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Modification of Values for the Horizontal Force of Tillage Implements Estimated from the ASABE Form Using an Artificial Neural Network

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Abstract: The famous empirical model for the horizontal force estimation of farm implements was issued by the American Society of Agricultural Biological Engineers (ASABE). It relies on information on soil texture through its soil texture adjustment parameter, which is called the Fi -parameter. The Fi-parameter is not measurable, and the geometry of the plow through the machine parameter values are not measurable; however, the tillage speed, implement width, and tillage depth are measurable. In this study, the Fi-parameter was calibrated using a regression technique based on a soil texture norm that combines the sand, silt, and clay contents of a soil with R^2 of 0.703. A feed-forward artificial neural network (ANN) with a backpropagation algorithm for training purposes was established to estimate the modified values of the horizontal force based on four inputs: working field criterion, soil texture norm, initial soil moisture content, and the horizontal force (which was estimated by the ASABE standard using the new—Fi-parameter). Our developed ANN model had high values for the coefficient of determination (R^2) and their values in the training, testing, and validation stages were 0.8286, 0.8175, and 0.8515, respectively that demonstrated the applicability for the prediction of the modified horizontal forces. An Excel spreadsheet was created using the weights of the established ANN model to estimate the values of the horizontal force of specific tillage implements, such as a disk, chisel, or moldboard plows. The Excel spreadsheet was tested using data for a moldboard plow; in addition, a good prediction of the required horizontal force with a percentage error of 10% was achieved. The developed Excel spreadsheet contributed toward a numerical method that can be used by agricultural engineers in the future. Furthermore, we also concluded that the equations presented in this study can be formulated by any of computer language to create a simulation program to predict the horizontal force requirements of a tillage implement.

Keywords: tillage; moldboard plow; horizontal force requirements; soil texture norm; machine learning; agricultural tractor

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1. Introduction

Soil tillage, i.e., the initial and fundamental stage of every system of agricultural production, requires tremendous energy [1]. It is a process that mechanically changes or manipulates the soil using various plows by cutting, pulverizing, and inverting to provide favorable conditions for crop growth and acceptable yield [2,3]. Primary tillage and secondary tillage operations are the basic steps through which to provide good seed bed preparation for planting purposes. In the context of primary tillage, moldboard, disk, and chisel plows are the most common implements for effective soil tillage. However, tractor and tillage implement matching is the key factor for obtaining high operating efficiency in actual field operations [4]. Furthermore, farm managers usually employ information on the horizontal force or power needed to match agricultural tractors with tillage equipment [5]. Moreover, draft requirement of tillage implement is essential for appropriate tractor implement matching and the guess of fuel consumption at different operation conditions [6]. The draft of a tillage implement is affected by soil physical properties such as dry bulk density and soil moisture content, tillage speed, and tillage depth [7]. However, reducing the draft force of tillage implements was continuously one of the most vital aims of researchers [8]. Thus, it is highly important to select the operation parameters and the implements used to cultivate agricultural products [9]. A great deal of research was conducted on the subject of predicting the draft force needed by agricultural implements, and numerous methods for doing so were already developed. The earliest technique was the mathematical-analytical technique, and numerous mathematical models were created to forecast the draft force exerted by tillage tools [10]. The high price of measuring devices and field experiments to acquire draft data of a tillage implement can support to develop a model to estimate such data. The deployment of these models will facilitate an overall reduction in data collection costs and the optimization of the affecting variables. When the measurement of performance indicators for tillage implements such as draft force is not accurate, the recorded draft data are incorrect and will, therefore, give a different from the performance of the agricultural machine [11]. On the other hand, the famous empirical model for draft force (DD) estimation is the ASABE model [12], which can be described as follows:

$$\mathrm{DD} = \mathrm{Fi} \times \left(\mathrm{A} + \mathrm{B} \times \mathrm{S} + \mathrm{C} \times \mathrm{S}^2\right) \times \mathrm{L} \times \mathrm{d} \quad (1)$$

The draft values of the tillage implements were estimated using Equation (1); however, this relied on the information for soil texture through its soil texture adjustment parameter, called Fi, which is not measurable. Having said this, Fi is a dimensionless soil texture adjustment parameter that has different values depending on soil texture; it is not measurable but assumed, and it is characterized as coarse, fine, or medium. Furthermore, the soil is defined as high in clay content in fine soil textures, the soil is considered as loamy soil in medium textures, and in coarse texture, the soil is considered sandy soil. Moreover, DD is dependent on the tillage speed (S) and tool width (L) of the tillage implements (when using chisel plow, it represents the number of tools), as well as the tillage depth (d), which are all measurable. Additionally, the DD value depends on the geometry of the tillage tool through assuming the parameters of A, B, and C, as is shown in Equation (1). However, A, B, and C are constant parameters of machine-specific values, which are assumed for the tillage implement type [12]. The constant parameter A is a function of soil strength, while the coefficients of B or C are related to tillage speed, and they refer to the influence of the working speed on horizontal forces. All parameters in Equation (1) have typical values that are stated with an expected range or variance due to variations in the type of tillage equipment and soil texture group [12]. The goal of Equation (1) is to offer a preliminary prediction equation that can be used with a variety of soil conditions. Equation (1) provides a reasonable estimate for tillage implement draft, but it also warns that, within the same wide textural soil class, a range in draft of up to 50% can be anticipated [13]. To overcome the assumptions of the Fi-parameter in Equation (1), Tianmanee et al. [14] proposed a mathematical model to predict the Fi-parameter as follows:

$$\mathrm{Fi} = \frac{\mathrm{DD}}{\left(\mathrm{A} + \mathrm{B} \times \mathrm{S} + \mathrm{C} \times \mathrm{S}^2\right) \times \mathrm{L} \times \mathrm{d}} \quad (2)$$

Using Equation (2), Tianmanee et al. [14] found that the calculated soil texture parameter (Fi) for disk plow that is operated in loamy sand soil varied between 1.4–1.5. These values were greater than the soil texture parameter guidelines of the ASABE [12], which states it as 0.45–0.70. However, the soil texture parameter (Fi) appeared to be unique in the instance of that soil texture. Thus, it is important to clarify the Fi-parameter for the purposes of accurate draft data. Furthermore, in the study of Kumar et al. [15], Equation (1) was modified by adding two correction factors (K_1 and K_2) as follows:

$$DD = K_1 \times \left(Fi \times \left(A + B \times S + C \times S^2\right) \times L \times d\right) + K_2 \tag{3}$$

The correction factors K_1 and K_2 in Equation (3)—which were 1.735 and 1618, respectively—were introduced to accommodate for changes in the horizontal force for a moldboard plow operated in sandy clay loam soil.

According to the above reviews, the values of the horizontal force of tillage implements change rapidly according to the assumed Fi-parameter in Equation (1); furthermore, this trend is unpredictable in certain cases. Therefore, the tractor and tillage implement matching did not fit, fuel consumption increased, and operating efficiency was reduced. In order to overcome the required suitable Fi-parameter, it was evident that field experiments are required in different soil textures; however, this is time-consuming and requires suitable arrangements and equipment for draft measurements to be carried out for the purposes of relevant analysis and for the calculation of state predictions, as well as to realize the strong effectiveness of an accurate estimation of the Fi-parameter. Therefore, the available generated data from previous research works in the field can be obtained to a certain extent, and the approximate trend of the Fi-parameter can be determined through regression analysis or other methods. This is of great significance for monitoring the actual draft data performance of tillage implements of different soil textures, thus saving operational costs and reducing the error rate of the original ASABE model [12].

Numerous research papers used Equation (1) to estimate the implement horizontal force for different purposes. Askari et al. [16] employed Equation (1) to assess and confirm the values of the horizontal force requirements of mounted tillage implements that were using an innovative three-point hitch dynamometer. The magnitude of error in the horizontal force values between measurement and calculation was $\pm$12%. Igoni et al. [17] used Equation (1) to create a predictive dimensional model using a dimensional analysis technique for the estimation of tractor fuel consumption during the ridging process. Jyoti et al. [6] used Equation (1) to obtain the horizontal force requirements of tillage implements and compared them with the actual measurements by using a pull-type load cell. Shukla and Pandey [18] used Equation (1) to develop an Android application for predicting the stability of a tractor. Sadek et al. [19] used Equation (1) with a mathematical model created by a discrete element method to compare the predicted horizontal force for high plowing speeds during the process of plowing with a disc plow. The results indicated that the percentage of relative error fluctuated from 8% to 14%. Kim et al. [20] used Equation (1) to validate the precision of their actual-time tillage depth determination by establishing a regression model between the measured horizontal force and the predicted data. The accuracy was assessed by the coefficient of determination (R^2), which was around 0.715. Other researchers offered various applications for objectifying the usefulness of using the ASABE form [12] in establishing computer programs, which are frequently used to support farm machinery managers in decision making regarding how to select machinery and power requirements [21].

Researchers use different types of the force meter to acquire the forces acting on the tillage implements during the plowing process; in particular, the draft force [22]. Others applied different statistical approaches and models to predict the draft force acting on the agricultural implements [23–29]. However, to compensate for the shortcomings of using the ASABE model [12], researchers developed and evaluated intelligent computing methods, such as artificial neural network models and fuzzy knowledge-based models, which led to greater progress in the application of many technologies. In addition, these developments provide the possibility to solve complex agricultural engineering problems, particularly the draft force prediction of agricultural implements [30–37]. After entering the relevant parameters for the implement, soil, and working conditions, these intelligent models could provide a straight estimate of the draft force of a tillage implement. However, to train these models, experimental values had to be acquired from a field experiment or a soil bin experiment. Additionally, the intelligent models did not take into account the connection between the draft force and the input parameters that are intended to improve the comprehension of the tillage process and mechanism [10].

Al-Hamed et al. [32] prepared an ANN model with a backpropagation algorithm to estimate the horizontal force required to pull a disk plow. The proposed ANN model used ten input variables: tillage depth, tillage forward speed, sand contents in the soil, clay contents in the soil, silt contents in the soil, disk configurations such as disk diameter; disk angle, tilt angle, soil bulk density, and soil moisture content. The coefficient of determination for the validating points of the ANN model were changed between 0.915 and 0.934. Akbarnia et al. [37] employed an ANN model with a backpropagation algorithm to estimate the horizontal force required by a chisel plow possessing a two-winged share in a loam-textured soil. The input variables were tillage depth, forward speed, and the width of the wing share. The ANN model estimated the horizontal force with a small error associated with the measured values. Pentoś and Pieczarka [38] established an ANN model to estimate the horizontal force of agricultural implements. However, they employed soil moisture content, soil texture, soil compaction level, horizontal deformation, and vertical load as input variables in their ANN model. The coefficient of determination was 0.945 for the horizontal force determination in the model with the testing dataset. Çarman et al. [39] set up an ANN model employing the backpropagation algorithm to predict the specific draft force requirements of a moldboard plow in a clay loam soil; this was achieved by using tillage depth and plowing speed as the input layer, and the specific draft force requirements of moldboard plow as the output layer. This was an attempt to use intelligent algorithms to predict the draft requirement of the tillage implements, with an error of less than 1% when compared to the measured draft values. Further research work was required to demonstrate the generalized value of the developed ANN in other soil conditions. Furthermore, Nitin et al. [40] estimated tractor power take-off (PTO) performance using a backpropagation ANN model. Twenty dissimilar variables were considered as the inputs for a PTO tractor performance expectation. The data that were employed as inputs to train the ANN model were acquired from 141 reports that belonged to tractor test procedures, and which were run between year 1997 and year 2013. The optimum ANN model structure was assigned by a trial-and-error procedure, and 30 different ANN structures were tried. For prediction, an ANN model with two hidden layers that had 40 and 35 nodes in both the first and second hidden layers, respectively, gave the maximum performance. The ANN model can construct a simulation of a tractor's performance; it also allows the optimal setting of dissimilar variables, as well as can improve the decision making of a producer in the proposal of new tractor. Furthermore, scientific revisions showed that usual regression methods might produce biased outcomes, as they are unable to gauge the multicollinearity between independent variables [41]. Therefore, a crucial and optimal selection would be to use ANN, which classifies the linear and non-linear ways while fitting statistical models on to the original data [42].

To the best of our knowledge, despite extensive literature examination, no study on the prediction of the soil texture adjustment parameter (Fi) was used in ASABE form [12]. In addition, this method being used to modify the values of the draft force of tillage implements, as estimated from the form of ASABE [12] by using an ANN model, was also not tested yet. The importance of conducting this research lies in the fact that the draft force is a vital factor in determining the energy requirements of tillage implements for various purposes, including cost analysis, fuel consumption prediction, and matching agricultural tractors with the correct tillage implements. The ability to accurately predict the modified draft force of tillage implements, based on ASABE form [12], through the use of machine learning models such as ANN can help in producing better farm machinery management and utilization of the available resources. Furthermore, an accurate prediction draft force can also aid in mitigating the potential of using tillage implement management approaches that are associated with consuming diesel fuel, which is a significant concern in many parts of the world. By accurately predicting the draft force of tillage implements, farm machinery engineers can determine the variables that will offer less draft force for tillage implements when conducting tillage operation on a specific soil texture. This is possible because the user can change tractor power, tillage speed, tillage depth, implement width, soil bulk density, and soil moisture content as needed to achieve a lower energy for the plowing process. Conducting this research in the study area is necessary because the draft force of tillage implements can vary significantly depending on the specific soil texture and other factors. Therefore, it is essential to develop models that are tailored to the unique characteristics of the study area to achieve accurate predictions, or so that they can be used in many parts of the world. Moreover, the novelty of the paper lies in developing a new soil texture parameter that can address the effect of soil texture on the draft force of tillage implements.

Hence, the main objectives of this research were the following: (1) to create a regression model that can predict the soil texture adjustment parameter (Fi) that is used in ASABE form [12]; (2) to develop an ANN model to modify the values of the draft force of tillage implements that are estimated from the form of ASABE [12], and which are based on a wide range of working variables; (3) to obtain the results from a statistical performance evaluation with an ANN model, and to achieve the importance of certain predictor variables; and (4) to create a useful Excel spreadsheet to serve as an easy tool through which to obtain the values of the modified draft force of tillage implements that are based on wide range of working variables.

2. Materials and Methods

2.1. Sources of the Required Data for Modeling the Modified Horizontal Force via the ANN Method

In this study, two sources were considered in order to acquire the necessary information for modeling, via the ANN method and the modified horizontal force. The main source was from actual tillage field experiments using a chisel plow. These tillage experiments were run in three soil textures (three sites). The soil in the first experimental field (site) had a silty clay loam with 52% sand, 18% silt, and 30% clay, and was situated in an agricultural soil. The soil in the second field (site) experiment had a clay texture of 44.4% clay, 15% sand, and 40.6% silt. Finally, the soil in the third field (site) experiment had a clay texture with 17.7% silt, 28.5% sand, and 53.7% clay. The analysis of each soil texture was performed according to the standard procedure, which is the generally the best used process in agricultural machinery investigation [20].

For each soil texture, undisturbed soil samples from five random spots, obtained through the topsoil layer at a soil depth of 30 cm, were hand-selected by means of a soil sampling apparatus. The soil samples were weighed via a digital balance, and the weight of each soil sample was recorded and put in polythene bags. The samples of the soil were dried in an electric oven, and was kept at 105 °C for 24 h. The dried samples of the soil were re-weighed, and the weight was again noted in order to calculate the levels of the initial soil moisture content based on a dry weight and initial soil bulk density. Two agricultural tractors were used in the tillage experiments for measuring the horizontal force (draft) of the chisel plow, as is described in [6,43–48]. In the first and second experimental sites, the chisel plow under study was mounted at the rear of Ford tractor (main tractor) model TW15 with a diesel engine of 110 kW at 2300 rpm with help of three-point hitch of the tractor. A hydraulic dynamometer (pull type) was attached to the front of Ford tractor. An auxiliary tractor Lamborghini tractor model 1106 with a diesel engine of 110 kW at 2500 rpm was used to pull the chisel plow mounted through dynamometer. The auxiliary tractor pulled the chisel plow mounted tractor in neutral gear with the implement in operating condition.

The idle draft force was also recorded in the same field when chisel plow was in lifted position. The difference draft at operating and idle condition gave the draft required to pull the chisel plow. The tillage operation was repeated for all the investigated runs and draft data for each run were recorded. A Kubota M1 tractor (70 kW) and Belarus (67 kW) were used as main and auxiliary tractors, respectively, at the first experimental site.

A chisel plow, with seven shanks arranged in two rows, weighed 460 kg (4.51 kN), had a total width of 175 cm, and was employed in field experiments. The typical tillage speeds were changed by choosing different gears in the tractor manual transmission, and the plowing depth was fixed by using the hand located on the tractor. The tillage depth controller and the tillage depth data were recorded in three replications. The tillage depths were recorded using a steel measuring tape and by using the undisturbed surface as a reference. A straight distance of 25 m was used as a practice distance prior to the beginning of the experimental runs to permit the tractor and the chisel plow to reach the desired tillage speed and depth. The tillage time was recorded for each run of 20 m. To obtain the tillage speed, the distance was separated by the time taken to complete the run. The tillage experiments for the continuous measurement of variables were conducted on a 100 m straight section. The horizontal force was determined under different levels of tillage speeds, dissimilar tillage depths, and different levels of initial soil moisture content; all of the levels of variables were under different tractor power settings (Table 1).

Table 1. Levels of tractor power, initial soil bulk density, tillage depth, initial soil moisture content, tillage speed, and the number of data points using a chisel plow in the experimental sites.

The Experimental Sites	Tractor Power (kW)	Tillage Depth (cm)	Tillage Speed (km/h)	Initial Soil Moisture Content (% db)	Initial Soil Bulk Density (g/cm^3)	Number of Data Points (-)
First experimental site	67	14.0	2.5, 3.8, 4.8	18.2	1.28	3
Second experimental site	82	10, 12, 14, 15	3.5, 4.8, 5.7	18.2	1.40	12
		10, 12, 15	4.8	18.2	1.40	3
Third experimental site	82	10, 13, 15, 16	2.5, 3.4, 4.8	17.4	1.35	12
		10, 14, 17, 18	2.4, 3.5, 4.6, 5.1	17.6	1.30	12
		10, 13, 14, 16	2.5, 3.2, 5.1	20.1	1.38	12
		9, 11, 14, 16	3.2, 3.7, 4.7, 6.9	19.8	1.36	16
Total Data Points						70

The other source of the required data that was directly related to our study was from the available prior literature. The data were acquired for different tillage implements, such as chisel, disk, and moldboard plows [49–57]. The compiled dataset comprised the horizontal forces that match with the variables of tractor power; plow width; the percentages of silt, sand, and clay contents in the soil; tillage depth, initial soil bulk density; tillage forward speed; and the initial soil moisture content.

2.2. The Methodology Steps of This Study

The soil texture norm (STN, dimensionless), which combines all the soil contents of sand, silt, and Oskoui and Harvey [58] defined clay, as follows:

$$\mathrm{STN} = \frac{\log\left(\mathrm{Ca}^{\mathrm{Si}} + \mathrm{Sa}\right)}{100} \tag{4}$$

In Equation (4), Sa signifies the sand content percentage in the experimental soil. Also, Si and Ca symbolize the percentages of silt and clay in the soil, respectively. Oskoui and

Harvey [58] confirmed that the STN reveals the sound effects of all three-soil contents, and it fluctuates for dissimilar groupings of silt, clay, and sand. However, according to Table 2 (from ASABE [12]), we assigned values of the Fi-parameter according to values from ASABE [12] and to the soil texture; however, Table 3 shows the assigned values of the Fi-parameters that were used in our data to create a regression model to predict a new Fi-parameter based on soil texture norm (STN). However, we arranged the data in two columns in Excel, column for Fi-parameter based on soil texture and column for Fi-parameter according to values from ASABE [12]. Then, we tested all the fit functions in the Excel spreadsheet and we found that the following formula was the best:

$$\mathrm{New} - \mathrm{Fi} - \mathrm{Parameter} = 0.684788 + 0.978029 \times \mathrm{STN} - 0.75159 \times \mathrm{STN}^2 \quad (5)$$

Table 2. Values of A, B, C, and the Fi-parameter for estimation drafts as produced via Equation (3) from ASABE [12].

Implement	Width	Machine Parameters			Soil Parameters		
					Fi-Paramter		
					F1	F2	F3
	Units	A	B	C	Fine	Medium	Coarse
					Soils With High Clay Content	Loamy Soils	Sandy Soils
Moldboard plow	m	652	0.0	5.1	1.0	0.70	0.45
Chisel plow for 5 cm straight point	Tools	91	5.4	0.0	1.0	0.85	0.65
Disk gang, single for primary tillage	m	124	6.4	0.0	1.0	0.88	0.78

Table 3. Assigned values of the Fi-parameter according to values from ASABE [12].

Implement	Soil Texture	Fi-Paramter Acording to Soil Texture
5 cm straight point	Clay	1
	Clay loam	0.85
	Sandy	0.65
	Sandy clay loam	0.65
	Silty clay	0.85
Disk gang, single for primary tillage	Clay	1
	Clay loam	0.88
	Loamy sand	0.78
	Sandy loam	0.88
Moldboard plow	Clay	1
	Clay loam	0.7

Numerous research papers claimed that the draft force of tillage implements are affected by many variables namely: soil texture, soil moisture content, tillage depth, tillage speed, tractor power, soil bulk density, implement width, etc. Thus, in our research, we combined most of these variables in one variable called working field criterion (WFC) and other variables like soil texture and soil moisture content were considered as inputs; additionally, the important input was the draft force which was determined by the new—Fi-parameter. However, these variables were considered to be four inputs to predict the modified draft force of tillage implements. The working field criterion (WFC) to combine all working parameters; these are denoted by tractor power (TP, kw), initial soil bulk density (BD, g/cm^3), tillage depth (d, cm), tillage speed (S, km/h), and plow width (L, cm). They were combined into one variable as follows:

$$\mathrm{WFC} = \frac{\mathrm{TP} \times 1000 \times 3.6}{\mathrm{BD} \times 9.81 \times \mathrm{L} \times \mathrm{S} \times \mathrm{d}^2} \quad (6)$$

where the constants 1000, 3.6, and 9.81 are conversion values. Additionally, the other inputs for the ANN model were the soil texture norm, initial soil moisture content, and horizontal force, as estimated with Equation (1) and by using the new—Fi-parameter, which can be determined by Equation (5). In addition, the research steps to obtain the modified horizontal force with the ANN model are as follows:

- Collecting the clay content in the soil (percentage), sand content in the soil (percentage), and silt content in the soil (percentage);
- Calculating the STN with Equation (4);
- Calculating the new—Fi-parameter with Equation (5);
- Collecting the tillage depth (d, cm), tillage speed (S, km/h), tractor power (TP, kW), initial soil bulk density (BD, g/cm^3), the plow width (cm) for disk and moldboard plows, and the no. of tools for chisel plows;
- Calculating the WFC with Equation (6);
- Selecting the parameters in Equation (1) for chisel plows (Table 2) as follows: No. of tools, A = 91, B = 5.4, C = 0, tillage speed, and tillage depth;
- Calculating the horizontal force estimated from Equation (1) using the new—Fi-parameter for the chisel plows;
- Selecting the parameters in Equation (1) for the moldboard plow (Table 2) as follows: A = 652, B = 0, tillage speed, tillage depth, and plow width;
- Calculating the horizontal force estimated from Equation (1) using the new—Fi-parameter for moldboard plows;
- Selecting the parameters in Equation (1) for disk plows (Table 2) as follows: A = 124, B = 6.4, C = 0, tillage speed, tillage depth, and plow width;
- Calculating the horizontal force estimated from Equation (1) using the new—Fi-parameter for disk plows.

Finally, Table 4 illustrates the number of data points and the statistical criteria of the acquired data that were used in this study for three different tillage implements (disk, chisel, and moldboard plows).

Table 4. The statistical criteria of the acquired data used in this study for three different tillage implements (disk, chisel, and moldboard plows).

Working Parameters	Statistical Criteria				
	Minimum	**Maximum**	**Mean**	**Standard Deviation**	**No. of Data Points**
Tractor power (TP), (kW)	44.76	104.44	60.77	17.47	377
Initial soil moisture content (MC),(% db)	6.31	28.73	20.20	4.41	377
Initial soil bulk density (BD), (g/cm^3)	1.07	1.78	1.32	0.12	377
Soil texture norm (STN),(-)	0.03	0.84	0.50	0.27	377
Old Fi-parameter (-)	0.65	1.00	0.92	0.13	377
New—Fi-parameter (-)	0.713	1.003	0.924	0.108	377
Tillage depth (d), (cm)	10.00	30.00	20.47	4.52	377
Tillage speed (S), (km/h)	1.50	9.00	3.96	1.28	377
Plow width (L), (cm)	34.51	385.00	122.81	39.98	377
No. of chisel tools (-)	5	15	8.04	2.75	90
Working field criterion (WFC), (-)	0.019	2.328	0.134	0.213	377
Horizontal force determined using Equation (1) and new—Fi-parameter (DD), (kN)	0.42	25.72	14.88	4.33	377
Measured horizontal force, (kN)	0.38	25.85	16.92	5.01	377

2.3. *Artificial Neural Network Development*

An effective analytical technique for modeling complicated, multidimensional, and highly nonlinear interactions is the artificial neural network (ANN) [59]. Thus, ANNs are engaged to aid with explaining the compound practical issues in agricultural endeavors [60].

Artificial neurons, which are a huge number of simple processing components that are arranged in layers, constitute an ANN. Multilayer perceptron (MLP), also known as a feed forward network that was trained by using one of the learning methods (specifically a backpropagation algorithm), is the most widely used ANN architecture for predictive modeling. The input layer and output layer are the two primary layers in MLP. Additional (hidden) layers are sandwiched in between the input and output layers. In most cases, synapses fully connect neurons in adjacent layers. The quantity of input and output variables in the model is represented by the number of nodes in the input and output layers, respectively.

To create an ANN model, at least three layers—the input layer, the hidden layer, and the output layer—must be present (Figure 1). Nodes that correspond to input variables are present in the input, whereas nodes that relate to output variables are present in the output. The input layer is used to distribute the inputs to a variety of hidden layers, each of whose outputs is linked to an output layer; this is then connected to the inputs of the following layer by connection weight. The weighted connections make it possible for data to pass across layers more simply since the node generates a weighted total of all its net inputs after accepting the data from the layer before it, which is as follows:

$$t_i = \sum_{j=1}^{n} \left(w_{ij} \times x_j + b_i \right) \tag{7}$$

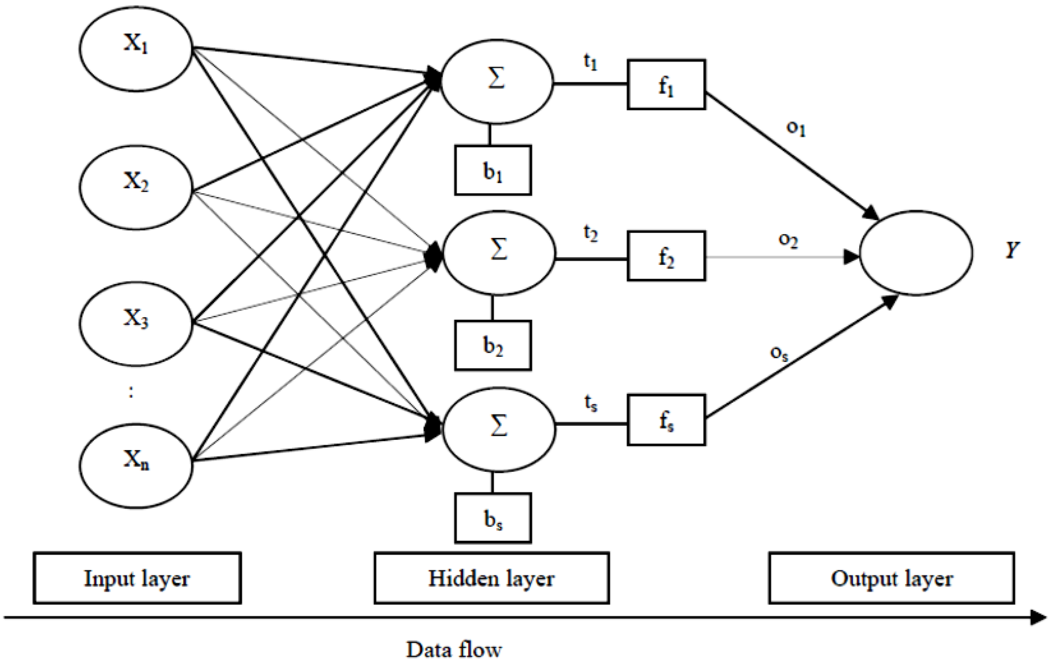


Figure 1. The feed-forward ANN back propagation layers and connections.

In Equation (7), the number of inputs is n, the weight of the link between nodes i and j is w_{ij}, the input from node j is x_j, and the bias is b_i. The weighted value is then subjected to a transfer function $f(t_i)$ to determine the node output (O_i):

$$O_i = f(t_i) \tag{8}$$

There is no set rule for how many neurons should be in a hidden layer, yet this has a substantial impact on the quality of the model. Therefore, a trial-and-error method was used in this study to estimate the ideal number of neurons that should be in the hidden layers. The commercial neural network program of Qnet 2000 for Windows was used to run ANN simulations [60]. The Qnet backpropagation neural modeling system is capable of making predictions in response to the modeler's artificial input vector [61]. Its ANN design was decided to be an MLP with a single hidden layer. The input layer had four nodes in it: working field criterion (WFC), soil texture norm (STN), initial soil moisture content (MC), and the horizontal force, which was estimated with Equation (1) using the new—Fi-parameter (DD). The output was one variable: the modified horizontal force (MHF) for any of the tillage implements (chisel, disk, and moldboard plows). A total of 377 data points were obtained, and they were divided into training, test, and validation sets at random in 70:15:15 ratios. The minimum and maximum input as well as the output parameter values are shown in Table 2. Using the following equation, the Qnet 2000 [60] standardized these values into the range (0.15–0.85) as follows:

$$\mathrm{V} = \frac{(\mathrm{v} - \mathrm{v_{min}})}{(\mathrm{v_{max}} - \mathrm{v_{min}})} \times (0.7) + 0.15 \tag{9}$$

In Equation (9), v stands for the input and output parameters' original values (measured values), V is the parameter's normalized value, and v_{max} and v_{min} are the input and output parameters' maximum and minimum values, respectively, in the training dataset.

The hidden layer's number of neurons was set during the ANN model construction process to be between 5 and 35. The neurons had sigmoidal and hyperbolic tangent transfer functions. The algorithm randomly selected the initial weights and biases of the neurons. The training data comprised 263 patterns, the testing data set was 57 data points, and the validation data set comprised 57 data points. The training process's evaluation of the model's quality was based on the correlation coefficient and training error values of the two metrics. The ANN model chosen at the conclusion of the training procedure was the one that provided the smallest training error while still having a decent correlation. The final network included 4 neurons for the input layer, 20 neurons for the hidden layer, and 1 neuron for the output layer, and this was achieved after multiple attempts to change the network topology (Figure 2).

2.4. Calculation of Variable Contribution Percentage on Predictors

Predictive modeling often refers to an ANN as a "black box" when it is deployed. However, a number of approaches were put forth by academics to ascertain the role played by each independent input variable in an ANN model. Due to a variety of model types, an ambiguous model structure, the random initialization of connection weights, etc., choosing the best ANN model might be challenging. As a result, the outcomes can be deceptive when a single ANN architecture is employed to extract the contribution of variables [62,63]. Therefore, in this work, the suggested ANN model was computed by using the findings of predictor variable contributions with the methods outlined by Vesta Services [60].

2.5. Criteria for Evaluating ANN Model Performance

The created ANN model can be assessed using multiple criteria by comparing the model predictions to the measured values in the testing, training, and validation datasets. The root mean square error (RMSE) and mean absolute error (MAE) are two examples of these criteria [64]. The measured and predicted values are visually compared using scatter plots.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(\mathrm{P_i} - \mathrm{P_A})^2}{\mathrm{N}}} \tag{10}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}} \times \left| \sum_{i=1}^{N}(\mathrm{P_i} - \mathrm{P_A})^2 \right| \tag{11}$$

In Equations (10) and (11), N is the total number of observations, and P_i and P_A are the predicted modified horizontal force for tillage implements and measured values, respectively.

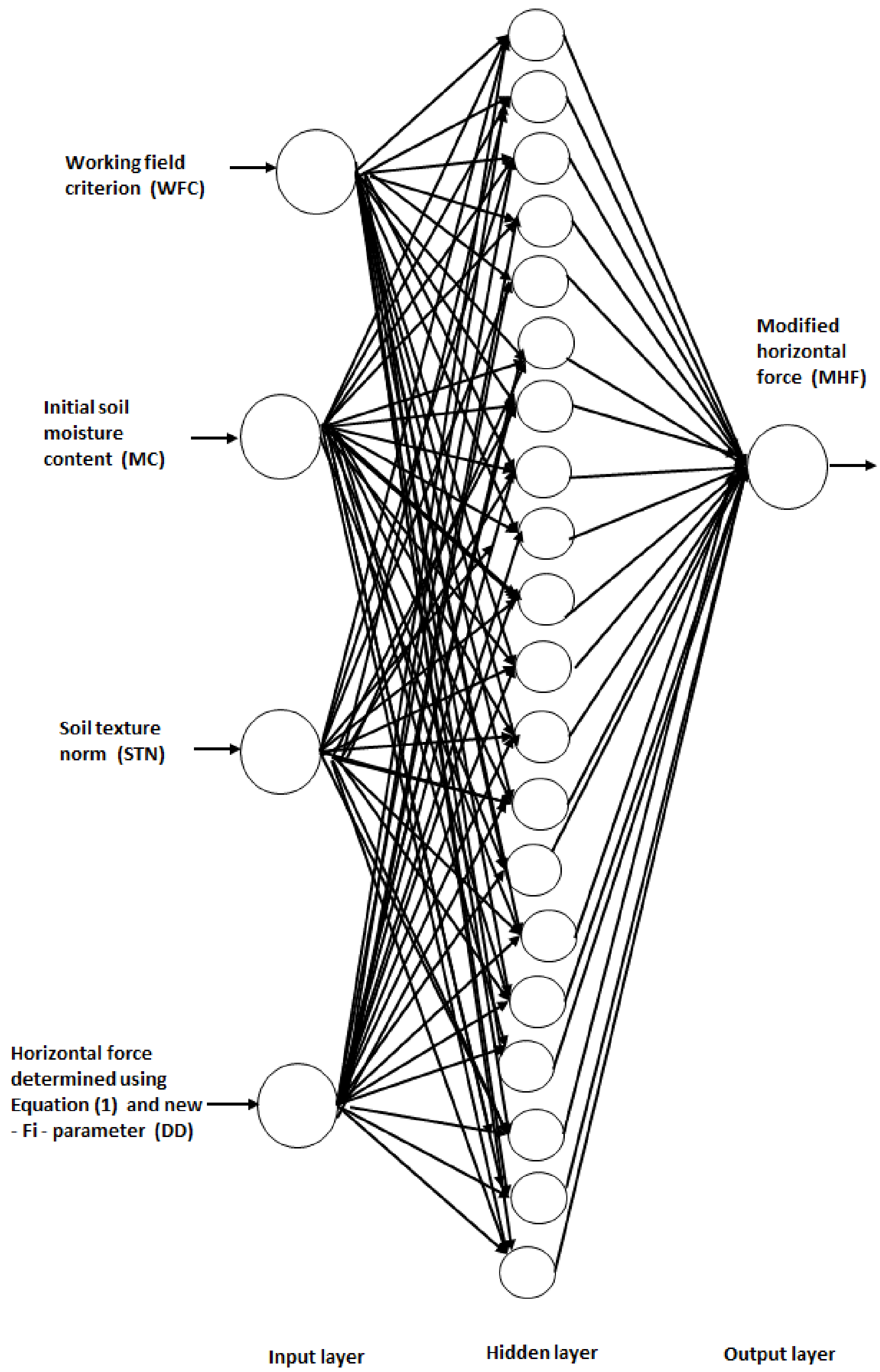


Figure 2. The best ANN structure (4-20-1) for predicting the modified horizontal force (MHF) of tillage implements.

2.6. The Required Equations for Creating the Excel Spreadsheet

Using the measured data, the ANN model was trained. Working field criterion (WFC) (dimensionless), soil texture norm (STN) (dimensionless), initial soil moisture content (MC) (%db), and horizontal force were determined by Equation (1) using the new—Fi-parameter (DD) (kN), which acted as inputs. The output was the modified horizontal force (MHF) for a tillage implement like chisel plow, moldboard plow, or disk plow. The three network layers, four input nodes, one output node, one hidden layer with twenty nodes, sigmoid transfer function, learn rate of 0.002854, momentum of 0.8, and iteration of 600,000 were some of the characteristics of the ANN used in the current study. For calculating the MHF, each input and equation, which were used to compute the normalized value of each input, were normalized. The maximum and minimum values for the inputs are shown in Table 4. However, the normalized values of the inputs are as follows:

$$WFC_N = \frac{(WFC_A - WFC_{min}) \times 0.7}{(WFC_{max} - WFC_{min})} + 0.15 \quad (12)$$

$$STN_N = \frac{(STN_A - STN_{min}) \times 0.7}{(STN_{max} - STN_{min})} + 0.15 \quad (13)$$

$$MC_N = \frac{(MC_A - MC_{min}) \times 0.7}{(MC_{max} - MC_{min})} + 0.15 \quad (14)$$

$$DD_N = \frac{(DD_A - DD_{min}) \times 0.7}{(DD_{max} - DD_{min})} + 0.15 \quad (15)$$

WFC_N, WFC_{max}, WFC_{min}, and WFC_A are the normalized, maximum, minimum, and measured values of working field criterion, respectively. STN_N, STN_{max}, STN_{min}, and STN_A are the normalized, maximum, minimum, and measured values of the soil texture norm, respectively. MC_N, MC_{max}, MC_{min}, and MC_A are the normalized, maximum, minimum, and measured values of the initial soil moisture content, respectively. DD_N, DD_{max}, DD_{min}, DD_A are the normalized, maximum, minimum, and measured values of the horizontal force, as determined by Equation (1) when using the new—Fi -parameter, respectively.

Next, the summation equations as indicated in Equation (7) were computed for the modified horizontal force with the connection weight values obtained from the trained ANN model (Table 5). There were 20 summation equations, which were as follows:

$$Sum1 = 0.1986 \times WFC_N + 0.6715 \times STN_N - 0.5673 \times MC_N - 0.9352 \times DD_N + 0.0433 \quad (16)$$

to

$$Sum20 = 0.1127 \times WFC_N + 0.72032 \times STN_N + 1.0166 \times MC_N - 3.0348 \times DD_N + 1.351 \quad (17)$$

Then, a transfer function (sigmoid) was applied to the weighted value (there were 20 equations) in order to determine the node output F1, F2, F3, F4, F5, F6, . . . , F20, which is given in Equation (9) as follows:

$$F1 = \frac{1}{((1 + \exp(-Sum1)))} \quad (18)$$

To

$$F20 = \frac{1}{((1 + \exp(-Sum20)))} \quad (19)$$

Next, the summation equation in the final layer was again computed for the modified horizontal force using the connection weight values obtained from the trained ANN model, which were as follows:

$$\begin{aligned} SumQ = {} & 1.74604 \times F1 + 7.64956 \times F2 - 1.77976 \times F3 + 7.47171 \times F4 - 0.89896 \times F5 + 4.91783 \times F6 \\ & + 1.1986 \times F7 - 2.04111 \times F8 - 1.86761 \times F9 - 5.33443 \times F10 + 10.35458 \times F11 \\ & + 1.69787 \times F12 + 4.62275 \times F13 + 0.090114 \times F14 - 7.62866 \times F15 - 1.17958 \times F16 \\ & - 1.90186 \times F17 - 8.60109 \times F18 - 1.58669 \times F19 + 2.55003 \times F20 - 0.43512 \end{aligned} \quad (20)$$

Then, normalized node output (FF), which represents the normalized target from the trained ANN model (modified horizontal force) was computed as follows:

$$FF = \frac{1}{((1 + \exp(-SumQ)))} \quad (21)$$

Next, modified horizontal force (kN) was computed as follows:

$$\text{Modified horizontal force, (MHF, kN)} = \frac{(\text{FF} - 0.15) \times (\text{DD}_{\text{max}} - \text{DD}_{\text{min}})}{(0.7)} + \text{DD}_{\text{min}} \quad (22)$$

To determine the relative error, the predicted value (P_i) by the measured value (P_A) was subtracted and then the absolute of that number by the measured value to obtain the relative error was divided. We can then multiply by 100 to obtain the percent error (PE, %) as follows:

$$\text{PE}(\%) = \frac{|(P_i - P_A)|}{P_A} \times 100 \quad (23)$$

Table 5. Connection weight values for Equations F1, F2, F3, F4 … … .., F20 for the modified horizontal force calculation (for F2, it could put Sum2, for F3, it could put Sum3 and so on).

Weights	Input Variables				Basis (b_i)
	WFC_N	**STN_N**	**MC_N**	**DD_N**	
W_{1j}	0.1986	0.6715	−0.5673	−0.9352	0.0433
W_{2j}	−5.7815	−2.7118	−3.9312	−1.1553	3.6839
W_{3j}	0.7341	0.8987	1.2139	0.1118	0.1409
W_{4j}	−11.6507	−4.9535	−1.0653	8.1518	0.8038
W_{5j}	0.0264	0.5578	0.7884	0.1693	0.0233
W_{6j}	1.4715	−1.9147	7.9025	3.7653	−5.9760
W_{7j}	−1.0805	1.9518	1.5860	1.4205	0.6643
W_{8j}	0.8163	0.2288	−0.5599	−2.9521	−0.3651
W_{9j}	−0.0259	−0.0534	1.0571	0.6236	−0.5466
W_{10j}	2.7837	6.4499	−18.5676	−7.1681	5.6709
W_{11j}	15.1903	5.0058	−0.3010	−4.4041	−2.2968
W_{12j}	−1.2594	2.4725	1.7532	1.6324	0.4469
W_{13j}	−3.2729	6.3007	4.1236	−1.4847	−1.5261
W_{14j}	−0.0491	0.2883	−1.8606	−0.9303	−1.1285
W_{15j}	−3.7142	−4.2561	6.8057	1.8025	0.2621
W_{16j}	−0.2554	0.2380	0.8167	0.4158	−0.1122
W_{17j}	−0.5280	−1.2007	2.0617	0.8477	1.3782
W_{18j}	9.2521	6.0748	1.6795	−1.0984	−1.7335
W_{19j}	0.1171	0.7396	1.2181	0.0506	0.0642
W_{20j}	0.1127	0.7203	1.0166	−3.0348	1.3510

3. Results and Discussion

3.1. Analysis of the New—Fi-Parameter

A regression model was proposed, as described in Equation (5), to predict the new—Fi-parameter. However, Table 6 shows the regression statistics for establishing the new—Fi-parameter regression model Equation (5). Important information about how to fit the model to the data can be found in the regression statistics. The R-squared (R^2) value, also called the coefficient of determination, is widely accepted as a scale for assessing regression analysis [65]. It revealed how accurately the model predicted the response variable's potential to change. The R^2 value falls within a certain range of numbers (0, 1). R^2 would equal one if the model and data were perfectly matched; hence, the closer it is to that value, the better the model fits the data [66].

Table 6. The regression statistics from Excel for establishing Equation (5).

Regression Statistics	Value
Coefficient of determination	0.703
Adjusted coefficient of determination	0.702
Standard error	0.0706
No. of observations	377

3.2. Pearson's Correlation Coefficients for Explanatory Variables

The Pearson's correlation coefficients between the explanatory variables were determined prior to creating the ANN model, as is shown in Table 7. The correlation coefficients between the input parameters were relatively low, as is seen in Table 5. There was just a slight negative correlation, with a coefficient value of r = −0.559, between the working field criterion and the horizontal force that was estimated by Equation (1) when using the new—Fi-parameter. This was due to the working field criterion being constituted of five variables (tractor power, soil bulk density, tillage depth, tillage speed, and implement width), all of which exhibited a strong effect on the horizontal force requirements of tillage implements, as was shown in previous studies [55–59]. Additionally, we observed the moderate positive correlation, with a coefficient value of r = 0.544, between the soil texture norm and horizontal force estimated by Equation (1). However, the positive correlation (r = 0.347, Table 5)—between the initial soil moisture content and the horizontal force estimated by Equation (1) when using the new—Fi-parameter—indicated that that moisture content had a direct relation with the horizontal force estimated by Equation (1). This same trend was observed in previous studies [57,58]. However, in other research papers [55,67–72], the inverse relationship between the initial soil moisture content and horizontal force was observed. The drop in horizontal force caused by increased soil moisture content can be attributable to both the change in soil resistance and the decrease in soil failure force [67].

Table 7. Pearson's correlation coefficients (r) between the explanatory variables ($p < 0.05$).

Input Variables	Working Field Criterion (WFC)	Soil Texture Norm (STN)	Initial Soil Moisture Content (MC)	Horizontal Force Determined Using Equation (1) Using New—Fi-Parameter (DD)
Working field criterion (WFC)	1			
Soil texture norm (STN)	0.018	1		
Initial soil moisture content (MC)	−0.181	0.346	1	
Horizontal force determined using Equation (1) using new—Fi-parameter (DD)	−0.559	0.544	0.347	1

Soil texture has a clear effect of a draft force; however, when compared to sandy soil, Novak et al. [73] found that a cultivator's horizontal force increased by around 30% when working in clayey soil. Additionally, according to Chen et al. [74], sandy loamy soil has the greatest values and coarse sand soil have the lowest values of horizontal force with a broad sweep plow. The study's findings show that increasing the working field criterion causes the modified horizontal force to decrease, while increasing the soil texture norm and initial soil moisture content causes the modified horizontal force to grow.

3.3. Performance of the Development of the ANN Model

Unlike traditional statistical methods, the ANN approach is a data-based strategy. Therefore, prior understanding of the connections between the input factors is not necessary in this instance [75]. Additionally, non-linear ANN models can be used to infer relationships between the input and output parameters that are more trustworthy and robust [76]. Although helpful, the published material does not cover all aspects of ANN theory and methodology [77,78]. The selection of training algorithms and functions for ANN development depends on the nature of the problem and the dataset [79]. Additionally, the performance of the ANN model was evaluated based on various metrics, such as the root mean squared error, mean absolute error, and the coefficient of determination. By carefully monitoring the training process and evaluating the performance of the ANN model using appropriate metrics, we developed an ANN model with a high prediction accuracy. However, the ANN model used in this study was a feed-forward-type ANN with a backpropagation algorithm for training purposes. It was established to estimate the modified values of the horizontal force based on four inputs: working field criterion, soil texture norm, initial soil moisture content, and horizontal force, as estimated by the ASABE standard when using the new—Fi-parameter. Table 8 depicts some numerical data for inputs, measured draft force (output), and predicted modified horizontal force using the developed ANN model (target).

Table 8. Some numerical data for inputs, measured draft force (output), and predicted modified horizontal force using the developed ANN model (target).

Inputs				Output	
WFC: Combined Different Variables (-)	**STN: Representing Soil Texture (-)**	**MC: Soil Moisture Content (% db)**	**DD Calculated Using ASABE form by the Modified Fi-Parameter (kN)**	**Measured: Draft Force Measured in the Field Experiments or from Previous Studies (kN)**	**Predicted: Modified Horizontal Force (kN)**
0.019	0.042	6.31	3.49	6.15	6.55
0.075	0.105	7.34	16.47	11.00	11.92
0.036	0.105	7.34	23.68	15.90	14.87
0.152	0.105	7.34	7.69	5.54	5.07
0.073	0.105	7.34	11.05	8.33	8.47
0.095	0.105	7.34	8.32	6.56	6.19
0.046	0.105	7.34	11.96	9.60	9.51
0.031	0.105	7.34	13.08	10.58	10.80
0.050	0.105	7.34	9.88	8.01	7.96
0.065	0.105	7.34	9.10	7.41	7.04
0.024	0.105	7.34	14.20	11.92	11.91
0.108	0.457	8.26	19.55	16.30	16.50
0.053	0.457	8.26	13.67	15.41	15.35
0.065	0.042	11.58	1.87	3.25	3.51
0.126	0.030	13.82	10.45	16.67	16.54
0.074	0.030	13.82	10.99	18.15	18.66
0.058	0.030	13.82	11.51	19.06	19.15
0.463	0.596	14.69	3.14	2.19	2.71
2.232	0.596	14.69	1.72	1.30	0.95
0.277	0.596	14.69	4.06	3.15	3.58
1.339	0.596	14.69	1.84	1.62	1.61
2.328	0.596	14.69	0.42	0.38	0.63

The established ANN model in this study used a dataset to train the ANN configurations with the various numbers of neurons in the hidden layer, the number of epochs, as well as the various initial connection weights that are made up of neurons with various transfer functions. Thus, several epochs and neurons were evaluated by trial and error in order to find the best configuration for the ANN in terms of predicting the modified values of the horizontal force of certain tillage implements.

The best ANN configuration should have low values of MAE and RMSE, as well as a high R^2 [62]. The best ANN configuration from the network construction employed a single hidden layer with twenty nodes. Table 8 provides more information on the characteristics of the best ANN architectures. For the normalized data, the training error value was calculated to be 0.045099. For the training, testing, and validation datasets, as shown in Table 6, our ANN model demonstrated high values of R^2, as well as low values of RMSE and MAE. These outcomes demonstrated the high accuracy and great generalizability of our existing ANN for forecasting the modified horizontal force of tillage instruments. The RMSE, MAE, and R^2 values for the best ANN configuration for the testing dataset were 2.105 kN, 1.349 kN, and 0.8175, respectively (Table 9). In the training, testing, and validation datasets, the performance of the anticipated values for the modified horizontal force is shown in Figure 3. In addition, the accuracy of the ANN model's predictions can be evaluated by comparing the predicted horizontal force with measured values that are determined through the field measurements. Additionally, the model's accuracy can be improved by adjusting the model's hyper parameters and optimizing the training process [80]. Overall, an ANN model can be a useful tool for predicting the modified horizontal force for the selected tillage implements and for ensuring that the established model is suitable for frame machinery management purposes.

Table 9. Performance evaluation parameters for predicting the modified horizontal force of the established ANN for structure 4-20-1.

Dataset	R^2	RMSE, kN	MAE, kN	No. of Data Points
Training	0.8286	0.733	0.255	263
Testing	0.8175	2.105	1.349	57
Validation	0.8515	2.523	2.155	57

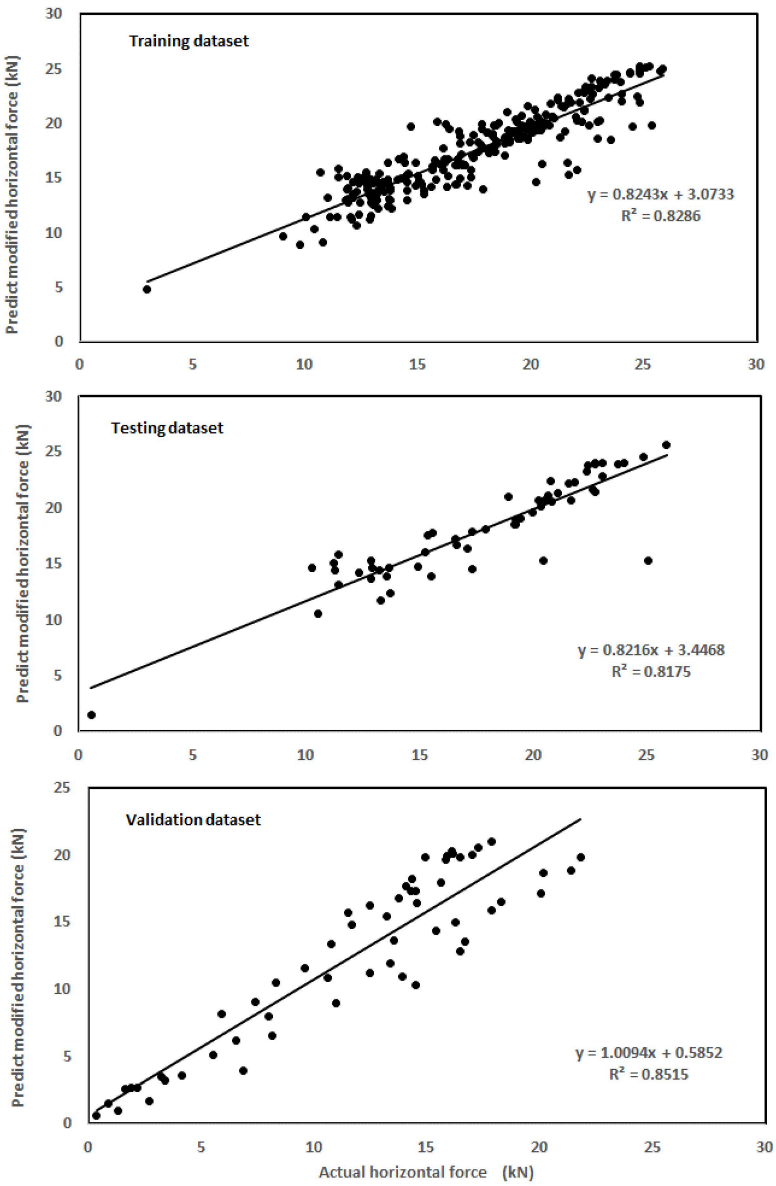


Figure 3. Relationship between the measured horizontal force and predicted modified horizontal force (MHF) using the training, testing, and validation datasets.

The use of ANN models for predicting the draft force of tillage implements can save time and resources by providing quick and accurate predictions for energy requirements without the need for extensive field testing. It can also help farmers make informed decisions about matching a mechanization unit. However, there are also limitations in using ANN models for predicting the draft force of tillage implements and other parameters. The accuracy of the ANN model is contingent on the quality and quantity of the training data used [80]. Additionally, the model's accuracy may decrease when applied to data with significant differences from the training dataset [80]. Various studies are available on the draft force, which is modeled by ANN method, for tillage implements [81]; however, the former ANN modeling approaches did not attempt to modify the draft force of ASABE draft form [12]. Hence, the authors of this paper presented this applied ANN model for predicting the modified draft force of the famous primary tillage implements that are used for farm machinery management purposes. Compared to other studies, the present work stands alone with a novel approach; it has significant value in formulating the soil Fi-parameter used by ASABE [12] for the purposes of draft determination and for modifying the famous draft force that is detailed in the ASABE form [12]. In conclusion, ANN modeling proved to be a valuable tool for predicting the modified draft force of certain primary tillage tools and for ensuring that the prediction data are suitable for farm machinery management. However, the model's limitations must be considered when interpreting its results. Hence, the results of this study should be used as a complement to traditional field-testing rather than as a replacement. There was no limitation of the investigated ANN model to different types of farm implements. However, the potential challenges or variations in the performance will depend on the quality and quantity of the training data used.

3.4. Examining the Effects of Independent Input Variables

By using the Qnet2000 software program, the analysis of the contributions for the independent input variables was accomplished [60]. Figure 4 presents the analysis of the independent input variables contribution by the ANN model (4-20-1). As per Figure 4, the horizontal force that was assessed by the ASABE form (DD) had the biggest impact on the modified horizontal force when using the new—Fi-parameter and the working field criterion: 36.10% and 28.05%, respectively. The modified horizontal force was less affected by the soil moisture content and soil texture norm parameters by 14.66% and 21.19%, respectively.

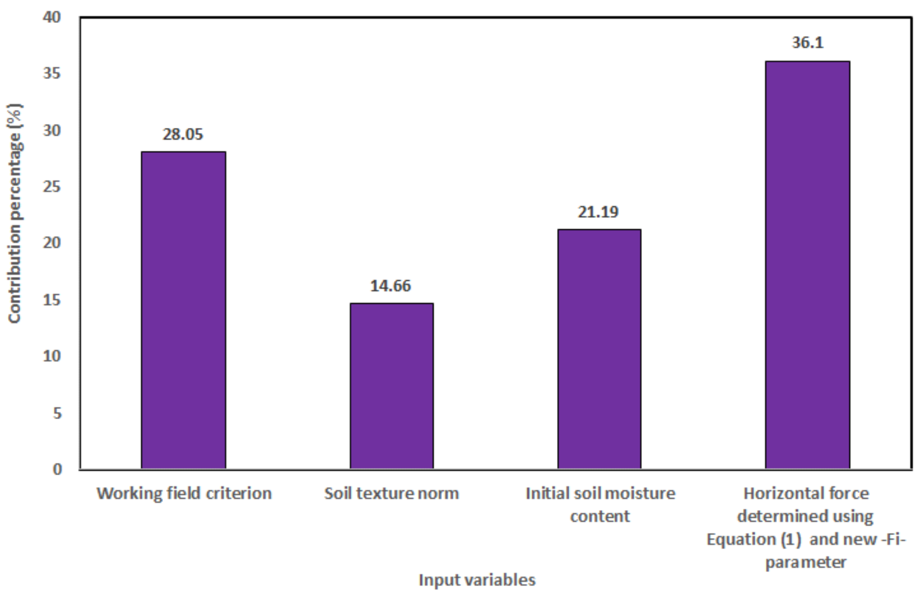


Figure 4. Analysis of the independent input variables contributions by the ANN model (4-20-1).

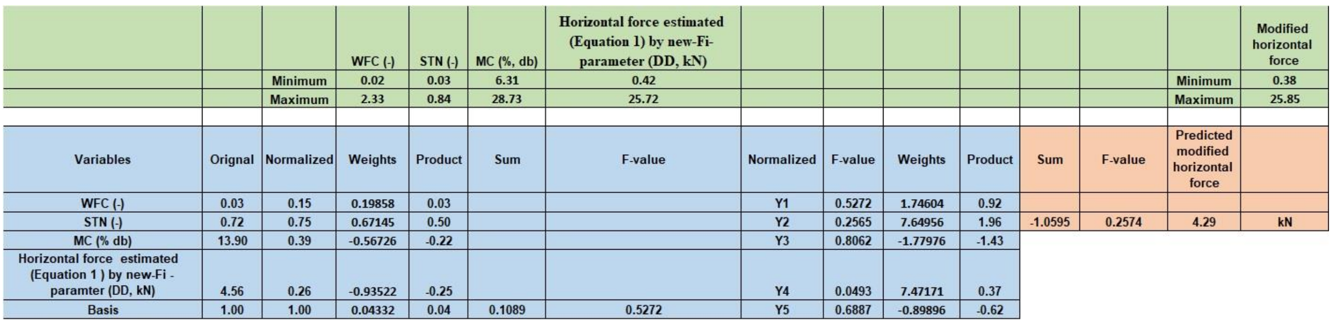
3.5. Creating an Excel Spreadsheet for Calculation of the Modified Horizontal Force (MHF)

Through using the developed equations (from 12 to 22) that were based on the extracted weights from the trained ANN model, an Excel spreadsheet was created. The Excel spreadsheet can be used to manage the variables that will offer a lesser draft force for tillage implements (disk, chisel, and moldboard plows) when conducting tillage operation on a specific soil texture as the user can change tractor power, tillage speed, tillage depth, implement width, soil bulk density, and soil moisture content to achieve a lower draft force. The created Excel spreadsheet was tested to estimate the modified horizontal force, using the data for a moldboard plow (Table 10); however, a good prediction of the required horizontal force with a percentage error (PE) of 10% was achieved. However, a screen capture of the developed worksheet template for the determination of the modified horizontal force using ANN model is shown in Figure 5.

Table 10. The data for moldboard plow use for estimating the modified horizontal force in the created Excel spreadsheet.

Variable	Value	Unit
Tractor power	40	(kW)
Sand percentage	25	(%)
Silt percentage	15	(%)
Clay percentage	60	(%)
Soil texture	Clay	(-)
Soil texture norm	0.705655	(Dimensionless)
Working field criterion	0.062147	Dimensionless
Initial soil moisture content	13	(% db)
Soil bulk density	1.35	(g/cm^3)
Tillage depth	18	(cm)
Tillage speed	5	(km/h)
Implement width	1.08	(m)
New—Fi-parameter	1.000647	(Dimensionless)
Measured horizontal force	11.01	(kN)
Horizontal force determined using Equation (1) and new—Fi-parameter (DD)	12.68	(kN)
Predicted MHF using ANN model based on the created Excel spreadsheet	9.91	(kN)

$$\mathrm{PE} = \frac{|(9.91-11.01)|}{11.01} \times 100 = 10\%$$



			WFC (-)	STN (-)	MC (%, db)	Horizontal force estimated (Equation 1) by new-Fi-parameter (DD, kN)								Modified horizontal force
		Minimum	0.02	0.03	6.31	0.42							Minimum	0.38
		Maximum	2.33	0.84	28.73	25.72							Maximum	25.85

Variables	Orignal	Normalized	Weights	Product	Sum	F-value	Normalized	F-value	Weights	Product	Sum	F-value	Predicted modified horizontal force	
WFC (-)	0.03	0.15	0.19858	0.03			Y1	0.5272	1.74604	0.92				
STN (-)	0.72	0.75	0.67145	0.50			Y2	0.2565	7.64956	1.96	-1.0595	0.2574	4.29	kN
MC (% db)	13.90	0.39	-0.56726	-0.22			Y3	0.8062	-1.77976	-1.43				
Horizontal force estimated (Equation 1) by new-Fi -paramter (DD, kN)	4.56	0.26	-0.93522	-0.25			Y4	0.0493	7.47171	0.37				
Basis	1.00	1.00	0.04332	0.04	0.1089	0.5272	Y5	0.6887	-0.89896	-0.62				

Figure 5. Screen capture of worksheet templet for the determination of the modified horizontal force using ANN model.

4. Conclusions

In this study, the Fi-parameter—which is not measurable and assumed to describe soil texture in the famous empirical model created by the American Society of Agricultural Biological Engineers (ASABE) for the horizontal force estimation of tillage implements—was calibrated using a regression technique based on soil texture norms; it combined the sand, silt, and clay contents in a soil with an R^2 of 0.703. The purpose was to measure the Fi-parameter to modify the empirical model issued by ASABE to give accurate draft values for tillage implements. Additionally, a set of variables—tractor power, plowing speed, initial bulk density, implement width, and tillage depth—were formulated into one variable, which was labeled the working field criterion, to represent working conditions. The relationships between the working field criterion, the soil texture norm, the initial soil moisture content, the horizontal force estimated from the ASABE model based on the new Fi-parameter as independent variables, and the modified horizontal force as a dependent variable, were all accurately and mathematically modeled by an ANN with a configuration of 4-20-1. The results suggested that establishing an ANN model as an operative tool can be used for accurately predicting draft force of tillage implements in this study: R^2 value of 0.8515, MAE value of 2.155 kN, and RMSE value of 2.523 kN). This was achieved by using the validation dataset of the modified horizontal force for certain tillage implements such as chisel, moldboard, and disk plows.

The relative contribution of Input variables was assessed using the established ANN model. The modified horizontal force was most significantly influenced by the working field criterion and horizontal force by 28.05% and 36.10%, respectively (as was calculated by the ASABE form when using the new—Fi-parameter). It should be underlined that the selection of suitable parameters (i.e., tractor power, tillage depth, tillage speed, and implement width) are essential for the effective tillage management of certain soil parameters such as texture, bulk density, and moisture content. Through using the developed equations based on the extracted weights from the trained ANN model, an Excel spreadsheet was created. This spreadsheet can be used to manage the variables that will produce a lesser draft force for tillage implements when they are being used to conduct tillage operations on a specific soil texture. This is possible, as the user can change the tractor power, tillage speed, tillage depth, implement width, and the soil bulk. Additionally, the developed Excel spreadsheet contributes a numerical method that can be used by agricultural engineers in the future. Furthermore, we can recommend to use the ASABE form to estimate the draft force for a tillage implement by replacing Fi-parameter with the new—Fi-parameter developed in this study as the new—Fi-parameter for soil texture is now measurable.

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