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Optimisation of Performance Parameters of Farm Machinery for Economic Sustainability in Irrigation Scheme

(A Case Study of Giriyan Irrigation Scheme, North Central Nigeria)

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ABSTRACT

The efficient utilization of farm machinery is key to strategic management for sustainable agricultural mechanization and economic sustainability. This study optimized agricultural input-output performance parameters of farm machinery for economic sustainability at the Giriyan irrigation scheme in North Central, Nigeria. A survey using structured questionnaires was conducted to assess the level of utilization of farm machinery in the scheme. Field data were obtained through soil analysis and real-time measurements of tractor performance using sensor-based instrumentation. An Artificial Neural Network (ANN) model was developed with nine input variables, two hidden layers (8–5 nodes), and five output variables to evaluate utilization index, mechanization index, capacity utilization index, specific fuel consumption, and profitability index. The best topology structure for the ANN model developed was 9-8-5-5. The model achieved high prediction accuracy with coefficients of determination (R^2) values of 0.9902, 0.9943, 0.9819, 0.9823, and 0.9979 for utilization index, mechanization index, capacity utilization index, specific fuel consumption, and profitability index, respectively. The results revealed that operational cost, rated implement width, tractor power, and tillage depth were the most influential parameters for optimizing specific fuel consumption and good profitability of farm machinery investment at the Giriyan irrigation scheme of North Central Nigeria. The ANN model demonstrated strong predictive capacity, with training and testing Mean Squared Error (MSE) values of 0.0528 and 0.0349, L/kWh, respectively. The ANN model provides a good decision-making support tool for farm managers, and policy makers can also design targeted subsidies and strategic frameworks that encourage farm managers to adopt energy-efficient machinery to improve farm machinery performance, optimize energy use, and promote sustainable agricultural mechanization in many irrigation schemes in North Central Nigeria.

INTRODUCTION

Farm machinery utilisation is the adoption of various machinery and equipment to enhance agricultural practices, improve production, and increase the level of agricultural mechanization (Al-Sager *et al.* 2024). The agricultural machinery performance is enhanced by working on the field capacity to improve agricultural productivity. This is evaluated by using advanced technologies of measurement. The adoption of cloud-compliant sensors has enhanced the performance of agricultural machinery significantly and also reduced energy wastage in various agricultural operations (Al-Sager *et al.* 2024; Al-Miran and Jasim, 2025).

A good agricultural mechanization system for irrigation practice requires a good template for evaluating the tractor's overall energy efficiency and some other key parameters that could ensure effective return on investment for the economic sustainability of the investment (Peng *et al*., 2022). However, computer simulations and mathematical models are modern techniques used to establish experimental field parameters for tractor utilization and other agricultural machinery. These tools are used to assess the effective performance of agricultural machinery and obtain good results for investment sustainability and the growth rate of the agricultural mechanization process (Dahab *et al.,* 2016).

The basic models to aid the effective utilization of farm machinery for economic sustainability in irrigation schemes are the Artificial Neural Networks (ANN) model, which has universal approximation of function and has been applied in many research works as developed by Zangeneh *et al.* (2010). Lower Niger River Basin Development Authority possessed major and minor irrigation schemes, and out of the viable minor schemes, the Giriyan irrigation scheme has been facing challenges of the key parameters soil-implement relationship for tillage operation of farm machinery performance, hindering the economic sustainability of investment. The Giriyan scheme provides a critical, unique baseline for evaluating the limits of public agricultural mechanization, located in Koton-Karfe Local Government Area of Kogi State, and serves as a vital representative model for mid-sized, high-stress public floodplains (*fadama*) that face severe structural, environmental, and financial constraints. This narrow operational process creates soil resistance, requiring a high-draft-power tractor matched with other key variables to have economic sustainability in the scheme. This specific soil-machine interaction directly accelerates the fleet's mechanical breakdown rate and hinders tillage operation for machinery productivity to enhance economic sustainability in the irrigation scheme. Despite extensive literature addressing the broad macro-variables of farm machinery adoption, machinery ownership models, and soil-machine dynamics within Nigerian agriculture (Takeshima *et al,* 20215), critical micro-environmental stresses and capital productivity gaps remain unaddressed in the current body of agricultural mechanization and public asset management literature. Therefore, this study optimised the key variables that determine proper farm machinery utilization for sustainable agricultural mechanization in the Giriyan irrigation scheme, North Central Nigeria.

MATERIALS AND METHODS

Data collection

Structured questionnaires were distributed to the relevant personnel in the Giriyan irrigation scheme. Data were collected from the structured questionnaires to determine the seasonal pattern and productivity, and hours of utilization of farm machinery for economic sustainability at the Giriyan irrigation scheme. The sample size determination was calculated using proportional allocation (N_n). The formula developed by De Vera *et al.* (2022), as presented in Equation 1, and fifteen (15) questionnaires were administered to the relevant personnel and the participants in the selected scheme. This procedure was carried out to collect relevant information on educational level, demographic status, maintenance culture, seasonal pattern, and hours of utilization of farm machinery for economic sustainability at the Giriyan irrigation scheme. In various schemes, such as qualitative insights data.

$$N_n = \frac{N_h}{N} \qquad (1)$$

Where N_n: proportional allocation, N_h = baseline population within the specific irrigation scheme (h) N = cumulative baseline population Vacross the entire scheme (N = 49)

The baseline population distribution (T_n) was derived in the scheme as presented in Equation 2.

$$T_n = N_1 \qquad (2)$$

Where N_1 is the population at the Giriyan scheme with a corresponding population value of 49.

Thus, the calculated samples using Equations 1 and 2 were presented in Table 1.

Table1: proportion allocation of questionnaires distributed

Irrigation scheme	Stakeholder Population	Calculated sample	Distributed questionnaires
Giriyan	49	14.9	15
Total	49	14.9	15

Data Source Allocation and Memory-Bias Mitigation

To ensure strict respondent memory decay over a 13-year timeline, a rigorous data source allocation was enforced. Specifically, no operational or financial indicators ranging from the 2012-2024 panel longitudinal frameworks were generated through unstructured historical memory reconstruction. However, variables were strictly allocated to their primary institutional and physical source origins as follows:

Institutional Financial Variables (Operation and Maintenance, O&M): continuous allocation was enforced. Specifically, no operational or financial indicators ranging from the 2012-2024 panel longitudinal frameworks were generated through unstructured historical memory reconstruction. However, variables were strictly allocated to their primary institutional and physical source origins as follows:

i. Institutional Financial Variables (Operation and Maintenance, O&M): continuous annual time–series observations for Annual Revenue Generated (ARG), initial machinery procurement costs, annual average operating expenses, and localised operation and maintenance budgetary pools were extracted directly from the audited LNRBDA financial year booklets and official financial ledgers published at the close of each respective fiscal cycle between 2012 and 2024.

ii. Physical Machinery Run-Times (U_{hr}). Continuous machine operational data were compiled directly from physical, on-site mechanical tachometer readings and daily operator logbooks maintained by the scheme's Engineering Departments. The structured questionnaires distributed to technical personnel were restricted to validating current operational capacities, cross-checking specific historical data points, and categorizing qualitative management frameworks.

iii. Mechanical Reliability Indicators such as Failure Rate (FR), Mean Time Before Failure (MTBF), and Mean Time To Repair (MTTR): Machinery failure rates and breakdown histories were extracted directly from institutional workshop requisition ledgers, job cards, and spare parts replacement records kept by the Central workshop and Engineering maintenance units.

iv. Demographic and Human Capital Metrics ($Lit_{i,t}$). The technical literacy index of the active workspace was the primary variable captured directly from the current structured questionnaire responses (N=15), which recorded verified educational certificates, technical school diplomas, and formalized mechanical training records of active scheme personnel

Moreover, to resolve minor discrepancies between field questionnaires and administrative ledgers, an ex-post data triangulation matrix was applied within ± 5% using Equation 3 as developed by Olayanju *et al*. (2022).

$$D_v = \frac{V_s - V_a}{V_a} \times 100 \qquad (3)$$

Where D_v = Relative variance index, V_s= Field Survey questionnaires variable, V_a = Audited archive financial yearbooks or workshop requisition logs.

Secondary Institutional Validation Data

To cross-validate the primary survey responses, secondary institutional data were extracted directly from internal requisition logbooks, technical repair registers, and audited financial year booklets covering 2012 – 2024 operating years. These datasets provided comprehensive records of annual capital budget appropriations, operation and maintenance disbursements, physical asset machinery records, and Annual Revenue Generated (ARG).

Application of ANN on Neural Designer XL

This is software designed to facilitate the application of ANN to solve complex data analysis problems. It has a general-purpose tool that enables ANN to be applied across numerous fields of application, such as Approximation/Regression, Data Classification, Data Forecasting, and Pattern Recognition, but for this study, Data Forecasting was used. The transfer functions or activation functions introduce non-linearity into the neural network, ranging between 0 and 1 or -1 and 1. The study applied linear and hyperbolic tangent functions, and the output obtained serves as an input to other nodes in the network model. Mini and Bharat (2024) mentioned other activation functions such as linear, symmetric saturating linear, positive linear, hard limit, and symmetrical hard limit. Yadav *et al.* (2025) classified the variable data set for the ANN model into training, testing, and validation sets. Optimisation of performance parameters of farm machinery for economic sustainability in an irrigation scheme requires t variables. Krenker *et al.* (2009) highlighted the working principle and computational functions of ANN elements that consist of operations of the individual neurons and the way they are connected. The individual neurons calculate the output using the sum of the inputs and the activation function. Signals are received from input neurons ($X_1, X_2, X_3 \ldots\ldots\ldots X_m$) and are multiplied by their corresponding weights (W_1X_1, W_2X_2, $W_3X_3 \ldots\ldots\ldots\ldots\ldots W_nX_n$)

(i) the weighted signals are summed [sum = W_1X_1+W_2X_2+ W_3X_3 …….. W_nX_n (Owolabi, 2013) (4)

(ii) the calculated sum is transformed by an activation function [F(sum)]

(iii) the transformed sum is sent to other neurons by repeating the steps i-ii

Data normalisation for ANN model development

The data normalisation process is known as Min-Max scaling, and is highlighted in Equation 5 as stated by Owolabi (2013) to ensure that it is fit for the ANN models.

$$X_{NORM} = \frac{X - X_{MIN}}{X_{MAX} - X_{MIN}} \quad (5)$$

Where

X_{NORM} = normalised dataset scaled between 0 and 1

X = original value of the dataset

X_{MIN} = minimum value of the dataset

X_{MAX} = maximum value of the dataset

The data collected was split into a training set, a test set, and a selection (validation) set using the method developed by Al-Sager *et al.* (2024), in which the training set size should be 10 times larger than the number of networks for parameters to accurately perform on the test data with 90% accuracy. A total of 1118 data sets were employed for the ANN model in the Giriyan irrigation scheme. The training, testing, and selection values are 896 (80.1%), 167 (14.9%), and 55 (4.92%), respectively.

The input data was collected in MS Excel to train the network by adapting the weights of the network until the stopping criterion is met. The training process was subjected to 3600 iterations using the Gradient Descent Algorithm of a Feed Forward Back Propagation Neural Network, and the training process stopped when a satisfactory minimum error was achieved at various epochs. The network's output (target values) was compared with the expected values. The second phase of the model formulation of the ANN includes data validation that has not previously been applied to the neural network, which was used to test the performance of the model and measure how well the neural network has learned to generalise the capability of the optimisation performance of farm machinery. The largest portion was used to train the model to identify patterns and relationships of input-output variables, and the selection (validation) dataset was used to validate the model during development, while the testing dataset was applied to evaluate the performance of the ANN model.

Training Process of the ANN Model

The training process of the network is the estimation of parameters and optimal connection weights that are determined by minimising an objective function. The training of the ANN developed went through a 3600-iteration process, and this simulation ends when all patterns are classified correctly within a selected range of accuracy, and the steps involved are shown in Figure 1. During the training process, the network compares the generated values with the target values and minimizes the errors by adjusting the weights. This is called Feed Forward Back Propagation (FFBP). The setting of training and topology parameters is regarded as the programming phase in the development of an ANN model. The factors considered include:

(i) data requirements, preprocessing, and data input/output encoding

(ii) selection of neural network type, architecture, and learning parameters

(iii) training the prototype and testing the prototype.

Field studies were also conducted for soil analysis to determine soil textural class, bulk density, and moisture content. Tillage operations were carried out to determine the specific fuel consumption and other key parameters, such as depth of operation and forward speed, using an ESP-32 Microcontroller device. The overall data obtained were used to develop an ANN model using the Neural Designer XL software package to obtain an input-output relationship for the economic sustainability of farm machinery utilization in the Giriyan irrigation scheme.

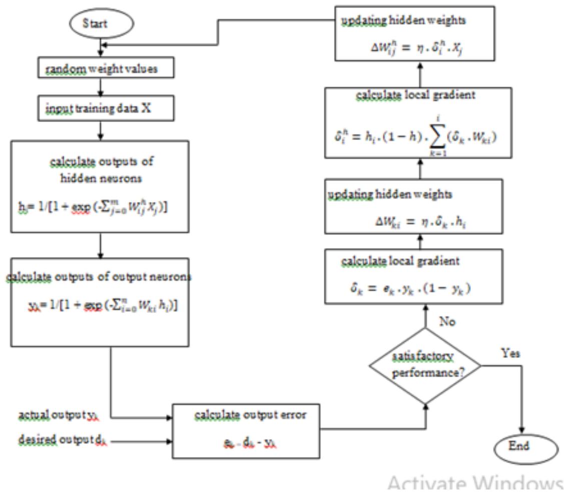

Figure 1: Flow diagram of the procedure of the training process of the ANN model

Mapping out the study area

The research work was conducted in the Giriyan irrigation scheme, longitude 6.7978 °E and latitude 8.0912 °N, belonging to the Lower Niger River Basin Development Authority (LNRBDA) in Koton Karfe Local Government Area of Kogi State. It has a total land coverage of 500 ha. The rainfall patterns of the scheme are bimodal, having a wet and dry season cropping pattern. The wet season is from March to August, and the short wet season ranges from August to November, with an annual temperature of 25 – 33 °C. The annual rainfall ranges from 1500 to 2200 mm. The area consists of upland and *fadama,* which are suitable for the cultivation of crops such as maize, guinea-corn, rice, vegetables, and sugarcane (LNRBDA, planning and design, 2015).

A Massey-Ferguson 375 tractor of 2WD with a capacity of 75 hp was used along with an MF four-bottom disc ridger on a 3-ha land in the scheme for the analytical process. Two YF-S201 Hall Effect flow sensors were installed at strategic positions to capture the injector pump aspiration of the inflow and Outflow of the tractor engine to measure the specific fuel consumption. These sensors were connected to an electronic microcontroller ESP-32 board that could receive signals and process the digital pulses sent by the sensor, with the combined ability to save the data and transmit the same over the internet for remote retrieval.

A digital stopwatch (ATP Model) with an accuracy of 0.01 s that can measure elapsed time for up to 24 h was used to measure the start and the end of operation to determine the hours of utilization of farm machinery in the scheme. The data acquisition system and positioning of sensors on the MF375 Tractor are shown in Figures 2 and 3.

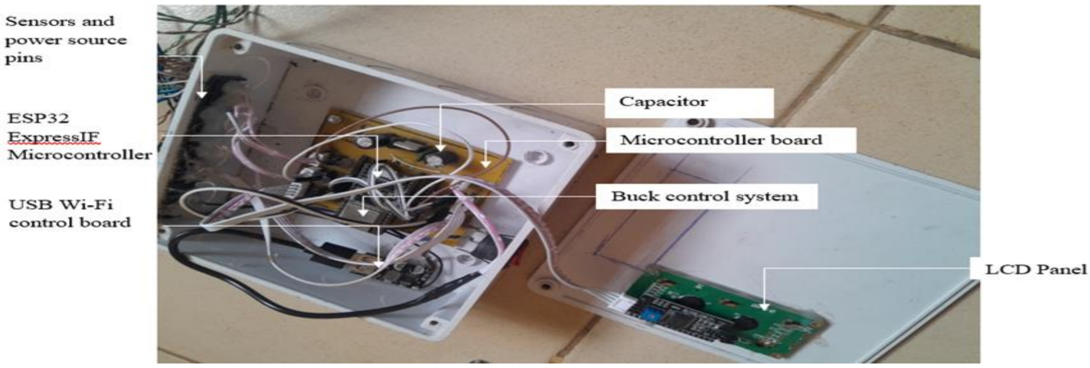

Figure 2: Performance data acquisition system

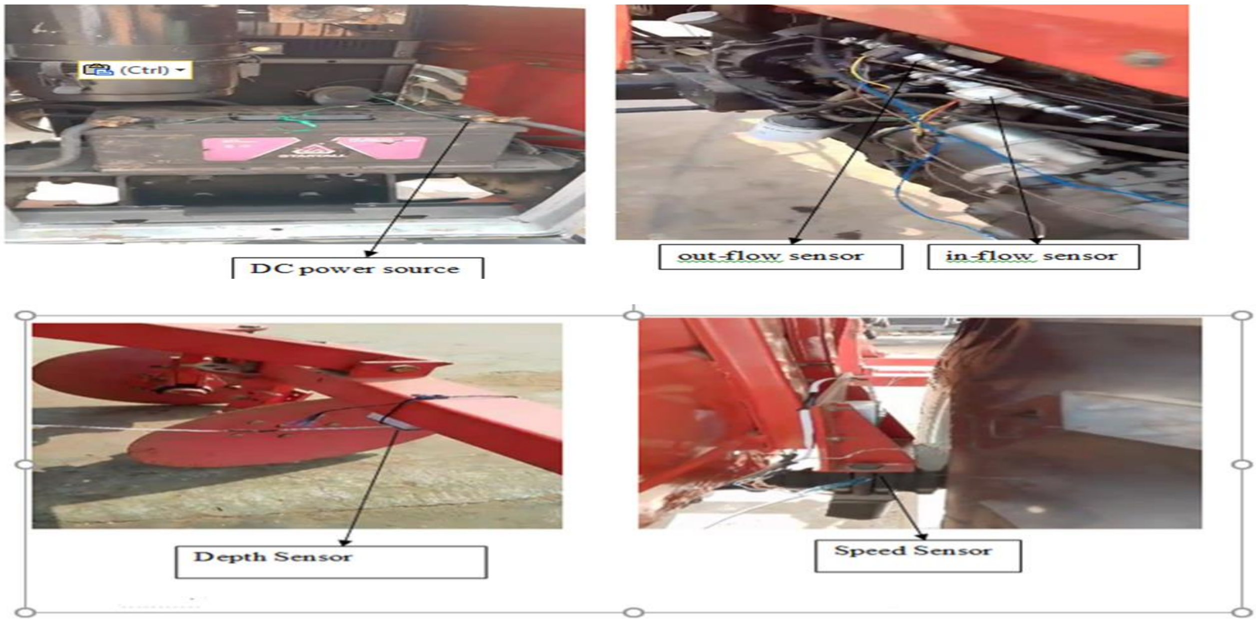

Figure 3: Positioning of sensors on the MF 375 tractor during field operation

Fuel Consumption and Efficiency Equations

The key equations used in the ESP-32 Microcontroller-based fuel consumption monitoring system include:

Fuel flow rate in liters per minute (l/min)

The sensor pulses were converted to fuel flow rate using Equation (6)

$$\text{Formula: } Q = \frac{N}{PR} \quad (6)$$

Where Q = Flow rate (l/min), N = Pulse count from the flow sensor, PR = Pulse rate (Pulses per liter)

Net fuel consumption (l/min)

Thus, to calculate the difference between inflow and outflow fuel rates, Equation (7) was used

$$FC = Q_{In} - Q_{out} \quad (7)$$

Where FC = Net fuel consumption (l/min), Q_{in} = Fuel inflow rate (l/min), Q_{out} = Fuel outflow rate (l/min)

Fuel Consumption per Distance in liters per kilometer (l/km)

The process of calculating the fuel used per kilometer by converting speed to km/h is highlighted in Equation (8)

$$FC_d = \frac{FC}{T} \times 1000 \quad (8)$$

Where FC_d=Fuel consumption per kilometer (l/km), FC = Net fuel consumption (l/s), T = Speed (m/s).

Overall fuel efficiency in kilometers per liter (km/l)

The overall energy efficiency of farm machinery indicates the overall performance of the operation, and it is a key factor in establishing the investment sustainability of farm machinery for the productive agricultural mechanization process. Then, Equation (9) was used to obtain the energy efficiency

$$\eta = \frac{T}{FC} \quad (9)$$

where η = fuel efficiency (km per liter), T = speed (km/h), FC = net fuel consumption *(l*/h)

Equation (4) measures the distance traveled per liter of fuel. This equation is used to monitor fuel usage and efficiency in real-time.

Tractor speed (m/s)

The forward speed of operation is calculated using Equation (10)

$$\mathrm{T} = \frac{\Delta \mathrm{d}}{\Delta \mathrm{t}} \quad (10)$$

Where T = Speed (meters per second), Δd = Change in distance (meters), Δt = Time interval (seconds)

Depth calculation using an ultrasonic sensor

The HC-SR04 ultrasonic sensors were connected to the NodeMCU ESP32 microcontroller to measure the depth and forward speed of operation, which in turn sent the information to the cloud through the ESP32 microcontroller. The HC-SR04 contains one ultrasound sender and one receiver, and the principle of depth measurement involves a short ultrasonic pulse transmitted at time 0 and reflected by an object and received after a time interval, the echo time. Then, the speed of the ultrasound in air, c = 340 m/s, andthe time τ, the depth of cut of the operation is given by the simple relation as shown in Equation (11)

$$\mathrm{d} = \frac{\mathrm{c}\tau}{2} \quad (11)$$

where d = depth of cut (cm), c = 340 m/s, τ = time (sec)

Determination of soil moisture content

The methods and equations developed by Michael (2009), as presented in Equation (13), were adopted to determine soil moisture content. The weight of the soil samples was taken before and after oven drying the soil samples at a temperature of 105 °C.

$$M_{sc} = \frac{W_{SM} - W_{OD}}{W_{OD}} \times 100\% \quad (13)$$

Where M_{sc} = soil moisture on dry weight basis, g, W_{SM} = weight of moist sample, g, W_{OD} = weight of oven-dry soil sample, g.

Performance Evaluation by ANN Model Selection

The performance evaluation of the ANN model used six statistical indicators, and goodness-of-fit These indicators were Mean Squared Error (MSE) coefficient of determination (R^2), correlation coefficient (r), Mean Absolute Error (MAE), Mean Absolute Percentage Error ($MAPE$), and Root Mean Squared Error ($RMSE$) as indicated in Equations (14 – 18) (Zangeneh *et al.*, 2010).

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(Y_{estimated}-Y_{target}\right)^2 \quad (14)$$

$$R^2=\frac{\sum_{i=1}^{n}\left(Y_{estimated}-Y_{target}\right)^2}{\sum_{i=1}^{n}\left(Y_{estimated}-Y_{mean}\right)^2} \quad (15)$$

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left(S_i-O_i\right) \quad (16)$$

$$MAPE=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left(Y_{estimated}-Y_{target}\right)}{Y_{target}}\times 100\right) \quad (17)$$

$$RMSE=\sqrt{\frac{1}{N}}\sum_{i=1}^{N}\left(Y_{estimated}-Y_{target}\right)^2 \quad (18)$$

Where $Y_{estimated}$ = estimated values of$i$th, Y_{target} = actual values of the ith, Y_{mean} = the mean of actual values to estimate ratio values, S_i is predicted values, O_i = observed values, N = number of observations in training and testing datasets.

The input-output relationship was obtained to identify the significant variables that are the most important for farm machinery utilization and economic sustainability at the Giriyan irrigation scheme, North Central Nigeria, using the methodologies of graphical evaluation and numerical approaches developed by Milad *et al.,* (2014); Al-Sager *et al.*, (2024).

RESULTS AND DISCUSSION

Results of the Soil Analysis at the Giriyan Irrigation Scheme

The analytical results from composite sampling provide average values for the sampled area. The total points of soil samples obtained were 5 for both moisture content and bulk density at the Giriyan irrigation scheme. Each sample taken from the scheme was analyzed separately so that variability in soil properties could be determined. The geospatial data results (Moisture content and Bulk density) obtained for each sample taken for this scheme are presented in Table 2. The data reveal notable heterogeneity across the sampling points, which reflects the dynamic nature of the soil physical environment under irrigation management. Soil moisture content across the scheme exhibited wide variations, ranging from a minimum of 7.8% (Point 4, Row 4) to a maximum of 23.0% (Point 1, Row 3). Conversely, locations such as Point 5 displayed relatively moderate moisture ranges between 9.58% and 14.6%, which is an indication of non-uniform water application across the irrigation scheme.

The bulk density values fluctuated between a minimum of 1.56 g/cm^3 (Point 1, Row 3) and a minimum of 2.10 g/cm^3 (Point 1, Row 5). The majority of the recorded values consistently exceeded 1.70 g/cm^{3,} and the elevated bulk density values across the Giriyan scheme suggest a highly compacted subsoil matrix, which requires heavy agricultural machinery. Table 3 contains the summary of soil texture classes for each field in the scheme. The spatial distribution of soil textures across the five fields indicates a heavy dominance of fine-textured, cohesive soils. Textural classes such as sandy clay, silt clay, and clay loam comprise the vast majority of the profile configurations across all the sampling areas. Fields 1, 2, and 3 are entirely dominated by clay-bound textures (sand, clay, and silt clay) with only minor variations occurring in isolated layers (e,g silt loamy in Field 3, Row 3). Field 4 displays slightly lighter profiles, varying between silt loam and silt clay, while Field 5 incorporates a marginal shift toward coarser fractions with a silt-sandy layer in Row 3. The high frequency of clay-heavy classifications (sandy, clay, and silt clay) explains the elevated bulk density values (> 1.80 g/cm^3) as described in Table 2.

Performance Evaluation by the ANN Model for the Giriyan Irrigation Scheme

Table 4 highlights the statistical dataset for the Giriyan irrigation scheme, outlining the maximum, minimum, mean, and standard deviation obtained for the input variables used in the developed ANN model. The mean values of tractor power, rated implement width, tillage depth, forward speed, fuel consumed/operation, moisture content, and bulk density for this model were 62.21 hp, 127.44 cm, 20.71 cm, 3.74 km/h, 14.62 L/h, 10.52 %, and 2.13 g/cm, respectively. The mean values for the cumulative cost of operation and specific fuel consumption are ₦34,489.98 and 14.34 L/kWh, considering the tractor power of the 62.21 hp category.

Table 2: The moisture content and bulk density of various points selected in the scheme

Scheme	Moisture content (%)					Bulk density (g/cm^3)				
Giriyan	Point 1	Point 2	Point 3	Point 4	Point 5	Point 1	Point 2	Point 3	Point 4	Point 5
	12.8	14.8	13.8	14.4	12.5	1.93	1.86	1.90	1.83	1.89
	10.8	13.8	13.6	12.7	9.58	1.8	1.72	1.89	1.68	1.83
	23.0	13.3	16.4	12.6	14.6	1.56	1.89	1.88	1.79	1.93
	13.9	9.9	9.4	7.8	10.4	1.82	1.99	1.99	1.99	1.93
	11.0	14.0	14.6	14.5	14.1	2.10	1.87	1.84	1.90	1.87

Table 3: Summary of textural classes of the soil in the irrigation scheme

Scheme	Field 1	Field 2	Field 3	Field 4	Field 5
Giriyan	Sandy clay	Silt clay	Sandy clay	Silt loam	Sandy clay
	Sandy clay	Sandy clay	Silt clay	Sandy clay	Sandy clay
	Silt clay	Sandy clay	Silt loam	Silt clay	Sandy loam
	Silt clay	Clay loam	Sandy clay	Silt loam	Sandy clay
	Silt clay	Silty clay	Sandy loam	Silt clay	Silt clay

Table 5 shows the training results using the gradient descent method for the training process, and this includes some final states from the neural network, the loss index, and the optimization algorithm. The value of the training error is 0.0091, and this measures model performance on the dataset used to train the model, while the selection error values obtained are 0.0188 at 342 epochs after a 3600-iteration process, which depicts the model performance on data not used to train the model. The ultimate goal of this is to achieve a low selection error that could generalize well for the model developed, rather than simply memorizing the training data.

Table 4: Statistical dataset for the ANN model at the Giriyan irrigation scheme

Variables	Max	Min	Mean	Standard deviation
Tractor Power (hp)	83.94	53.26	62.21	7.67
Rated implement width (cm)	121.2	96.2	114.4	127.4
Tillage depth (cm)	25.13	15.77	20.71	3.35
Forward speed (km/h)	5.06	3.27	3.74	0.461
Fuel consumed/operation(L/h)	15.54	13.61	14.62	1.37
Operational cost (₦ : K)	6520.15	5600.94	6108.39	564.57
Cumulative cost (₦ : K)	6,102,000	6001.74	3448998	191256.23
Moisture content (%)	23.56	7.15	10.52	2.49
Bulk density (g/cm^3)	2.60	1.55	2.13	0.27
Utilization index (%)	3.48	0.36	3.25	3.12
Mechanization index (%)	29.48	14.82	5.54	12.43
Capacity utilization index (%)	0.580	0.7	0.77	0.818
Specific fuel/hour (*l/h*)	14.92	13.2	14.34	0.451
Profitability index (%)	2.080	0.96	1.35	0.089

The ANN model developed at the Giriyan irrigation scheme was a Multilayer Perceptron (MLP) using the back-propagation training method to train the ANN model. Figure 4a revealed the architectural topology developed for the ANN model, and the best model was obtained using nine input variables, two hidden layers with eight nodes in the first and five nodes in the second hidden layer, and five output variables with five nodes (9-8-5-5) as the best architectural structure for the Giriyan irrigation scheme. Figure 4b shows the training and selection errors at each epoch. The blue line represents the training error, and the orange line represents the selection error. The initial value of the training error was 1.0868, and the final value after 342 epochs was 0.0046. The initial value of the selection error was 0.756, and the final value after 342 epochs was 0.005. Table 5 highlights the best results for Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) of the ANN model developed for the Giriyan scheme.

Table 5: Training and selection errors results in the Giriyan irrigation scheme

Training Process	Value
Number of epochs	342
Elapsed time (hh mm ss)	00 00 02
Stopping criterion	Minimum loss decrease
Training error (MSE)	0.0091
Selection error (MSE)	0.0188

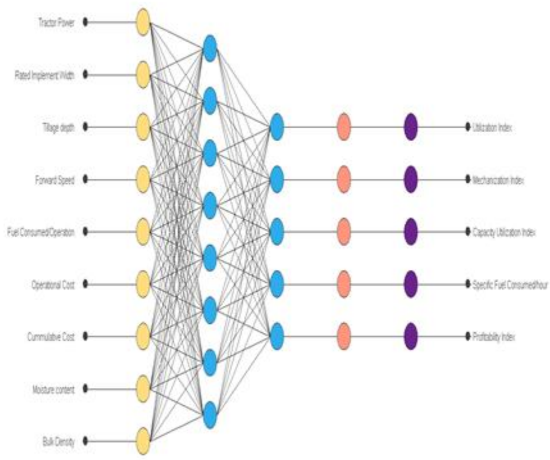

Figure 4a: Topology structure for Giriyan.

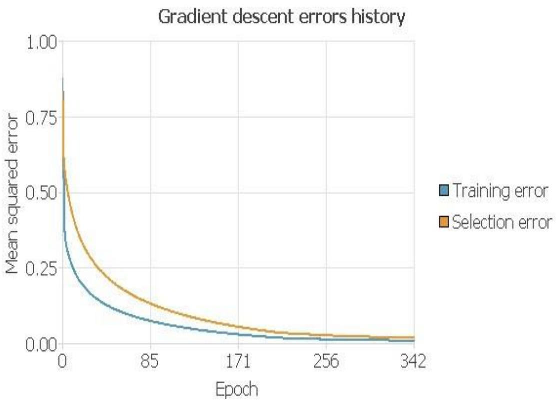

Figure 4b: Gradient descent errors for Giriyan

Table 6 shows the training values of MSE and RMSE obtained to be 0.0528 and 0.0850 L/kWh, while the values for the testing dataset were 0.0349 and 0.0306 L/kWh, respectively. The low value of MSE and RMSE shows the optimum utilization by accurately predicting specific fuel consumption relating to tillage depth and forward speed of operation at the Giriyan irrigation scheme, considering the category of tractor horsepower used for this field experiment under different field conditions as observed by Algezi and Almaliki (2022).

The goodness-of-fit of a statistical model was used to establish that the model is well correlated with the observed dataset and the expected values. This describes the versatility of the model in solving real-time issues and typically summarizes the discrepancy between observed values and the expected values for the ANN model developed. Figures 5 – 9 highlight the goodness of fit for the ANN model developed at the Giriyan irrigation scheme. The R^2(coefficient of determination) of the values obtained for utilization index, mechanization index, capacity utilization index, specific fuel consumption, and profitability index were 0.9902, 0.9943, 0.9819, 0.9823, and 0.9979, respectively. This predictive system shows high fidelity and directly corresponds with the methodological benchmarks established by Al-Sager *et al*. (2024), who utilized a similar network optimization framework to predict the specific fuel consumption of tractors during tillage operation.

The ANN model accurately and efficiently predicts the factors affecting farm machinery output, such as tillage depth and forward speed of operation, which are well understood and predictable in the Giriyan irrigation scheme. The best performance value was obtained with the profitability index, having the highest value of the coefficient of determination, R^2 = 0.9979. The R^2 of 0.9817 for specific fuel consumption indicates there is a strong relationship between the measured tillage depth and forward speed of operation for optimum farm machinery utilization to promote a high profitability index for the sustainability of the investment. By adopting the data splitting criteria of Al-Sager *et al*. (2024), wherein the training dataset is structured to be significantly larger than the network parameters to achieve validation generalizability, the 9-8-5-5 multi-layer perceptron topology successfully averted overfitting. While Al-Sager *et al.* (2024) highlighted the universality of back-propagation networks in isolating soil-implement performance variables, this study advances their findings by positioning these mechanical variables within a broader socio-economic and longitudinal framework (2012-2024). Consequently, the low MSE of 0.0528 and RMSE of 0.0349 achieved during testing validate the integration of cloud-compliant, real-time sensor streams (via ESP-32 microcontroller) as a superior step forward from traditional mathematical models, directly mirroring Al-Sager *et al.* (2024)'s advocacy for modern electronic data acquisition in smart farming. Moreover, variables such as tillage depth, rated width, implement forward speed, and specific fuel consumption exert a dominant influence across the network's predictive input-output variables due to a distinct soil-machine-implement mechanics characterizing the Giriyan irrigation scheme.

Table 6: Errors in the dataset of the ANN Model developed at the Giriyan irrigation.

	Training	Selection	Testing
Mean squared error (MSE)	0.0528	0.01506	0.0850
Root Mean Squared Error (RMSE)	0.0349	0.0375	0.306

Table 7: Errors of the output data for the ANN Model developed at the Giriyan irrigation scheme.

	UI	MI	CUI	SFC	PI
Relative Error (RE)	0.00523	0.002314	0.3806	0.37118	0.07585
Mean Absolute Percentage Error (MAPE)	0.4794	0.4608	1.7539	1.7169	0.4207
Absolute Error (AE)	0.1836	0.00018	0.8466	0.4122	0.0288
Coefficient of Determination (R^2)	0.9902	0.9943	0.9819	0.9823	0.9979

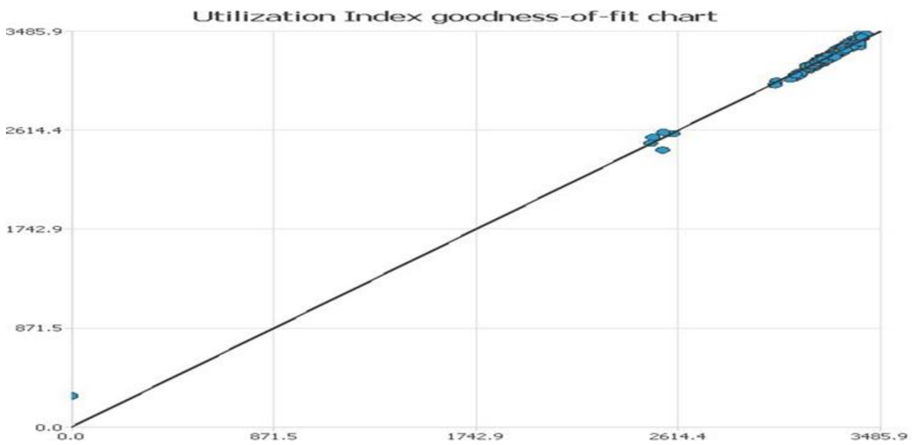

Figure 5: The predicted and target values for the utilization index at the Giriyan irrigation scheme

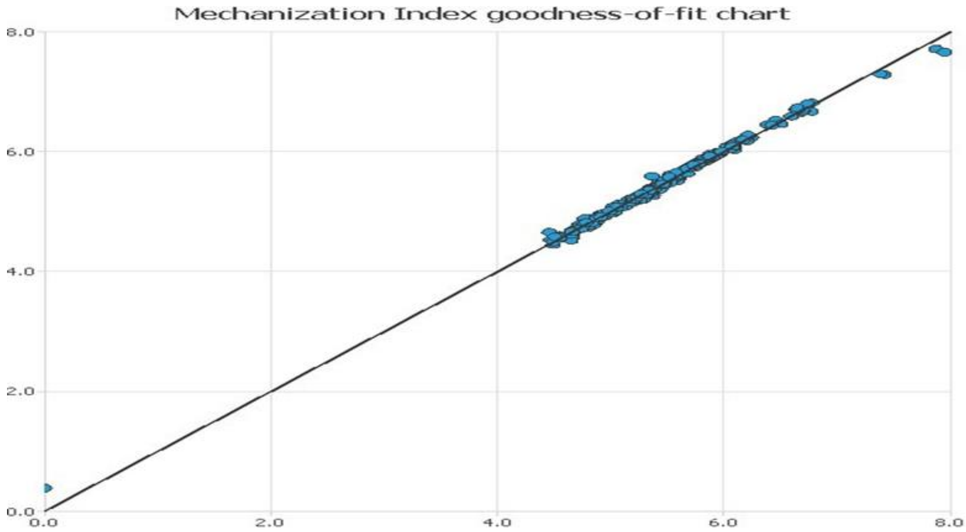

Figure 6: The predicted and target values for the mechanization index at the Giriyan irrigation scheme

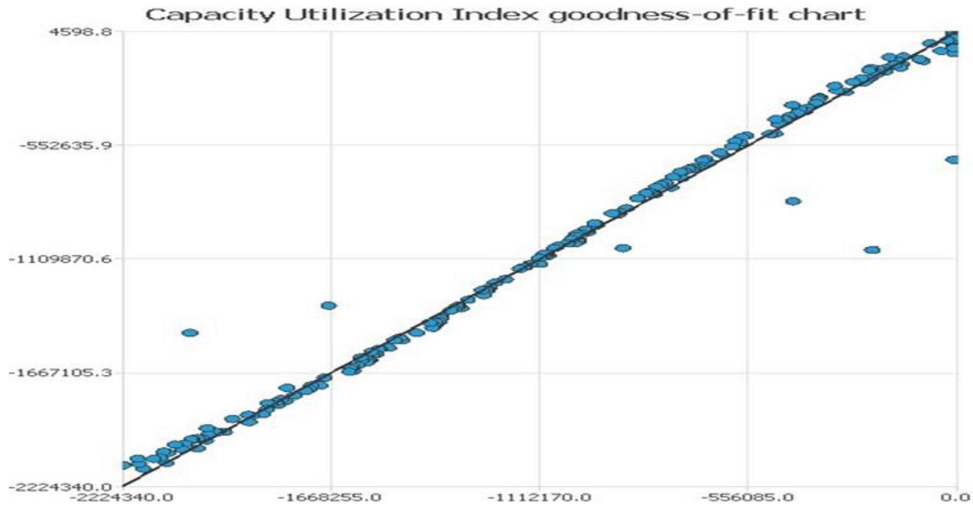

Figure 7: The predicted and target values for the capacity utilization index at the Giriyan irrigation scheme

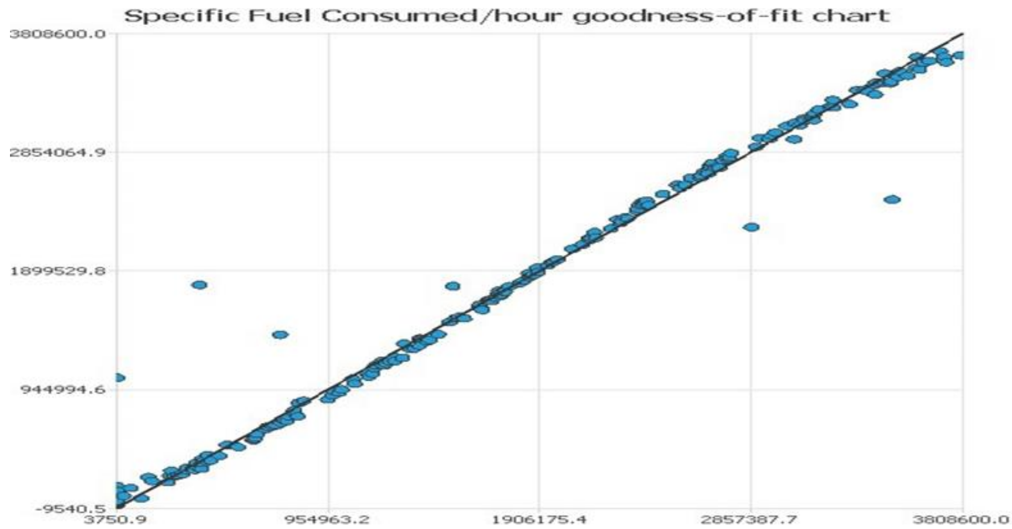

Figure 8: The predicted and target values for specific fuel consumption at the Giriyan irrigation scheme

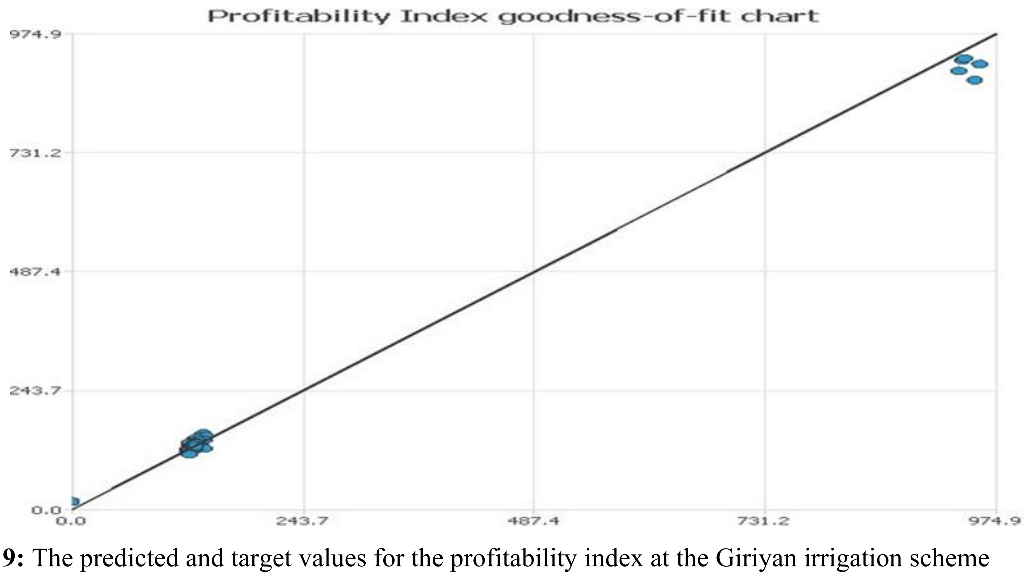

Figure 9: The predicted and target values for the profitability index at the Giriyan irrigation scheme

The results of the prediction performance for the output variables based on the testing dataset using the developed ANN model show that it provides high prediction accuracy compared to the field measurements, considering the close relationship of the scatter dataset along the regression line. The R^2 for the ANN developed at the Giriyan irrigation scheme has high prediction accuracy values of 0.9902, 0.9943, 0.9819, 0.9823, and 0.9979 for utilization index, mechanization index, capacity utilization index, specific fuel consumption, and profitability index, respectively. The best performance value was obtained with the profitability index, having the highest value of coefficient of determination (R^2) of 0.9979. Figures 10 – 14 highlight the input importance variables for all the output variables of the ANN model at the Giriyan irrigation scheme. The most relevant inputs for the utilization index were operational cost, rated implement width, and fuel consumed per operation, with values of 0.678, -0.155, and 0.056, respectively. Tractor power, forward speed, and rated implement width were the most important variables for the mechanization index, with corresponding values of 0.402, 0.210, and 0.154, respectively.

Then, the capacity utilization index also shares three important variables as rated implement width, operational cost, and tillage depth with values of -0.02, -0.012, and 0.011, respectively, while Tillage depth, rated implement width, and tractor power are the most important variables for specific fuel consumption with values of -0.015, -0.013, and -0.008, respectively. The other three important variables for profitability index were rated implement width, tractor power, and forward speed with values of 0.92, 0.037, and 0.011, respectively.

Figure 15 shows the three most significant importance means for the Giriyan irrigation scheme, with input variables of cumulative cost, rated implement width, and operational cost, corresponding to values of 0.38, 0.252, and 0.148, respectively.

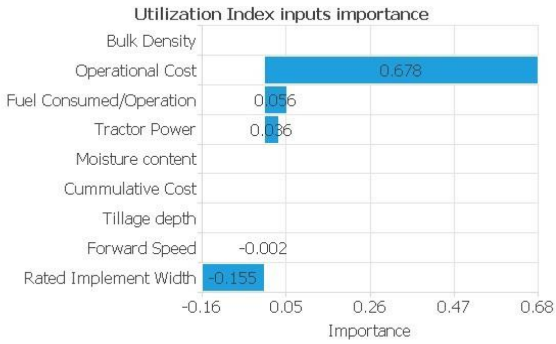

Figure 10: The inputs importance variable for the utilization index at the Giriyan irrigation scheme

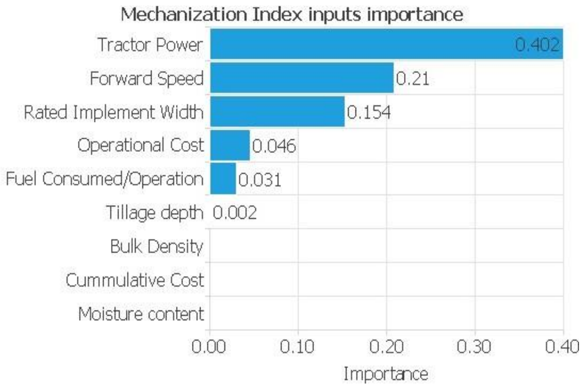

Figure 11: The inputs importance variable for the mechanization index at the Giriyan irrigation scheme

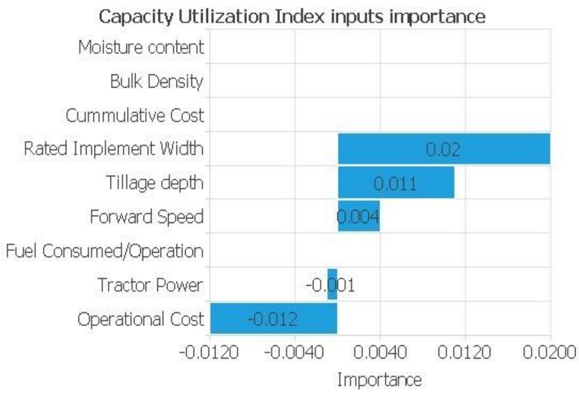

Figure 12: The inputs importance variable for the capacity utilization index at the Giriyan scheme

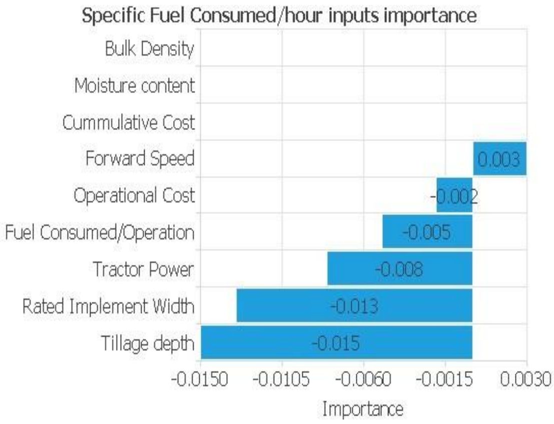

Figure 13: The inputs importance variable for the specific fuel consumed at the Giriyan irrigation scheme.

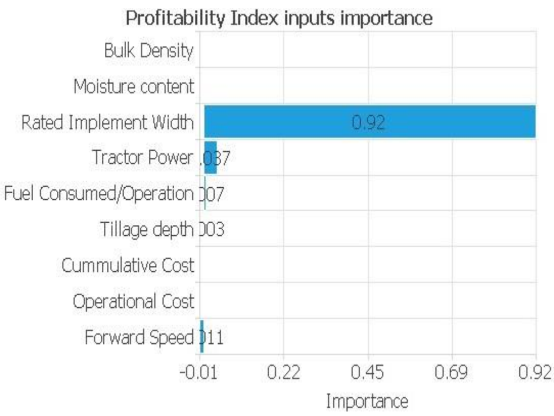

Figure 14: The inputs importance variable for the profitability index at the Giriyan irrigation scheme

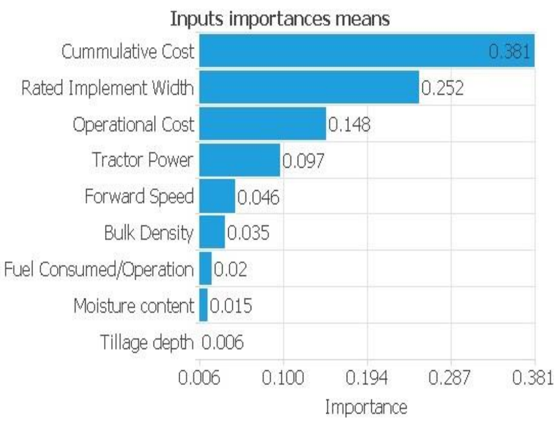

Figure 15: The importance variable for the inputs' importance means at the Giriyan irrigation scheme

CONCLUSION

Optimization of agricultural input-output performance parameters of farm machinery for economic sustainability at the Giriyan irrigation scheme, North Central Nigeria, was successfully carried out. Back propagation training technique with structural topology of 9-8-5-5 was suitable for predicting specific fuel consumption. The width of the implement has a significant impact on the quantity of diesel fuel required by the plough implement with the MF 375 tractor in the Giriyan irrigation scheme. Specifically, the rated implement, tillage depth, forward speed of operation, and specific fuel consumption values of 114.4 cm, 3.74 km/h, 20.71 cm, and 14.02 L/kWh are suitable for the optimisation of farm machinery utilisation for economic sustainability in the Giriyan irrigation scheme. ANN model has a good potential and promising value for the input-output relationship of specific fuel consumption, depth of cut, and rated width of implement per unit tractor power for a ploughing implement across a range of soil types at the Giriyan irrigation scheme. The model developed achieved high prediction accuracy and also possesses a good potential to assist a decision-making manager for strategic agricultural machinery utilization using the input-output relationship among the key parameters that determine good performance for farm machinery management in an irrigation scheme of North Central Nigeria.

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