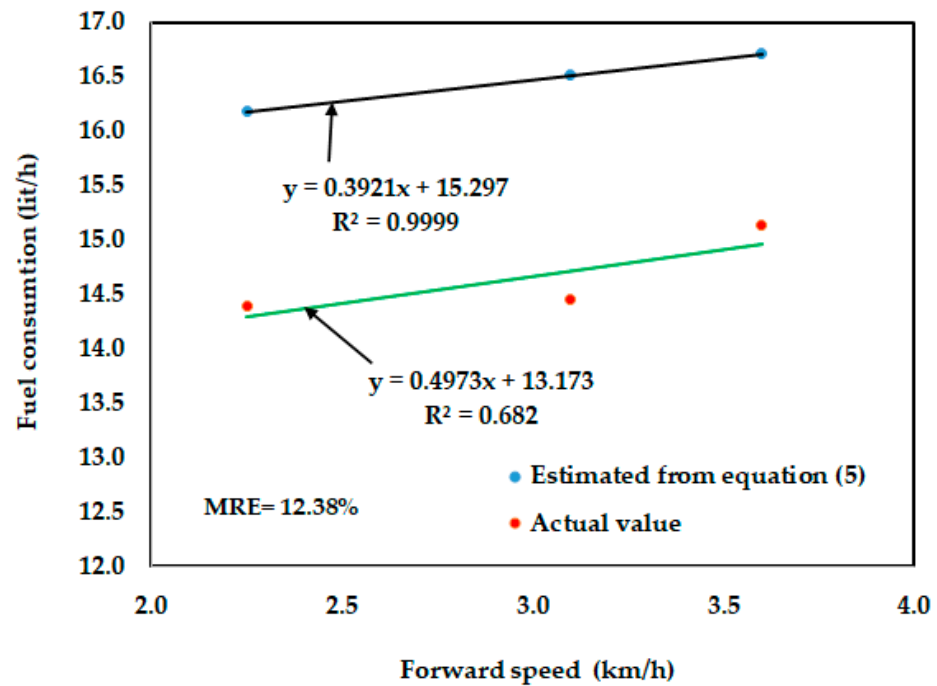


Figure 9. The relationship between fuel consumption values estimated by Equation (5) and the actual fuel consumption measured when the tractor operated on an asphalt track.

The mean relative error (MRE), shown on both curves, averaged 21.25% when comparing drawbar pull and 12.38% when comparing fuel consumption. The higher unpredictability and increased susceptibility to external variables associated with traction, as well as inherent measurement problems, are the main causes of the larger mean relative error (MRE) for drawbar pull force as compared to fuel consumption.

The field results were close to the predicted values. This outcome is significant because the regression models were derived from NTTL data collected under controlled conditions. Those tests measured drawbar pull and fuel use under controlled conditions. The aim was to achieve the best tractor performance. According to Moreno et al. [54], a prediction error of less than 10% indicates high accuracy, 10–20% suggests good accuracy, 20–50% indicates acceptable accuracy, and values above 50% are considered unacceptable. Similarly, ASABE Standards [31] report that relative errors between ± 12 and 50% are generally acceptable when drawbar pull equations are applied to agricultural equipment.

The regression analysis also showed strong relationships, with a coefficient of determination (R^2) of 0.9787 for drawbar pull versus forward speed (Figure 8) and (R^2) of 0.682 for fuel consumption versus forward speed (Figure 9). These findings confirm that drawbar pull and fuel consumption increase as forward speed increases. Similar trends were also reported [55–57]. In addition, the predicted drawbar pull values derived from Equation (4) followed a trend line comparable to the measured values. The slope of the predicted curve was 3.7934 compared to 3.8991 for the measured curve, as shown in Figure 8.

4. Conclusions

This study represents two effective mathematical models for estimating tractor fuel consumption and drawbar pull for FWA Massey Ferguson tractors using stepwise multiple regression. The empirical models were trained on a dataset from the Nebraska Tractor Test Laboratory (NTTL), in the USA, spanning the period from 1997 to 2016, and then evaluated using a dataset from a field experimentation. This helps to predict drawbar pull and fuel consumption with higher accuracy based on stepwise multiple linear regression. The influence of some independent variables on the outcomes were established using

NTTL data. The developed final multiple linear regression models with all the selected independent variables having a significant effect on drawbar pull ($R^2 = 0.907$) and fuel consumption ($R^2 = 0.911$). The accuracy of the predicted models and the measured values for the response variables during the pull operation traced out each other as closely as possible, confirming good agreement.

However, there are inherent limitations to extrapolating the results to other tractor models because this study was based on data acquired from a particular tractor model and limited field conditions. Thus, to validate the behavior of the developed regression models, other experiments can be conducted on other tracks or field conditions. However, the variables range used was seen in the text, but to apply the developed model on other tracks or field condition, a series of validation experiments should be conducted. Moreover, in order to further enhance the mathematical model's dependability and application, future research will concentrate on broadening the scope and variety of data for various tractor models and verifying the mathematical models under various operating circumstances. Finally, the developed regression models can be a viable tool for use in the planning of operational characteristics of a Massey Ferguson or other types within the investigated variables' ranges and input variables. It can be used to predict drawbar pull and fuel consumption during field operation using the input variables to enhance work quality and energy efficiency.

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