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PREDICTION OF POWER REQUIREMENTS AND SOIL COMPACTION IN RANDOM TRAFFIC FARMING IN NORTHERN IRAQ BY USING NEURAL NETWORKS METHOD

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Random traffic farming (RTF) is an approach in Iraq's cropping practices where uncontrolled machinery traffic frequently causes soil compaction. Predicting machinery draft force and resulting compaction under random traffic farming is therefore essential for improving machine efficiency and enhancing long-term soil sustainability. This study applies artificial neural networks (ANNs) for predicting draft force, soil penetration resistance, and bulk density under various operational parameters. These parameters included tractor mass (3000 kg vs 6000 kg), traffic intensity (0–3 passes), and tillage depth (150 mm vs 250 mm). Experimental fieldwork was conducted on silty clay soil at Ninawa governorate. Draft force (DF) was directly measured, while soil compaction was evaluated using soil penetration resistance (SPR) and bulk density (BD). Field experiment results indicated that machinery traffic was the most influential factor, a first pass increased SPR and DF by up to 76% and 113%, respectively. The ANN model demonstrated high predictive accuracy for DF ($R = 0.985$) and SPR ($R = 0.858$), though BD predictions were less accurate ($R = 0.631$). These findings highlight that ANN modelling is an effective tool for optimizing machinery use and traffic management in RTF systems, thereby supporting sustainable soil management in arid regions.

Keywords: random traffic farming; artificial neural network; draft force; soil compaction; sustainable agriculture

Agricultural mechanization plays an essential role in enhancing productivity in modern farming; however, it could raise significant sustainability issues. The dependence on heavier machinery for timely field operations induces soil structural degradation through soil compaction (Hamza and Anderson, 2005; McPhee et al., 2015; Keller et al., 2019; Galambošová et al., 2020; Hu et al., 2021). Many research studies demonstrated that soil compaction clearly leads to: increased soil hardness and mechanical resistance to tillage; reduced water infiltration; restricted root growth; and diminished biological activity; these ultimately result in increased draft force which reduces tillage efficiency; suppressed yields, and threatening long-term agricultural sustainability (Colombi and Keller, 2019; Luhaib et al., 2017; Shaheb et al., 2021; Mojžiš et al., 2024; Srivastava et al., 2024; Zhang et al., 2024). Draft force is a longitudinal pull required to move an implement that serves as a critical indicator (Bowers, 1989; Harrigan and Rotz 1995; Godwin, 2007; Holden et al., 2021). It reflects both immediate power demands (and associated fuel consumption) during tillage/seeding and the mechanical stress transferred to the soil, directly influencing compaction potential (Spoor et al., 2003; Arvidsson and Keller, 2007; Godwin and O'Dogherty, 2007; ASABE, 2006). These challenges are amplified under random traffic farming (RTF) systems, where uncontrolled machinery movement subjects large field areas to repeated, unpredictable wheel passes (Chamen et al., 2003; Tullberg et al., 2007; Kroulík et al., 2009; Antille et al., 2015, 2016, 2019; McPhee et al., 2020), a pattern particularly prevalent in regions like Northern Iraq.

In Northern Iraq's crop-production areas, particularly Ninawa governorate, soil compaction presents a major issue. Seeding and tillage operations often occur simultaneously during critical periods of soil wetness (Al-Dabag and Luhaib, 2023). In these conditions, they significantly reduce shear resistance, combined with elevated pore-water pressure, and drastically raise susceptibility to compaction (Horn et al., 1994; Terzaghi et al., 2009; Mitchell et al., 2005; Botta et al., 2006). Amplifying these vulnerabilities, the region's characteristically low topsoil organic matter resulting from repeated tillage operations (Abdullah, 2014; Gülser et al., 2020) and silt-dominated texture further diminishes natural resilience against deformation under the loads of machinery during essential fieldworks.

The accuracy of draft force and soil compaction prediction under particular RTF conditions is challenging. Conventional empirical models (Hettiaratchi and Reece, 1967; Godwin and Spoor, 1977; Perumpral et al., 1983; Hernanz et al., 2000; Defossez and Richard, 2002; Hohn et al., 2022) often fail to capture the strong spatial and temporal heterogeneity inherent in RTF patterns. Additionally, these models struggle to address the complex, nonlinear interactions among dynamic soil states, implement geometry, and operational parameters (Defossez and Richard, 2002; Godwin and O'Dogherty, 2007). The lack of region-specific calibration data for Northern Iraq's distinct agro-ecological zone presents an additional challenge.

Accordingly, accurately predicting both draft force and soil compaction within Iraqi RTF systems presents a substantial obstacle. This persistent knowledge gap hinders the development of adapted, sustainable mechanization strategies for the region. Addressing this critical need, our study develops and validates an artificial neural networks (ANNs)-based predictive framework specifically designed for Northern Iraqi RTF environments. It is hypothesized that ANNs, adept at identifying complex, non-linear relationships from multidimensional inputs (soil state, dynamic loads, pass history), will surpass traditional models in predicting draft force and soil compaction. This study presents a novel application of ANNs for predicting both draft force and soil compaction under RTF conditions particular to Northern Iraq, integrating experimental field data with data-driven modelling to support sustainable mechanization strategies. The contribution of this work lies in its potential to support the transition to controlled traffic farming (CTF) and sustainable soil management in arid regions, where mechanization-induced compaction poses a significant threat to agricultural productivity.

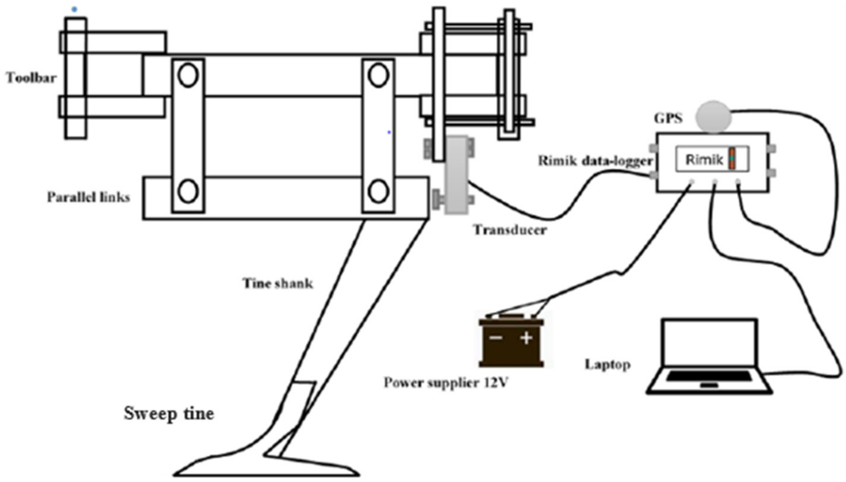

Fig. 1 Assembly of draft-sensing tine

Material and Methods

Field location

The field experiment was conducted in a farm (36.467° N, 43.184 °E) at Talkaif district in Ninawa Province, about 13 km northeast of Mosul city. The soil was silty clay with 6.55% of sand, 52.7% of clay, and 40.75% of silt. The bulk density of the soil was 1.31 g·cm^{-3} in the depth of 0–300 mm, and the soil moisture content was 17–19% in the depth of 0–300 mm. Historically, wheat and corn have been cultivated under a conventional tillage system. Therefore, a sub-soiler plough was used to alleviate historical compaction for field experiments. This was followed by moldboard and chisel ploughing. The soil was then repeatedly irrigated over two months to promote settling.

Field experiment design

In field experiments, draft force and soil compaction were measured under varying tractor weights, traffic levels, and tillage depths. The following parameters were tested:

– tractor weight: 3000 kg and 6000 kg;
– traffic conditions: the number of machine passes over the same area, categorized as zero traffic (no pass), single pass, double pass, and triple pass;
– tillage depth: 150 mm and 250 mm.

A Massey Ferguson 650 tractor and ITMCO G 285 tractor were used to collect the data of draft force and soil compaction during operation with special implement attached to the tractors. Their specification is shown in Table 1.

Experiments were conducted in a controlled field environment using a special tillage implement (Fig. 1). Draft force was measured using a transducer attached behind the shanks of the tillage implement. Soil compaction was assessed using two methods:

1. a penetrometer to record post-treatment penetration resistance;
2. core sampling to measure bulk density at varying depths (100, 200, 300 mm).

Each treatment combination was repeated four times in a randomized complete block design, and all measurements of draft force, bulk density, and soil penetration resistance were averaged across these four repetitions.

Table 1 Technical specifications of the tractors

Specification	Massey Ferguson	ITMCO G
Model	650	285
Weight (kg)	6000	3000
Gross power (kW)	103	56 kW
Front tire size	14.9–28/inflation (170 kPa)	7.5–16/inflation (150 kPa)
Rear tire size	18.4–38/inflation (150 kPa)	18.4–30/inflation (90 kPa)
Type of tire	bias-ply tires	bias-ply tires

Artificial neural network model development

The proposed ANNs were constructed using MATLAB version 2011 and its neural network tool (NN-Tool). The network architecture, including the input, output, and hidden layers, was systematically designed to achieve optimal performance.

Multilayer ANNs use back propagation (BP) to compare the network's actual output with target output. The difference, called the error, is sent backward from the output layer through the hidden layers to the input layer. This process is the reverse of the forward calculation phase. These networks do not have delay elements, as shown in Fig. 2.

The ANN model predicted draft force and soil compaction using experimental data.

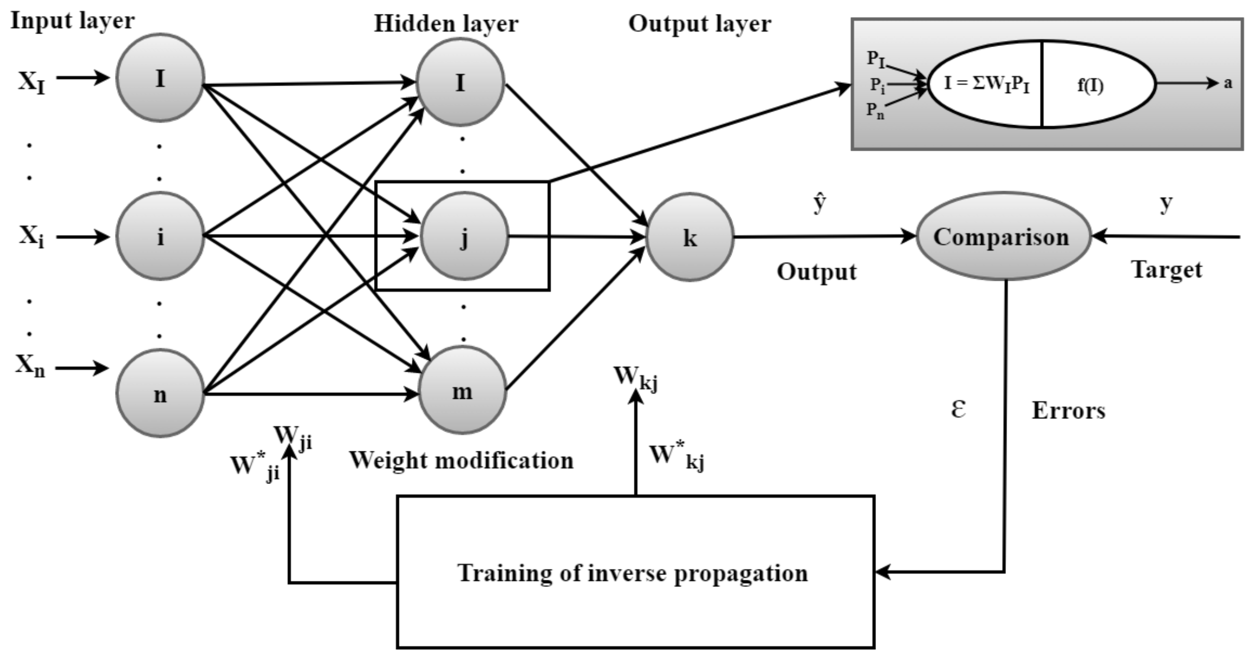

Fig. 2 Ideal model for a back-propagation network

Input layer

Five input nodes representing:
- Tractor weight (normalized 0–1 for 3000–6000 kg).
- Traffic count (one-hot encoded: [0, 0, 0] to [1, 1, 1] for 0–3 passes).
- Tillage depth (binary: 0 = 150 mm, 1 = 250 mm).
- Weight × traffic interaction term.
- Depth × traffic interaction term.

Hidden layers:
- First hidden layer: 10 nodes with ReLU activation, $f(x) = \max(0, x)$:
  - he-normal weight initialization $\left(\sigma = \sqrt{(2/n)}\right)$;
  - L2 regularization ($\lambda = 0.01$).
- Second hidden layer: 5 nodes with ReLU activation:
  - batch normalization between layers.
- Output layer:
  - single linear node (unbounded output), $f(x) = x$.

Output represents predicted
- Draft force in the first model.
- Soil penetration resistance in the second model.
- Bulk density in the third model.

Two hidden layers with 10 and 5 neurons were chosen after preliminary tests to find a balance between model accuracy and training time. The ReLU activation function was adapted for its non-linearity and to alleviate issues related to vanishing gradients. He-normal weight initialization was also employed to enhance stability and convergence.

Data normalization and model validation

Input data were normalized before training to accelerate the model convergence. Performance was assessed using the root mean square error (RMSE) and R-squared (R^2) metrics for both output variables.

Results and Discussion

Impact of input parameters

Figure 3 shows the percentage increase in (a) draft force, (b) bulk density, and (c) soil penetration in comparison with non-traffic conditions. The most significant increases were noted after the first pass of the tractors, with draft force, bulk density, and soil penetration resistance increasing by up to 116%, 13%, and 135%, respectively. This is consistent with the findings of Elaoud et al. (2017), who also observed in the regression equation that the tractor weight and the number of passes were the most significant factors in the soil compaction model. Also, the draft force required for the 6000 kg tractor was significantly higher than for the 3000 kg tractor, with increases of approximately 23% and 55% at the depths of 150 mm and 250 mm, respectively. The results showed that the increase in draft force was more pronounced at the deeper tillage depth of 250 mm. The Draft force increased by approximately 126% as tillage depth rose from 150 mm to 250 mm, whereas soil compaction exhibited a less pronounced increase relative to the effects of traffic.

Model accuracy

Draft force prediction

The error histogram with 20 bins, as depicted in Fig. 4, provides a visual representation of the distribution of prediction errors generated by the ANN model. These errors are calculated as the difference between the target values (actual measured draft force) and the model's predicted outputs (i.e., Errors = Targets – Outputs Errors = Targets – Outputs). In histogram, the blue, green, and red bars represent training, validation, and test set errors, respectively, while the yellow line marks zero error. The distribution shows that most errors are clustered around zero, which

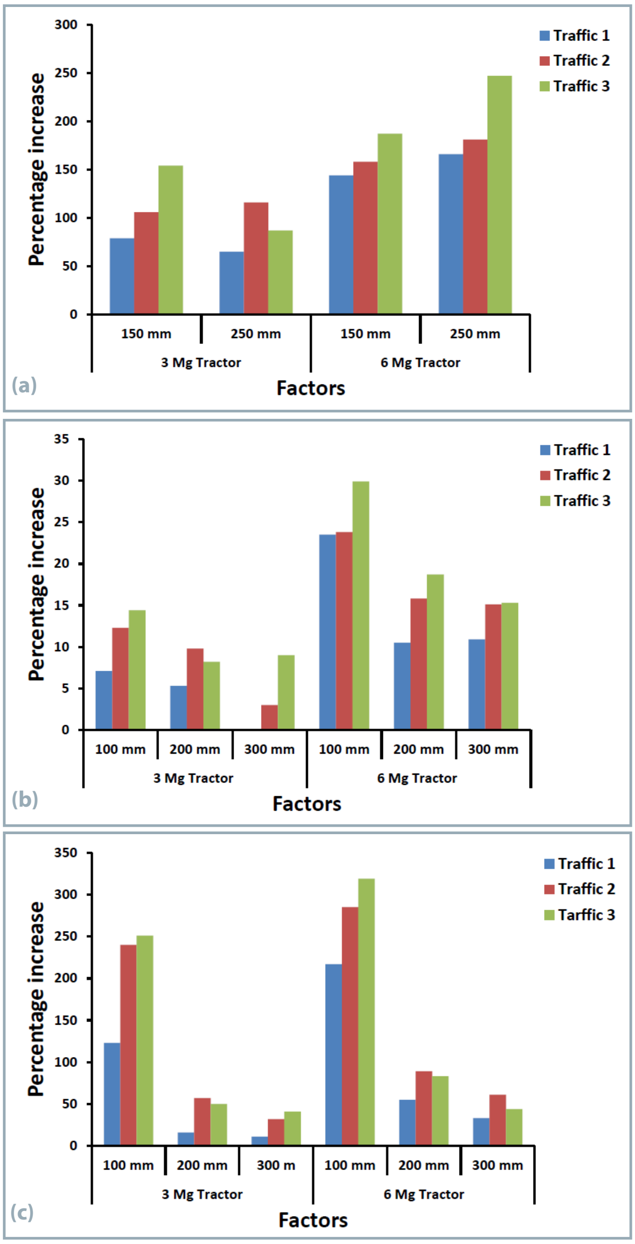

Fig. 3 Percentage increase in draft force (a); bulk density (b); and soil penetration resistance (c), relative to zero-traffic under different traffic levels and working depths

means the ANN predictions are close to actual values for most cases, while a few bars farther from zero show some cases with larger deviations (up to about ±1.4 units). This corresponds to localized variation in soil properties, which is common in field experiments and reflects natural heterogeneity rather than model deficiencies. The ANN model performance across all datasets: training errors (blue) indicate learning effectiveness, validation errors (green) reflect generalization capability during tuning, and test errors (red) demonstrate final real-world performance.

The mean squared error (MSE) progression across training epochs is illustrated in Fig. 5, providing insight into the network's learning dynamics and helping to identify potential over-fitting. During each iteration, the sum of squared errors (SSE) served as a metric to monitor performance adjustments. In the graph, training, validation, and test dataset errors are depicted by blue, green, and red lines, respectively, while the black line indicates the target error threshold. The model architecture comprised two hidden layers with five epochs. The MSE reached a value of 0.349 at the second epoch, which demonstrates stable convergence. The plots (Fig. 6) present the regression performance of the ANN model developed to predict draft force, separated into training, validation, test, and overall datasets. In each subplot, the horizontal axis represents the measured draft force values (Target), while the vertical axis represents the model's predicted values (Output). The solid colored lines depict the best fit for each subset, and the dashed diagonal lines mark the ideal one-to-one agreement between predicted and actual data. The training set shows a near-perfect correlation ($R = 0.99418$), indicating that the model closely matches actual values during learning. The validation set also maintains high accuracy ($R = 0.97465$),

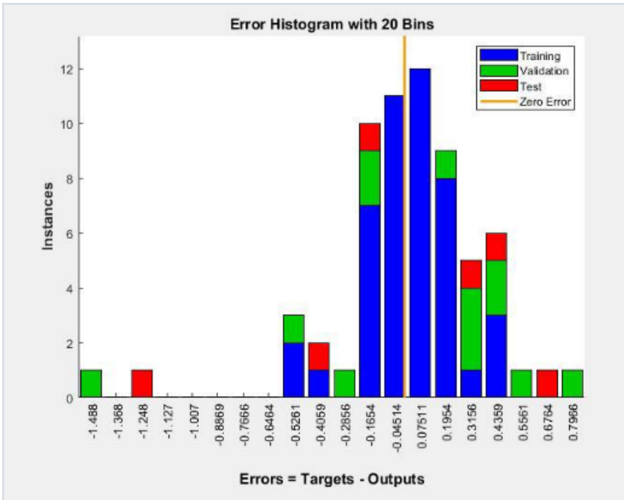

Fig. 4 Distribution of error histogram analysis for draft force prediction

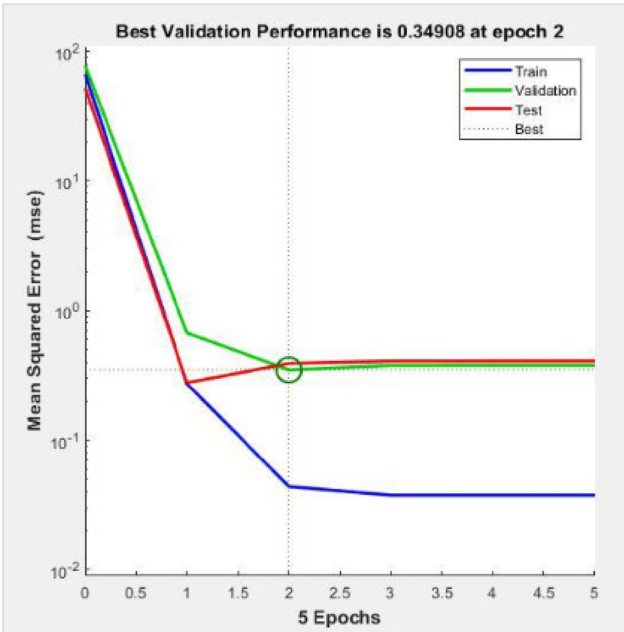

Fig. 5 ANN model performance chart of draft force prediction

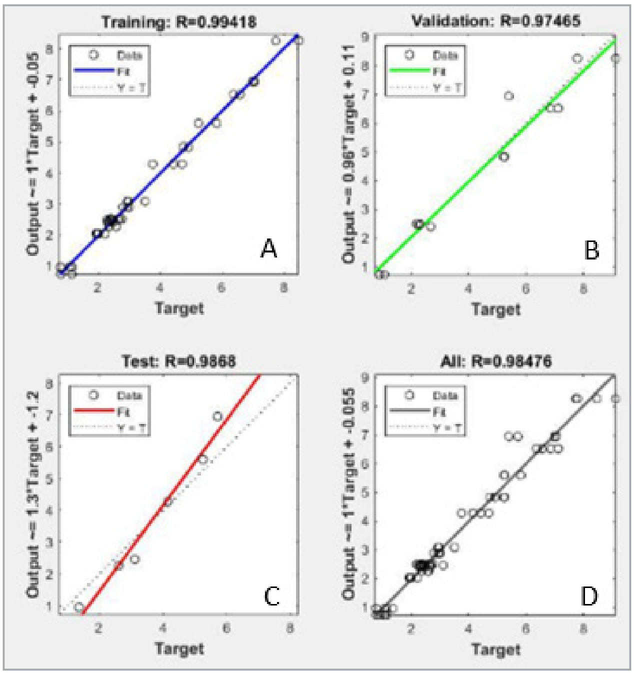

Fig. 6 ANN regression of draft force prediction chart for (A) training, (B) evaluation, (C) testing, and (D) overall tasks

suggesting strong generalization to unseen data. The test set achieves R = 0.9868, reinforcing the model's robustness. Across all data combined, the correlation remains very high (R = 0.98476), showing the ANN's consistent predictive ability. The slopes and intercepts in each equation are close to the ideal values of 1 and 0 respectively, confirming minimal bias in the predictions.

Soil compaction prediction

The model captured the influence of tractor weight, traffic conditions, and tillage depth on soil compaction index, which included bulk density and soil penetration resistance.

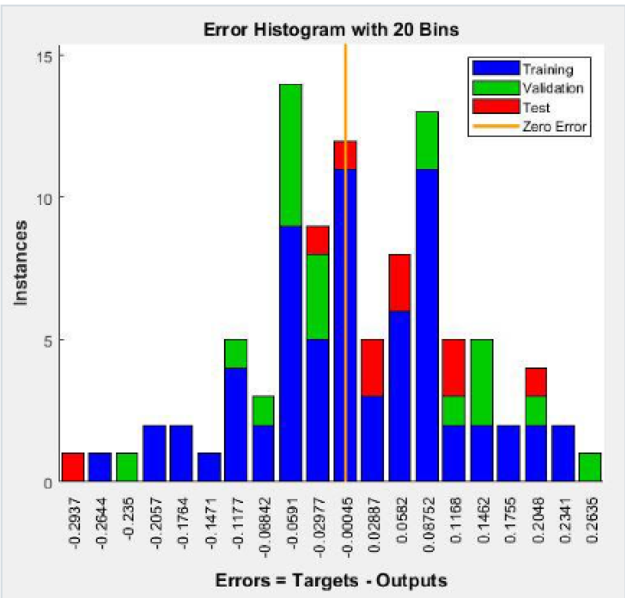

Fig. 7 Distribution of error histogram analysis for bulk density prediction

Figure 7 depicting the error histogram with 20 bins analyses the ANN model's bulk density prediction accuracy by plotting the frequency (*y*-axis) of errors (*x*-axis), where error = actual – predicted values. A tall, narrow peak near zero indicates high precision, while skewed distributions reveal systematic biases (e.g., over-prediction if skewed left). For bulk density, tight clustering around zero with minimal outliers would suggest reliable performance, whereas spread or asymmetry highlights specific prediction weaknesses. The 20-bin granularity balances detail and noise, helping identify error patterns – critical for refining model inputs or architecture to improve accuracy, especially for extreme soil conditions.

Figure 8 illustrates the MSE trend throughout the training cycles, offering valuable information about the model's learning behavior and enabling the detection of possible over-fitting issues. The SSE was utilized during every training iteration as a key indicator for tracking performance improvements. The graphical representation uses distinct colors to differentiate error types: blue for training data, green for validation data, and red for test data, with a black line marking the desired error level. The neural network structure included two hidden layers, achieving an MSE of 0.0164 by the first epoch, indicating consistent and stable learning progress throughout the training process.

Figure 9 shows the regression plots for the ANN model used to predict bulk density, separated into training, validation, test, and combined datasets. The correlation coefficient (R) is given for each subset, reflecting the strength of the relationship between predicted and actual values. The training set achieved R = 0.62232, indicating a moderate correlation, while the validation set had R = 0.57184, suggesting similar predictive consistency on unseen data. The test set, with R = 0.76537, showed a good agreement between predictions and measurements, suggesting good generalization for that subset. The overall correlation is R = 0.63128, which demonstrates the model's overall predictive ability. However, its lower accuracy compared to draft force model (R = 0.98476) is considered acceptable

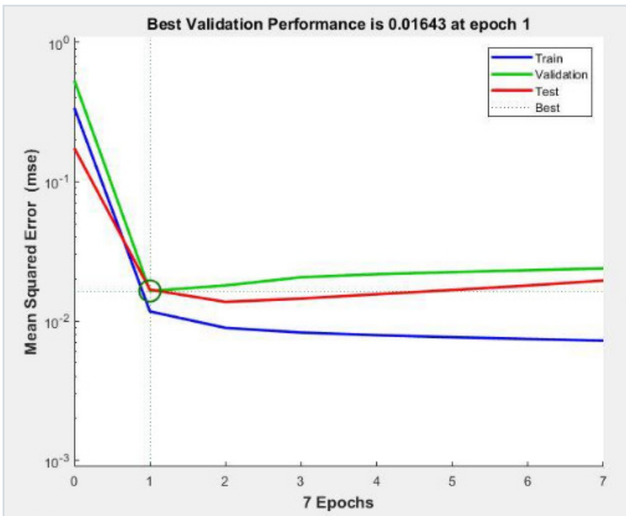

Fig. 8 ANN model performance chart of bulk density prediction

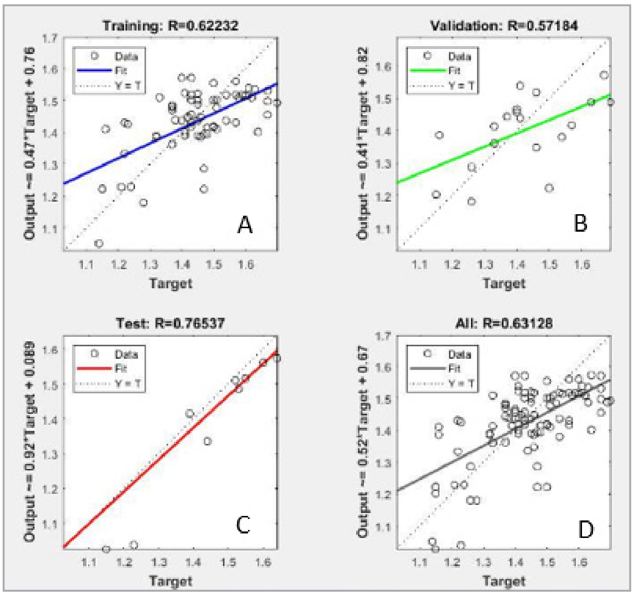

Fig. 9 ANN regression chart of bulk density prediction for (A) training, (B) evaluation, (C) testing, and (D) overall tasks

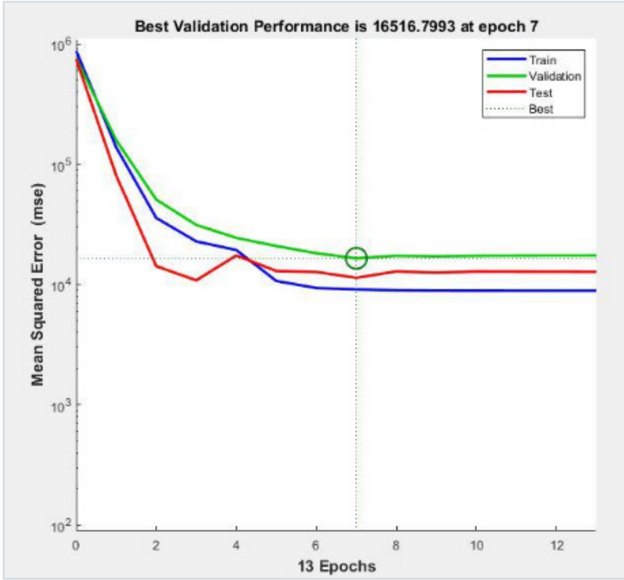

Fig. 11 ANN model performance chart of soil penetration resistance prediction

given the natural variability of soil. Improved accuracy is expected with larger datasets.

Soil penetration resistance prediction

Figure 10 illustrates the distribution of prediction errors from the ANN model used to estimate soil penetration resistance. Data are divided into 20 bins, with blue bars describing training data, green bars describing validation data, and red bars describing test data. The yellow vertical line indicates zero error, marking perfect prediction. Most errors are concentrated near zero, particularly between roughly -50 and +50, indicating that the model generally makes accurate predictions. A symmetrical distribution of errors around the zero line suggests minimal systematic bias. The relatively higher concentration of training set errors near zero compared to validation and test sets indicates strong learning performance, though some spread in the validation and test sets reflects natural variation and slight deviations in generalization.

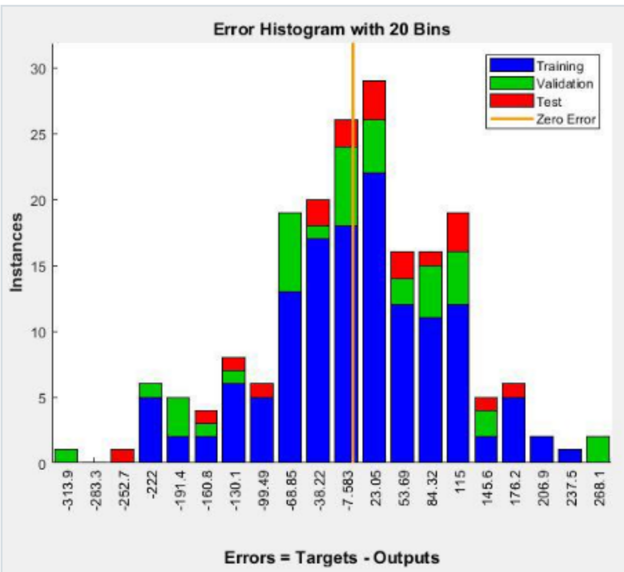

Fig. 10 Distribution of error histogram analysis for soil penetration resistance prediction

Figure 11 shows the change in MSE for the ANN model during training, validation, and testing when predicting soil penetration resistance. The x-axis represents the training epochs, while the *y*-axis is the MSE on a logarithmic scale. The blue, green, and red curves correspond to training, validation, and test datasets, respectively. The model reached its best validation performance at epoch 7, with an MSE of 16516.7993, which is marked by the green circle. Initially, all three curves show a steep drop in error as the model learns, followed by a gradual flattening that suggest convergence. The close alignment of the training and validation curves after epoch 7 indicates that over-fitting was controlled, while the test curve's stability confirms good generalization to unseen data. The selected epoch for the best validation performance represents an optimal balance between model accuracy and complexity.

Figure 12 presents the individual regression plots of the ANN model of soil penetration resistance prediction for each phase of the analysis: training, validation, testing, and the complete process. The training data exhibited the strongest linear relationship with a correlation coefficient of 0.8839. Model performance remained robust during the validation (R = 0.8025) and testing (R = 0.8029) phases, demonstrating consistent predictive capability across all operational segments. Hence, the ANN model demonstrated a high level of accuracy in predicting soil penetration resistance.

The penetration resistance model clearly outperforms the bulk density model, with R values approximately 0.2 higher across comparable datasets. This difference likely stems from the more direct relationship between measurable soil properties and soil penetration resistance compared to bulk density. The soil penetration resistance model demonstrates diminished performance variations

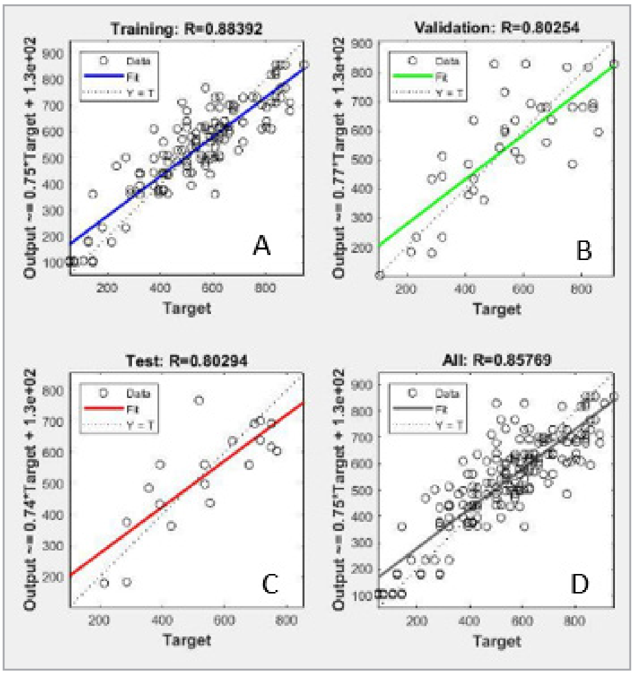

Fig. 12 ANN regression of soil penetration resistance prediction chart for (A) training, (B) evaluation, (C) testing, and (D) overall tasks

between training and testing phases ($\Delta R = 0.08$) in contrast with the bulk density model ($\Delta R = 0.14$), which indicates better generalization capability. These results are consistent with the findings of Rivera and Bonilla (2020) regarding model stability in soil property prediction. Bulk density prediction appears more sensitive to data quality and measurement techniques, as evidenced by the wider performance variance. This appears to be in agreement with the results obtained by Fariña et al. (2025) recommendation for standardized measurement protocols in bulk density studies.

In general, the ANN model for DF prediction revealed that the model produced results within the range estimated by the ASABE model (ASABE, 2006). Nevertheless, the ASABE model's predictions exhibit an accuracy margin of approximately ±50%, which is substantially lower than the accuracy achieved by the ANN model. Among the evaluated approaches, the ANN model indicated highly significant performance, producing DF predictions that closely matched observed data in comparison with those generated by the ASABE model. This appears to be in agreement with the results obtained by Abbaspour-Gilandeh et al. (2020), who also reported that the ANN model achieved higher accuracy and correlation coefficients for DF prediction than the linear regression model.

The results of this study revealed that the ANN effectively captured the complex relationships between machinery parameters and soil properties. Particularly, the ANN model accurately captured the effects of tractor weight, traffic conditions, and tillage depth on soil compaction. This predictive capability offers a valuable tool for optimizing machinery use and minimizing soil degradation.

The pronounced effect of traffic conditions on soil compaction emphasizes the necessity of minimizing machinery passes over agricultural fields. Soil compaction increased substantially after two or more passes, indicating that limiting field traffic can reduce long-term damage to soil structure. Additionally, model's sensitivity to the weight of the tractor indicates that using light machinery can decrease excessive DF, potentially lowering fuel consumption and reducing equipment wear.

Conclusion

This study developed an ANN framework to predict DF and soil compaction under RTF conditions in Northern Iraq. The model captured the complex, non-linear relationships between input variables, which included tractor weight, traffic conditions, and tillage depth. The results demonstrate that machinery traffic is the primary factor increasing energy demands for soil-engaging implements and exacerbating soil penetration resistance. The combined effects of soil densification and hardening present a substantial risk to soil structure health and long-term productivity.

The results demonstrate that the use of heavier tractor intensifies soil compaction and substantially raises DF requirements, reducing energy efficiency and increasing negative impacts on the soil ecosystem. This compelling evidence strongly advocates for a strategic shift away from conventional RTF practices. The adoption of CTF systems is strongly supported to confine compaction to permanent traffic lanes, thereby preserving the majority of the field area from detrimental wheel passes.

The bulk density attained moderate accuracy ($R = 0.63128$). It creates a useful benchmark for soil compaction prediction under RTF conditions. The model showed lower performance compared to the draft force and soil penetration resistance models ($R = 0.98476$, $R = 0.85769$, respectively). This result may be due to a higher sensitivity of BD to unmeasured variables or data limitations. Future enhancement to the prediction reliability of bulk density could be achieved through expanded data collection, inclusion of supplementary soil parameters, and implementation of ensemble modelling techniques.

Overall, the ANN model demonstrated superior predictive capability compared to traditional empirical models. Its development was based on a controlled dataset. To enhance its robustness and general applicability, future work should incorporate a wider variety of soil types, climatic conditions, and moisture contents. Integrating real-time sensor data provides the dynamic, in-field predictions necessary for developing precision agricultural management tools to foster sustainable soil stewardship in vulnerable arid regions like Iraq.

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