Prediction of Soil Compaction after Passage of the Powered Wheel Using Artificial Neural Network

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M.Tech. Thesis Part – 1

Submitted by

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LIST OF SYMBOLS AND ABBREVIATIONS

Particulars	Description
Eq.	Equation
ANN	Artificial neural network
CI	Cone Index
CIbefore	Cone Index before passing the tyre
CIafter	Cone Index after passing the tyre
Adam	Adaptive moment
R^2	Coefficient of determination
MSE	Mean square error
MAE	Mean absolute error
RMSE	Root Mean Square Error
ReLU	Rectilinear unit activation function
Tavg	Average Torque
Pmax	Maximum Pull
%	Percentage
et.al	And others
Fig.	Figure
Va	Actual velocity
Vth	Theoretical velocity
i	Number of inputs
j	Number of neurons in the first hidden layer
k	Number of neurons in the second hidden layer

CHAPTER 1
INTRODUCTION

1.1. General

The heavy agricultural machinery used for many field operations in modern agriculture poses a considerable risk to the soil through the degradation of physical, chemical, and biological soil functioning by compaction. This particular condition of high compactness that soils under conventional tillage systems present must be analyzed in order to improve tyre/soil relation. When agricultural soils are compacted the volume of the pore is reduced, and the aggregate crumbles and smaller intergranular pores are formed with non-accommodating faces. The major loss of the largest pores caused by soil compaction has the effect of changing the pore size distribution and hence the water retention characteristics.

Wheel traffic has a dominant influence on the structure and density of agricultural soils. In intensively farmed areas the entire soil surface may be covered by wheel tracks more than 5 times per year. Wheel load, inflation pressure, drawbar pull, soil condition, tyre size, and wheel slip are some of the factors that determine the amount of soil compaction.

The use of larger tyres and lower inflation pressures at a given load creates a larger contact area, which allows a reduction of the maximum stress in the contact area, σ_{max} (**Lamande and Schjonning, 2011**). **Hakansson** confirmed that among several processes leading to the deterioration of soil structure, subsoil compaction by vehicles with high axle loads seems to pose the most severe long-term threat to soil productivity. In deep subsoil layers, machinery-induced compaction is largely determined by the load on individual wheels, in contrast to the plough layer compaction, which is caused by smearing, it persists for a long time and may even be permanent as reported by **Hakansson and Reeder.**

Researchers have developed many prediction models for compaction. Many models have used simple indices such as bulk density, which is a often poor indicator of compaction damage. The model by **Soehne** predicts stress distribution in the soil profile, and using the soil compressibility functions, as caused by a certain traffic impact, the soil density profile, can be predicted. Some researchers have assessed soil compaction by measuring soil displacement. In this research, we have used the cone index as the parameter and have measured the percentage change in cone index value with respect to the initial value i.e. after and before passing the tyre.

In order to provide improved accuracy and more sustainable use of power resources, modelling approaches are becoming essential in the mechanization process. Soft computing has been increasingly popular in recent years for modelling and forecasting. Soft computing approaches such as statistical model development, machine learning, artificial neural network application, and fuzzy logic for exploratory data analysis have become quite popular. Artificial intelligence (AI) approaches have been widely applied in several fields, including agricultural operations, in recent years.

Artificial Neural Networks are a common tool for modelling complex input-output relationships (ANN). In some aspects, the ANN's learning process is similar to that of the human brain. This is because these networks understand the complicated relationship between input and target values (**Taghavifar, 2013).** Numerous research on the use of neural networks in agriculture can be found in the literature. However, a review of the literature revealed that the use of neural networks to predict soil compaction is limited. The capacity to automate the process of model selection and their ability to simulate nonlinear mapping are two advantages of using artificial neural networks over statistical methods.

ANN can be applied to solve problems involving complex relationships between variables. The essential features of an ANN are its ability to learn, and associate and is error-tolerant. Therefore, it is expected that ANN could simulate the soil compaction prediction by using valid parameters and will be comparatively effective from the existing empirical models.

1.2. Justifications

- With the use of heavier machines in agriculture, the problem of soil compaction has emerged. It should be alleviated as it hampers crop growth by reducing the pore spaces between soil resulting in a reduced rate of water infiltration and drainage.
- A large number of parameters such as wheel load, inflation pressure, tyre size, drawbar pull, soil conditions, and their interaction influence soil compaction. The usual method followed for minimizing compaction damage is by minimizing wheel load, and maximizing tyre-soil contact area, but quantitative predictions for individual cases are not easy.
- This makes it difficult to give farmers specific advice on minimizing compaction. In this situation, mathematical modelling is an inexpensive way of making reasonably confident predictions about unknown situations, without resorting to expensive fieldwork.

- So, experiments will be performed with varying pull, inflation pressure, wheel load, tyre size, and soil conditions in the Traction Lab of AGFE Department, IIT Kharagpur. The cone index before and after the operation of the powered wheel will be measured.
- To estimate the change in cone index an ANN model will be developed. The input parameters will be wheel load, pull, inflation pressure, and tyre size in different soil conditions.
- This model will help the farmers in choosing the proper size tyres for the reduction of soil compaction and hence, increment in the yield.

1.3. Objectives

The main goal of this study is to develop and validate an ANN model for predicting soil compaction. The specific objectives are:

1. To collect the soil compaction data after the passage of the powered wheel (13.6-28) at different loads and inflation pressures by varying pulls in different soil conditions.

2. To develop an ANN model to estimate soil compaction, after passing the powered wheel (13.6-28) in different soil conditions.

3. To test and validate the developed model under different operating and soil conditions.

CHAPTER 2

REVIEW OF LITERATURE

In this section, an attempt is made to review various aspects regarding the research work related to soil compaction, its mitigation and quantification techniques, as well as the use of Artificial Neural Networks for its prediction. Plenteous research work has been done worldwide on different aspects of soil compaction. The reviewed literature for the present study has been discussed under the following main headings:

- Causes, Effects, and Mitigation of Soil Compaction
- Prediction of Soil Compaction using Artificial Neural Network

2.1. Causes, Effects, and Mitigation of Soil Compaction

Raghavan *et al.* (1977) studied the variables involved in the soil-vehicle interaction in which they identified wheel slip as one of the most important. They also included soil types and conditions and the size of the tyres governing the performance of the machinery in the agricultural field. Field tests were conducted using tyres of size 42.9 × 71.1 cm, 46.7 × 76.2 cm, and 46.7 × 86.4 cm and during each test, slip values were noted for different pull forces. The result of the test showed that compaction was found at maximum b/n 15 and 25% slip and was less at higher slip rates and a maximum at 20% slip. The field results were in accordance with laboratory shear box tests.

Jakobsen and Dexter (1989) presented a computer program for the prediction of the influence of traffic on the compaction of agricultural soils. Simple equations were used for the calculation of stress distribution in soil under rubber tyres with different inflation pressures and different loads. The result showed that soil compression and wheel sinkage depend on a number of factors including the initial soil density, soil water content, time since the previous soil disturbance, the number of passes, and on possible horizontal soil displacement. The comparative study showed that a short duration of wheel load results in incomplete soil compression, as compared with the usual long-duration laboratory compression tests.

Jorajuria and Draghi (1997) conducted a comparative study of using either a light tractor with a high number of passes or a heavier one with a reduced amount of wheeling. Three different numbers of passes, with two tractors with different weights but the same ground pressure, were used to obtain six different traffic intensities. It was observed a decrease in the grassland yield ranging from 7 to 25% in out-of-track areas. The comparative study showed that for the same number of passes, the heavier tractor appears to give either the same or a greater reduction in grassland yield than the light tractor. On the basis of traffic intensity, the comparative study shows that lighter tractors with a larger number of passes can do as much or even greater damage than heavier tractors with fewer passes.

Sullivan *et al.* (1999) described a simplified model that allowed users to explore some of the main aspects of soil compaction. The model estimated soil bulk density under the centre line of a wheel track and used an analytical method to estimate the propagation of stress in the soil. It also included the influence of the effects of changes in tyre size, inflation pressure, and load on the contact area. Results of the model showed the potential of the model in selecting tyres and wheel systems for minimizing compaction.

Botta *et al.* (2002) quantified soil compaction induced by tractor traffic on a recently tilled non-consolidated soil, to match ballast and tyre size on the tractors used during secondary tillage. For simulation, a conventional 2WD, tractor was used using four configurations of bias -ply tyre rear tyres: 18.4 × 34, 23.1 × 30, 18.4 × 38, and 18.4 × 38 duals having two ballast conditions. Soil bulk density and cone index in a 0 to 600mm profile were measured before and after traffic. The result showed that topsoil compaction increased as did ground pressure, and subsoil compaction increased as total axle load increased and was independent of ground pressure. They further concluded that bulk density tended to be less responsive than cone index to the traffic treatments and topsoil compaction can be reduced by matching conventional bias-ply tyres with an optimized axle weight.

Ansorge and Godwin (2007) studied the effect of self-propelled wheels and a track with high axle loads (9-24t) on soil compaction. Soil displacement and soil density changes were assessed by embedding talcum powder lines as tracers into the soil during preparation. In addition, soil bulk density and penetrometer resistance were measured. It was observed that towed implement wheels with a 4.5t load caused similar soil displacement to the track with a load of 12t. The comparative study showed that the tracks with loads of both 10.5 and 12t compact the soil less than wheels at a 10.5t load in both weak and stratified soil. It was found that tyre inflation pressure had a significant influence on soil parameters and for reducing compaction a larger overall diameter was more beneficial than a wider tyre.

Botta *et al.* (2008) quantified soil compaction induced by tractor traffic on two tillage regimes: conventional tillage and direct drilling. For simulation, a conventional 2WD tractor was used, having four configurations of cross-ply rear tyres: 18.4-34, 23.1-30, 18.4-38, and 24.5-32, and four configurations of radial tyres: 18.4R34, 23.1R30, 18.4R38 and 24.5R32, with two ballast conditions in each configuration. Rut depth, bulk density, and cone index were measured before and after traffic in a 0-450mm soil profile. The result showed that subsoil compaction increased as total axle load increased and was independent of ground pressure. The comparative study showed that radial tyres caused less soil compaction than cross-ply.

Keller and Lamande (2010) highlighted some issues that need further consideration in order to improve soil compaction modelling. They focussed on analytical soil compaction models based on the work of Boussinesq (1885), Frohlich (1934), and Sohne (1953) for the calculation of stress propagation in soil. It was shown that knowledge of the effects of loading and soil conditions on the upper model boundary condition is inadequate. Also, the accuracy of stress transducers and therefore of stress measurements is not well known. The results showed large differences b/n soil stress-strain behaviour obtained from in situ measurements during wheeling measurements and those measured on cylindrical soil samples in standard laboratory tests. They identified differences in loading time, as the main reason behind large differences.

Hamza *et al.* (2011) conducted an experiment to study the influence of external load and soil water on compaction. Four soil water levels i.e. air-dry, 50% field capacity, field capacity, and saturation were combined with external load using different-sized tractors – no load (0kg), small tractor (2638kg), medium tractor (3912kg), and large tractor (6964kg). The results of the experiment were found by measuring soil bulk density, soil strength, and soil-water infiltration rate at 0-100, 100-200, and 200-300mm soil depths. It was shown that combined increases in soil water and external load increased soil compaction as indicated by an increase in soil bulk density and soil strength and a decrease in soil water infiltration rate.

Chamen *et al.* (2015) reviewed and analyzed the operational cost and benefits of soil compaction mitigation techniques. Several mitigation options involved subsoiling, targeted subsoiling, and ploughing and low ground pressure tyres, tracked tractors and controlled traffic farming were identified as soil compaction avoidance technologies. It was observed that for mitigating soil compaction, only targeted subsoiling resulted in a positive change to gross margin, between £0/ha for sandy soil, and £22/ha for clay soil while the rest increased gross margins significantly, ranging from £26/ha for tracked tractors on sandy soil to £118/ha for CTF on clay soil. However, these technologies resulted in decreased leaching and emissions of nitrogen and provided a win-win situation for farmers and the environment.

Damme *et al.* (2019) compared the effects of five generations of tyres on soil stress and soil structure, including two standard narrow tyres and three larger low-aspect-ratio tyres. Wheel loads of 2900 and 4300Mg were chosen for the front and rear axles respectively, and the load-rated inflation pressure ranged from 240 to 60kpa. The contact stress distribution was estimated using the FRIDA model and was used as input for the calculation of the vertical stress through the soil profile. The results showed that for a given wheel load, the tyre evolution reduced soil stress when the development included an increase in the tire-soil contact area and an associated decrease in the tyre inflation pressure. Also, a reduction in soil stress for newer tires was found due to a more even contact stress distribution.

2.2. Prediction of Soil Compaction using Artificial Neural Network

Sinha and Wang (2008) developed an Artificial Neural Network (ANN) prediction model which related the Permeability Coefficient (PMC), Maximum Dry Density (MDD), and Optimum Moisture Content (OMC) with the classification properties of the soils. The test soils were prepared from four soil components, namely, bentonite, limestone dust, sand, and gravel. These four components were blended in different proportions to form 55 different mixes. The MDD, OMC, and PMC estimated by the ANN model were compared with the actual MDD, OMC, and PMC values. The predicted values were very close to the values of the actual soil samples. The model evaluation resulted in an R^2 value of 0.987 for training and 0.98 for the testing dataset for MDD, the R^2 in the case of the OMC, values obtained were 0.94 for training and 0.96 for the testing dataset and an R^2 value in the case of the PMC, values obtained were 0.96 for training and 0.94 for testing datasets respectively.

AI-Saffar *et al.* (2012) developed an ANN model to predict the compaction parameter i.e. maximum dry unit weight (γ_{dmax})and optimum moisture content (OMC) using eight input parameters namely liquid limit and plastic limits, plasticity index, specific gravity, soil type, gravel, sand, and fines content. A database comprising a total of 177 case records of laboratory measurement were used to train the Multi-layer perceptron using the back-propagation algorithm. The training in this research was applied using Levenberg-Marquardt (LM) algorithm with a variable learning rate. The model evaluation for γ_{dmax} were shown in terms of MSE, R for training and testing dataset, Coefficient of Efficiency (CE), Variance account for (VAF), and Over-fitting ratio (OFR) and the values obtained were 0.001, 0.975 and 0.905, 73.51%, 73.51% and 0.928 respectively. And similarly, the model evaluation for OMC were shown in terms of MSE, R for training and testing dataset, Coefficient of Efficiency (CE), Variance account for (VAF), and Over-fitting ratio (OFR), and the values obtained were 0.001, 0.965 and 0.932, 70%, 72% and 0.965 respectively after 62 epochs and using Logsig-Logsig-Logsig activation function.

Taghavifar *et al.* (2013) employed a hybrid approach i.e. Artificial Neural Network (ANN) and Imperialist Competitive Algorithm optimization approach (ICA-ANN) for the prediction of soil compaction indices i.e. (Penetration Resistance and Soil Sinkage) under the effect of input variables (i.e. wheel load, tyre inflation pressure, number of passage, slippage, and velocity each at three different labels). The experimentations were carried out in a soil bin facility utilizing a single-wheel tester. The results were compared on the basis of a modified performance function (MSE-REG) and coefficient of determination (R^2). Comparative results elucidated that hybrid ICA-ANN with a feed-forward network was capable of producing an R^2 value for penetration resistance of 0.993 and an R^2 for soil sinkage of 0.992 whereas the ANN model with the same network was capable of producing an R^2 value for penetration resistance as 0.965 and an R^2 for soil sinkage as 0.958. Results were also compared for the cascade forward network, ICA-ANN showed an R^2 value of 0.998 for penetration resistance and 0.998 for soil sinkage whereas the ANN model with the same network showed an R^2 value of 0.975 for penetration resistance and 0.976 for soil sinkage.

Tipza *et al*. (2014) developed an Artificial Neural Network which related compaction characteristics i.e. maximum dry density (MDD) and optimum moisture content (OMC), permeability, and soil shear strength to soil index properties i.e. grain size distribution, specific gravity, and plasticity characteristics (liquid limit, plastic limit, shrinkage limit, and plasticity index). A database including a total number of 580 datasets was compiled, in which 155 datasets were used for modelling the permeability, 320 datasets for modelling MDD and OMC, and 105 cases for used for modelling effective friction angle of shearing. Six input variables were used for the ANN model for MDD, including gravel content (Gc), sand content (Sc), fine content (Fc), specific density (Gs), liquid limit (LL), and plastic limit (Pl). The model evaluation shown a Coefficient of Determination (COD), Root mean Square Error (RMSE), and Coefficient of Residual Mass (CRM) and the values were 0.92, 54.42 and 1.50E-04 respectively. The results of the sensitivity analysis performed on the OMC prediction model were obtained in terms of COD, RMSE and CRM and the values were 0.92, 199.11 and 4.92E-05 respectively. The results of the ANN model for permeability coefficient were shown in terms of COD, RMSE and CRM and the values were 0.99, 17.69, and 1.27E-05 respectively, input variables for this model were FM, LL, gravel content (Gc), Sand content (Sc), fine content

(Fc), and compaction degree (Cd) and output variable was logk. The ANN model for the effective friction angle were evaluated in terms of COD, RMSE, and CRM and the values obtained were 0.97, 51.63, and 0.0018 respectively. The input variables for this model were coarse content (Cc), fine content (Fc), liquid limit (LL), Soil bulk density (γ), and shearing rate (Sr).

Ardakani and Kardnaaij (2019) predicted the compaction parameters of soils i.e. maximum dry density (γ_{dmax}) and optimum moisture content (ω_{opt}) by neural network simulations using a database consisting of 212 soil samples. As the proctor test is relatively time-consuming and laborious, in the present research Group Method of Data Handling (GMDH) type neural network (NN) was used to estimate the compaction parameters of soils indirectly from more simply determined index properties such as liquid limit (LL), plastic limit (PL) and fine-grained content (FC) as well as sand content (SC). The statistical results for GMDH in the case of γ_{dmax} were expressed in terms R, RMSE, MAD, and MAPE, and the values obtained were 0.90, 0.60, 0.46, and 2.70 respectively for the training dataset and 0.93, 0.63, 0.46 and 2.68 respectively for testing dataset also while in case of $\omega_{opt,}$ results were expressed in terms of R, RMSE, MAD and MAPE and the values obtained were 0.91, 1.81, 1.37 and 7.53 respectively for the training dataset and 0.96, 1.79, 1.42 and 7.84 respectively for testing dataset. The predictability of the GMDH model datasets was statistically compared with the empirical equations and the least disparities were found. Therefore, it was concluded that developed ANN models were more efficient than the existing empirical formulas. At the end, sensitivity analysis of the obtained model was carried out to study the influence of input parameters on model outputs, and results showed that the LL and PL were the most influential parameters on the compaction parameters.

Kurnaz and Kaya (2020) estimated the compaction parameters (maximum dry density (MDD) and optimum moisture content (OMC)) of soils with four soft computing methods (Group Method of Data Handling (GMDH), Support Vector Machine (SVM), Bayesian Regularisation Neural Network (BRNN), and Extreme Learning Machine (ELM) and compared their performance. A wide database consisting of the index and standard proctor (SP) test results was used. The comparative model evaluation showed that the ELM method was the most successful method for the prediction of compaction parameter with Radial bias activation function and 24 neurons in the hidden layer on the prediction of OMC (R^2 = 0.9369 and MSE = 0.2224) while the best performance on the prediction of MDD was obtained with sine activation function and 6 neurons in the hidden layer (MSE = 0.4673 and R^2 = 0.9465).

Pham *et al*. (2020) developed an ANN model to predict the Soil Coefficient of Consolidation (Cv). 188 experimental results were used to construct the dataset for the model. For hidden layer construction, two choices were considered: a single hidden layer with 14 neurons or a single hidden layer with 26 neurons. The model result showed higher accuracy in the case of the hidden layer with 14 neurons. Comparative analysis showed RMSE, MAE, and R^2 values of 0.1446 in the first while 0.1851 in the second case, 0.09216 in the first while 0.1163 in the second case, and 0.9658 in the first while 0.942 in the second case respectively.

Cao *et al.* (2021) analyzed the influence of roller-related factors i.e. roller passes, vibration force, roller speed and vibration acceleration on Compaction Meter Value (CMV) representing compaction status of structure and predicted CMV based on these factors by Artificial Neural Network (ANN). The data were obtained by an integrated system installed on the roller. It included IC hardware and software, which measured the input parameters. The major findings were, with the growth of roller passes, CMV has a slightly slow increase at the beginning followed with a rapid rise, and eventually reaches stability. For vibration force and vibration acceleration, CMV showed a upward tendency with their rises. CMV increased firstly and then decreased as roller speed were increased and thus there was an optimal speed during the compaction construction. The model evaluation showed a R value of 0.9357, indicating that the data generated via, CMV prediction model was in good agreement with the measured ones. After sensitivity analysis, it was found that roller passes was the main indicator for compaction quality control in construction followed by roller speed, vibration force and vibration acceleration.

Othman and Abdelwahab (2021) estimated the compaction parameters i.e. optimum moisture content (OMC) and maximum dry density (MDD) using Artificial Neural Network (ANN). The grain size distribution, plastic limit, and liquid limits were used as the input parameters for the development of the ANNs because these variables can be easily estimated. Multiple ANNs (240 ANN) were tested, with different architectures and activation functions, in order to choose the ANN that provides the most accurate predictions. Results showed that the optimum ANN that provided the best predictions consisted of three hidden layers, two neurons per hidden layer, and employed the logistic activation function. This ANN provided high-accuracy results as it predicted the MDD with an R^2 value of 0.864 and OMC with an R^2 value of 0.924.

2.3. Concluding Remarks

- The heavy agricultural machinery used for many field operations poses a considerable risk to the soil through the degradation of physical, chemical, and biological soil functioning by compaction.
- To analyse it, researchers have used simple parameters like bulk density, Soil moisture content, Stress Distribution in the Soil profile but all these are poor indicator of compaction damage.
- This particular condition of high compactness that soils under conventional tillage systems present must be analyzed in order to improve tyre/soil relation.
- Wheel load, Inflation Pressure, Drawbar Pull, Soil Condition, Tyre Size, and Wheel Slip are some of the factors that determined the amount of soil compaction.
- The use of larger tyres and lower inflation pressures at a given load creates a larger contact area, which allows a reduction of the maximum stress in the contact area, σ_{max}.(**Lamande and Schjonning,2011**)
- However, a review of the literature revealed that the use of neural networks to predict soil compaction is limited.
- Therefore, it is expected that ANN could simulate the soil compaction prediction by using valid parameters and will be comparatively effective from the existing empirical models.

CHAPTER 3

THEORETICAL CONSIDERATION

3.1 Artificial Neural Network

An artificial neural network (ANN) is a theoretical reproduction of a whole sensory system of the human body that contains an assortment of neuron units that communicates with each other through connections of an axon. The nonlinear problems with deficient information can be dealt with this method. After getting trained, it can perform generalizations and predictions at very high speeds.

3.1.1 Neuron

For a better understanding of the neural network, the concept of a biological neuron is necessary. From the human cortex, an ordinary biological neuron is shown in **Fig. 3.1.** In the cerebrum, the neuron sends signals (the so-called neurotransmitters utilizes electrochemical media) to the other neurons by means of the dendrites (neuron’s input channels). The cell body produces an output signal, at a given moment, if the sum of these signals surpasses an absolute threshold value. That signal goes towards the axon after that is given to the next neurons. A message is passed starting from the one neuron to the next intersection point, which is known as synapse. The efficiency of the interceding synapse

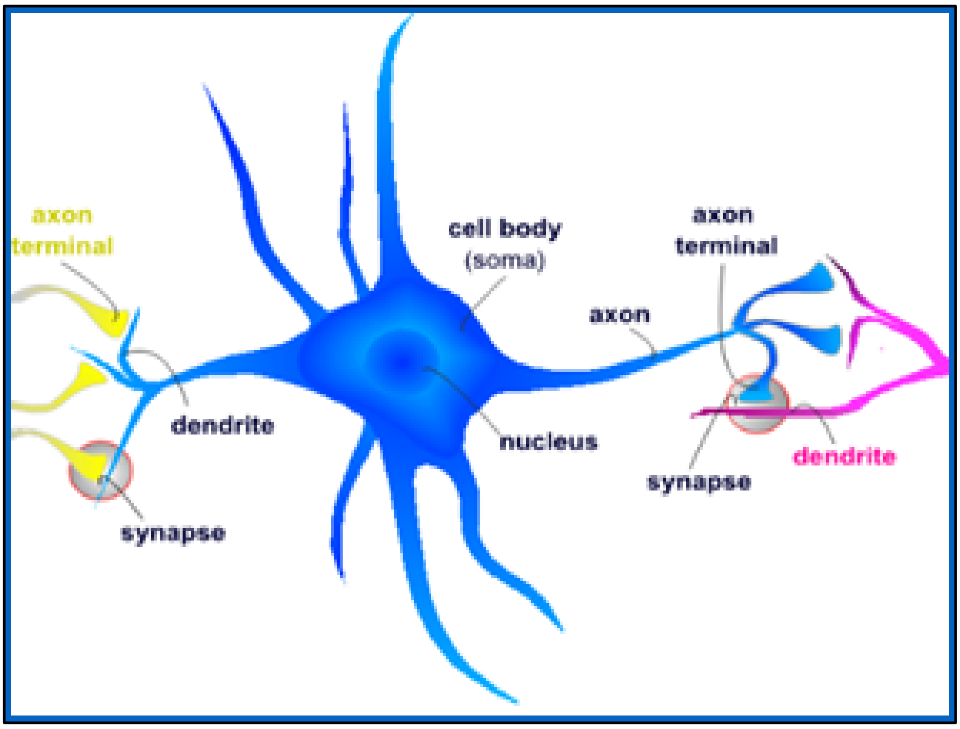


Fig 3.1. Biological Neuron

Modulates the magnitude of the impact of this signal on the next neuron. A computer-simulated or an ordinary artificial neuron is shown in **Fig. 3.2.** It mimics the function of a biological neuron.

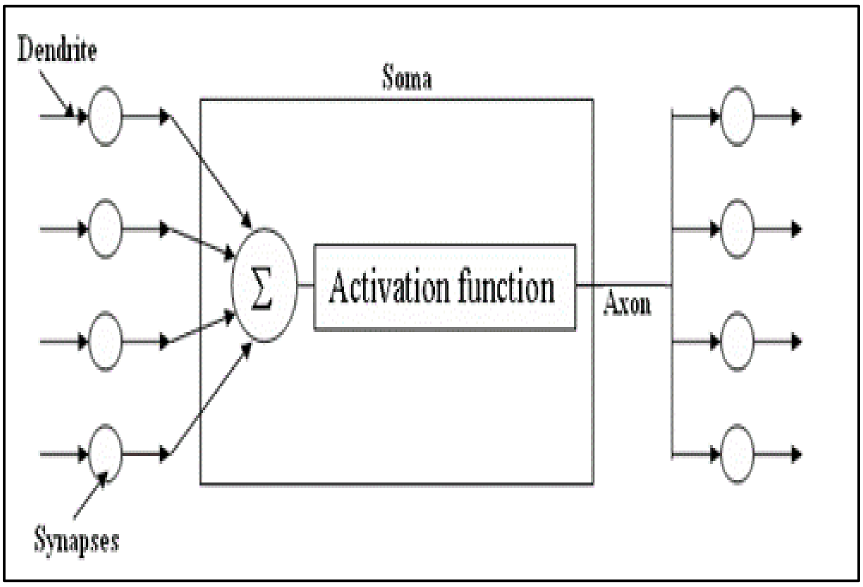


Fig. 3.2. An ordinary artificial neuron.

3.1.2. Basic Concepts of ANN

In a neural network, mainly two functions are performed by the neuron. From several connections, the inputs with their corresponding weights are added afterwards, a nonlinear function (Activation function) is applied to the sum. Via outgoing links, the result of the summed value is transferred to the other neurons. Different layers are used to make the network arrangement of the neurons. The inputs, which are received from the actual datasets are given to the first layer; next layers receive weighted outputs from the preceding layer as input, and the results are taken from the last layer as the outputs. Hyperbolic tangent function, sine or cosine function, sigmoidal function are the basic activation functions. The sigmoidal function is the most used function, but still, for the selection of transfer function, there are no rules **(Koehn, 1994; Rajasekaran and Pai, 2004; Sit, 2005)**. Besides, it is likewise not indisputably comprehended that there is a significant effect of the utilization of various types of transfer function on the network performance.

3.1.3. Topology of Network

The neural network topology can be defined about the internal architecture and how they are connected. Based on the connection patterns and by ordering of the neurons, the architecture of an ANN can be divided into three groups. Such as recurrent network (Hopfield, Elman,), feedforward network (multilayer feedforward, radial basis), and self-organising network (Kohonen). For different purposes, various types of systems might be utilized. The multilayer feedforward network is the most powerful and mostly accepted tool by researchers in the application of chemical engineering. As of late, the recurrent network (Elman) was in the trend and likewise increased **(Sit, 2005)**. The feedforward network can be defined as such because the given input parameters are sent in a single direction from the input layer to output layers via hidden layers. The determination of the topology is another essential task in ANN model development, in which the optimum number of hidden neurons and hidden layers are decided. **(Sit, 2005)** expressed that for an approximation of any continuous function with the best accuracy, a couple of the hidden layers are sufficient.

3.1.4. Training and Validation of Network

To build up a precise model using ANN, the necessary steps are the learning or training and validation procedure. A dataset of input and output pairs is repeatedly sent to the neural network in the training procedure. Until the specified input yields the ideal yield, the weights of all the considerable number of connections between neurons are balanced. By following these steps, the ANN learns the right information based on the response of input and output. For approval, the ANN is exposed to input patterns unseen during training and modifies them for getting the best and efficient model. For improving the model validity, an essential fitting criterion might be added. These methodologies might be the sum of squared error (SSE) and a mean squared error (MSE) which are calculated between the target and the network output.

A fruitful learning process includes three principle rules, i.e., learning rule, learning hypothesis and learning paradigm. They are learning paradigm worries about what data is taken care of to ANN. Two categories are defined of learning paradigm, to be specific, supervised and bruised learning. The network is prepared with the right response for each information in supervised learning while the right information isn't given in unsupervised learning.

Learning hypothesis tends to the preparation information, which is including issue identified with data quality, data quantity and calculation time. The more bulk training data can increase the accuracy of network generalisation. Be that as it may, this additionally increases the calculation time for the learning procedure. Another basic issue with respect to the learning procedure is data normalisation. The scaling or coding of training data is needed to prevent data with larger magnitude from overriding the smaller and impede the premature learning process.

Learning rule gives an idea about balancing the weights in the learning procedures. Learning rule can be divided into four primary types: Competitive learning (CL), Hebbian learning (HL), Boltzmann learning (BL) and Error-correlation learning (ECL). Backpropagation (BP) is the most well-known training algorithm because of its error-correlation learning rule. Gradient steepest descent method is the example of BP, which performs a search at the error surface. Two steps are involved in each iteration in BP: calculation in the single forward direction for producing the solution and backward propagation to adjust the weights, according to the already calculated error.

3.1.5. Feedforward and backpropagation ANN

An artificial neural network is a group of interconnected artificial neurons, cooperating with each other in a coordinated way. A layer of neurons acts as input and another as output. From the pairs of input (X) and output (Y) data, the neural network directly learns and builds up a relation between these pairs; however, it does not yield any mathematical condition relating the variables. The network can predict the correct output from an input data set that has not been recently utilized during the instructing. The number of neurons in the input layer and the output layer is made equal to the number of independent variables (nx), and the number of dependent variables (ny), respectively. Between the input and output layers, a hidden layer of neurons is included. A number of neurons in the hidden layer (nh) is usually made less than 2 times the number of neurons in the input layer **(Rajasekaran and Pai, 2004; Jagtap, 2006)**. In this manner, the network is created, is called feed-forward and backpropagation network.

In the process of training of the network, the weights of interconnecting lines between the input to hidden, U [nx, nh] and hidden to output, W [nh, ny] layer neurons are modified. The given input data fed to the input layer of neurons via output layer neurons leads to the particular output. Regularly, different input and output pairs of the data pairs are used in the learning process of the network. When learning becomes over, the network sets up estimations of relevant weights of interconnecting lines (U and W) and the threshold or bias values of the hidden and output layer neurons (T_h and T_o). The basic structure of a feedforward and backpropagation neural network is shown in **Fig. 3.3.**

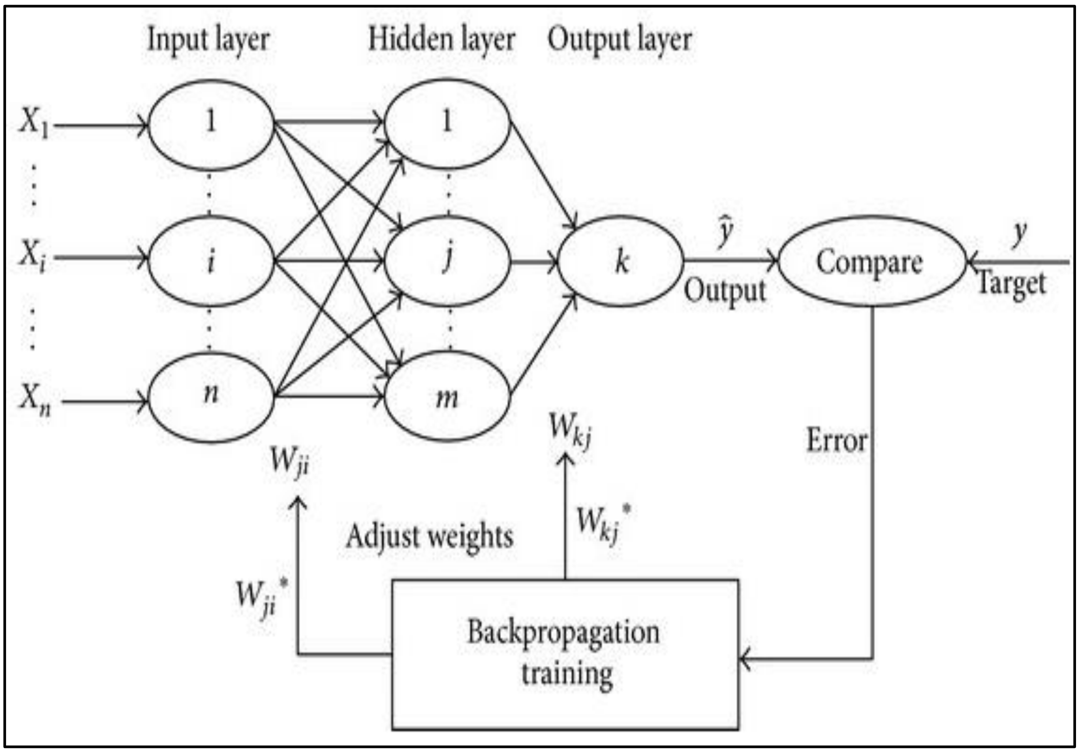


Fig. 3.3. The basic structure of a feedforward and backpropagation neural network.

3.1.6. Applications of ANN

Because of their universal approximation capabilities and flexible structure, ANNs are effective data-driven modelling tools for nonlinear systems dynamic modelling and identification. It provides a framework for combining different machine learning algorithms to process large amounts of data. Without task-specific instructions, a neural network can "learn" to execute tasks by examining examples.

ANN has a lot of applications: (i). Social Media, where ANN analyses user's profile, interests, current friends, and also their friends and various other factors to calculate the people you might potentially know. Another common application of Machine learning in social media is facial recognition. This is done by finding around 100 reference points on the person's face and then matching them with those already available in the database using convolutional neural networks. (ii). Marketing and Sales, where E-Commerce sites like Amazon and Flipkart uses ANN to identify the customer likes, dislikes, previous shopping history, etc. and then tailor the marketing campaigns accordingly. (iii). Healthcare, where ANN are used in Oncology to train algorithms that can identify cancerous tissue at the microscopic level at the same accuracy as trained physicians. Full-scale implementation of ANN has enhanced the diagnostic abilities of medical experts and ultimately has led to the overall improvement in the quality of medical care all over the world. (iv). Personal Assistants, like Siri, Alexa, Cortana etc., uses Natural language processing to interact with the users and to formulate a response accordingly. Natural language processing uses ANN that are made to handle many tasks of these personal assistants such as managing the language syntax, semantics, correct speech, the conversation that is going on, etc.

3.2 Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Its high-level built-in data structures, combined with dynamic typing and dynamic binding, make it very attractive for rapid application development, as well as for use as a scripting or glue language to connect existing components together. Python's simple, easy-to-learn syntax emphasizes readability and therefore reduces the cost of program maintenance. Python supports modules and packages, which encourages program modularity and code reuse. The python interpreter and the extensive standard library are available in source or binary form without charge for all major platforms, and can be freely distributed.

3.3 Jupiter Notebook

The Jupiter Notebook is an incredibly powerful tool for interactively developing and presenting data science projects. A notebook integrates code and its output into a single document that combines visualizations, narrative text, mathematical equations, and other rich media. In other words: it's a single document where you can run code, display the output, and also add explanations, formulas, and charts, and make your work more transparent, understandable, repeatable, and shareable. Using Notebooks is now a major part of data science projects across the globe. If your goal is to work with data, using a Notebook will speed up your workflow and make it easier to communicate and share your results.

Best of all, as part of open-source Project Jupiter, Jupiter Notebooks are completely free. You can download the software on its own, or as part of the Anaconda data science toolkit.

3.4 TensorFlow and Keras

Both TensorFlow and Keras are famous machine learning modules used in the field of data science.

TensorFlow is an open-source platform for machine learning and a symbolic math library that is used for machine learning applications. TensorFlow has a better graph representation for a given data rather than any other top platform out there. TensorFlow has the advantage that it does support and uses many backend software like GUI and ASIC. When it comes to community support TensorFlow has the best. TensorFlow also helps in debugging the sub-part of the graphs.

Keras is an open-source neural network library that runs on top of Theano or TensorFlow. It is designed to be fast and easy for the user to use. It is a useful library to construct any deep learning algorithm of whatever choice we want. Keras is the best platform out there to work on neural network models. The API that keras has a user-friendly where a beginner can easily understand. Keras has the advantage that it can choose any libraries which support it for its backend support. Keras provides various pre-trained models which help the user in further improving the models the user is designing.

3.5 Network Geometry

The number of connection weights and how they are organized are determined by network geometry. This is usually achieved by determining the number of hidden layers and the number of neurons in each of these layers. It has been demonstrated that a three-layer network (input-hidden-output) with sigmoid, rectilinear unit activation functions in thehidden layer and output layer can approximate the high degree of prediction accuracy, as long as the hidden layer has a sufficient number of neurons.

The number of model inputs determines the number of neurons in the input layer. The number of neurons in the hidden layers, and also the number of connection weights are key factor in the network. The importance of establishing a balance between having enough freeparameters (weights) to allow for approximate representation of the function and having toomany free parameters, which can lead to overtraining. The number of hidden layer neurons has a substantial impact on a network's performance: too few neurons will perform poorly, while too many neurons will over fit the training data. By Keeping the number of optimal hidden neurons is always desirable and will provide the better performance of the model, asit: (a) decreases the amount of time it takes to train the network; (b) helps the network achievehigher generalization performance; (c) avoids overtraining; and (d) makes it easier toexamine the trained network. A trial-and-error process must be used to select the optimal model and the appropriate number of neurons and hidden layers. To obtain the optimal number of hidden layer neurons for single hidden layer networks, gradually increase the number of neurons and hidden layers until no significant improvement in model performance is observed.

CHAPTER 4

MATERIALS AND METHODS

This chapter presents the description of the problem and methodology adopted for the collection of experimental data and modelling using ANN. Procedures used for developing the model and various criteria for evaluating the model are also included in this chapter.

4.1 Single – Wheel Tester

It supports the rolling wheel, a torque transducer, a ring transducer, wheel carriage, proximity sensors and brake dynamometer. A torque transducer is used to measure the torque coming at the wheel axle, a ring transducer is used to measure the drawbar pull, wheel carriage for carrying the whole setup, proximity sensors for measuring the actual and theoretical velocities, brake dynamometer for applying the frictional resistance to the motion of the wheel carriage by the use of varying drawbar pull. All the recorded readings are sent to the Data Acquisition system for further analysis. The rolling wheel's performance can be tested in terms of TE vs Slip, Pull vs Slip, Coefficient of Traction vs Slip graphs.

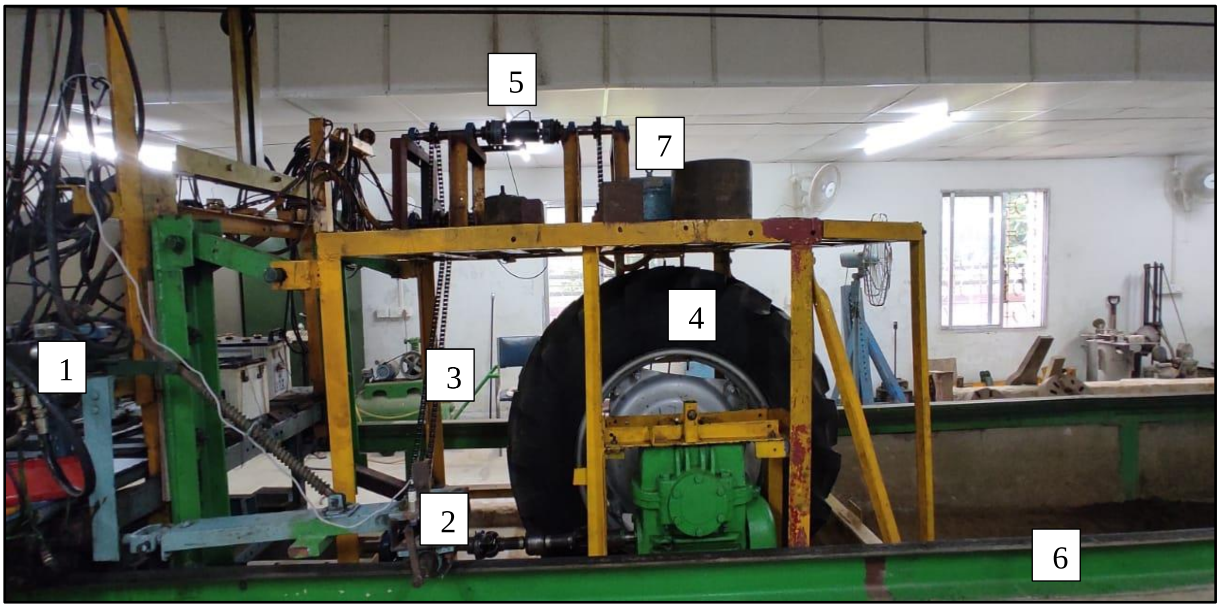


Fig. 4.1. Laboratory set up for single wheel testing in a soil bin

1. Hydraulic power system 2. Proximity Sensor 3. Chain drive
4. Test Wheel 5. Torque Transducer 6. Main frame 7. Induction Motor

4.1.1 Soil Processing Trolley

It consists of a rotary tiller, a leveller blade and a compaction roller; with the tiller in front and the roller at the rear. Compaction roller and leveller blade helps in compacting and levelling the tilled surface. Soft, medium and hard bed can be prepared through different number of passes of trolley in different soil moisture conditions.

Fig 4.2. Soil Processing Trolley

4.1.2 Drawbar Loading Device

It is provided to vary the horizontal pull of wheel tester. It consists of a steel drum of known diameter and length. The drum is mounted on a shaft with both ends supported on bearings. A show type braking arrangement is provided at one end of the shaft, which is operated by applying downward force by means of dead weights in a pan.

The wheel tester trolley is fitted with a steel wire rope, and the steel wire's other end is rolled on a drum. As the wheel turns, the rope come undone, and as a result, it turns the drum since it is given a positive drive mechanism. The drum's rotating motion can be limited by changing the drum's braking force. It is feasible through the variation of drawbar loads.

Fig 4.3. Drawbar loading device

4.1.3 Measurement of Torque:

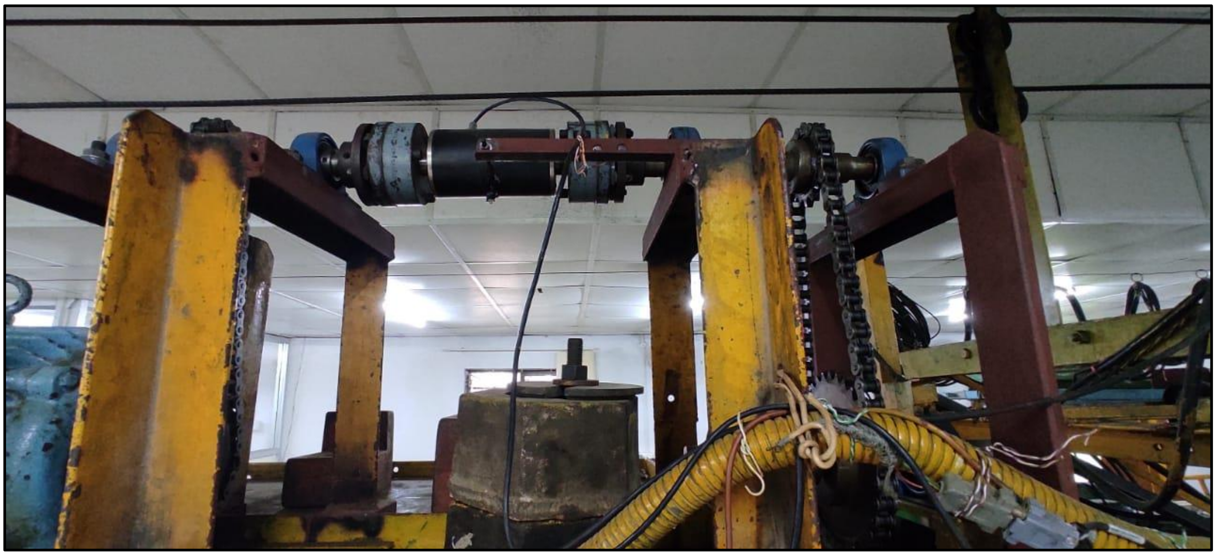


Fig 4.4. Torque transducer

A torque transducer was used to measure the input torque to the wheel axle, which was then recorded in DAS. For continuous measurement of dynamic torque, the torque transducer unit was connected in horizontal position between the prime mover (a 3-phase 7.46 kW induction motor) and the load shaft (driving sprocket) using two sets of flexible connection. The terminal box was given a steady 24 Volt DC. The DAS captured the output voltage from the terminal box. The applied torque was calculated as follows:

$$T = (t_1 - t_2) \times r \tag{4.1}$$

Where,

T = Applied torque

t_1 = tension at tight side, N

t_2 = tension at slack side, N

r = radius of rim, m

4.1.4 Measurement of Slip:

The actual and theoretical forward speeds of the wheel had to be measured in order to estimate the wheel slippage for each test. A proximity switch linked to the towing trolley sensed the rotation of the roller travelling over the steel rail, which was the actual forward speed measurement mechanism. A MATLAB programme was used to count the number of signal picks from the proximity switch, as well as the time corresponding to the first and last picks. The wheel's actual forward speed was determined as follows.

Actual Speed (Va) = $2 \times \pi \times r \times rps$

Where,

r = radius of roller

rps = $(Np - 1)/t$

t = time interval b/n 1^{st} and last pulse

Np = No. of pulses

Theoretical speed (Vth) = $2 \times \pi \times r \times rps$

Where,

r = radius of rolling wheel

rps = $(Np - 1)/8t$

t = time interval b/n 1^{st} and last pulse

Np = No. of Pulses

$$\text{Slip (\%)} = (1 - \frac{Va}{Vth}) \times 100$$

4.1.5 Measurement of Pull:

Four strain gauges with 120 resistances each were coupled together to form a Wheatstone bridge circuit on the 10 KN capacity ring transducer. Two couplers were installed on both ends of the transducer to connect it to the towing trolley and the drawbar pull loading mechanism. The strain gauge circuit of the transducer was connected to the DAS. The DAS provides a 5-volt DC voltage output to the transducer bridge. The ring transducer's tensile stress was gradually increased/decreased using dead weights and the accompanying output voltage was monitored.

4.1.6 Soil bin

The overall dimensions of the soil bin are 23.5 m 1.37 m 1.50 m and are made of cement concrete and bricks. Two 'C' cross section side rails (125 mm 65 mm 5 mm) were placed 1.37 m apart along the length of the soil bin to facilitate movement of the towing and soil processing trolleys. An electronic platform balance was installed at one end of the soil bin to measure the static weight on the test tyre. Sandy clay loam soil was placed in the soil bin.

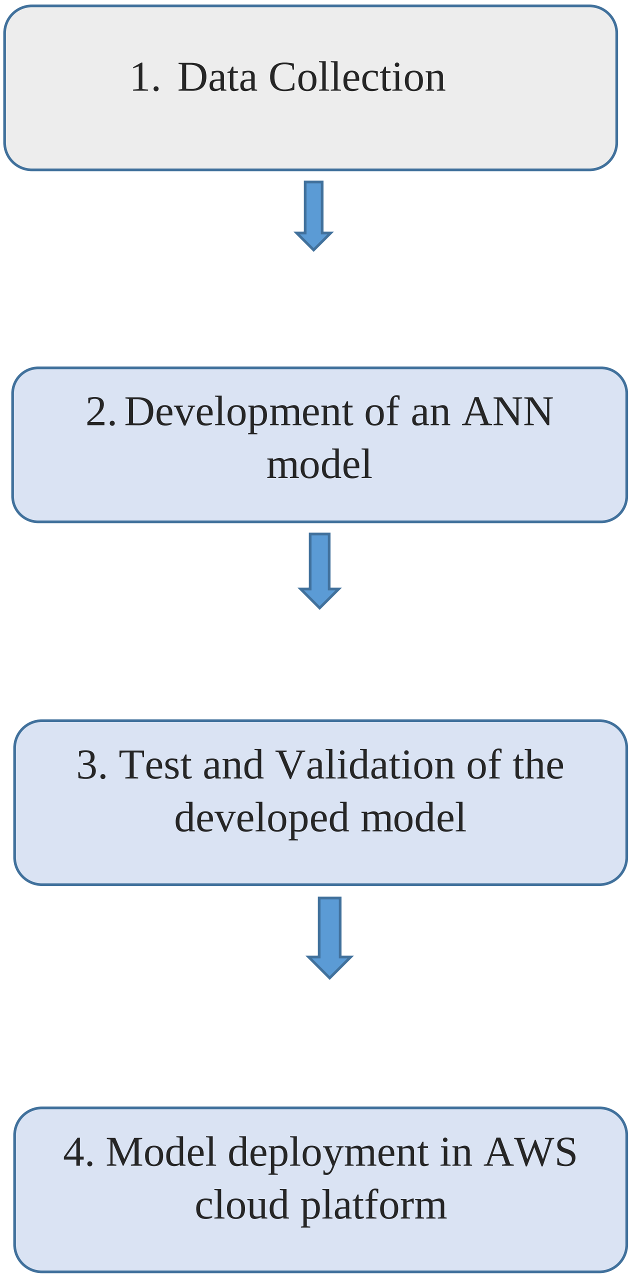
4.2 Test Procedure

Three soil beds were prepared namely Soft bed (450±50kpa), Medium bed (1050±50kpa) and Hard bed (1750±50kpa) from different number of passes of soil processing trolley. Each compaction level was achieved through different amount of hydraulic pressure applied from compaction device. Before carrying out the test, cone index of each bed were checked, if it was under the range then the powered wheel was allowed to pass on the prepared bed and cone index after was measured. So, soil compaction can be found out by

$$\frac{Cone\ index\ after - Cone\ index\ before}{cone\ index\ before} \times 100$$

Data obtained were tabulated in excel and graph was drawn b/n Cone Index after and Pull and results were noted. Average increase in Cone Index were also calculated in each soil bed graphs were drawn. Then an ANN model was developed keeping Pull, Inflation Pressure, Cone Index Before, Soil Condition, Tyre Size, Wheel load as the input parameter and Cone Index after as the output parameter.

4.3 Research Plan



4.3.1 Data Collection

Independent Parameters:	
Pull (N)	
Inflation Pressure (psi)	12 psi, 15 psi, 18 psi, 20 psi
Wheel Load (kg)	1000 kg, 1400 kg
Soil Condition	Soft Soil, Medium Soil, Hard Soil
Cone Index Before (kpa)	Soft – 450±50, Medium - 1050±50, Hard - 1750±50
Tyre Size (section width – rim dia)	12.4-28, 13.6-28, 14.9-28, 16.9-28
Dependent Parameter:	
Cone Index After (kpa)	

4.3.2 Development of an ANN Model

Feedforward and Multilayer backpropagation neural networks model was employed in this research to predict soil compaction from Agricultural tyres. Keras library was used in tensorflow environment, keras.Sequential was used to define the model, reLU and linear activation functions were used and in optimisers, Adam was used. Then the network was trained with 80% of the data and for testing and validation 20% of the data were kept.

Since there is no standard technique for determining the number of hidden layers or the number of neurons in each hidden layer, the number of neurons in each hidden layer was determined through trial and error. The number of hidden layers and neurons in the hidden layer were decided in this study by comparing the network's performance. In addition, among the layers, reLU and linear activation functions were used. On the scale of Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2), Root mean square error (RMSE), the best results were obtained after 500 epochs. The programming was done in Python 3 and Jupiter notebook was used to develop the model.

4.3.3 Selection of input and output variables

In order to better implement ANN structures, the input variables must be chosen in such a way that the input parameters impact the output parameter. This highly depends on the better understanding of the problem. In development of ANN architecture, in order to prevent confusing training process key variables must be introduced and unnecessary variables must be avoided. Statistical analysis was used to select input parameters in relation to output parameters.

For this statistical analysis, scatter plot was drawn to check whether input data is having linear or non-linear relation with the output data. Heatmap was also plotted to know the dependence of output variable with input variable. Input parameters to the model were Pull, Inflation Pressure, Soil Condition, Wheel Load, Cone Index Before passing the tyre, Tyre Size and Output parameter to this model will be Cone Index After passing the tyre.

4.3.4 ANN Formulation

The selection of an ANN architecture and the selection of a training algorithm are two steps in the development of an ANN. An ideal architecture is one that provides the minimum error between the actual and predicted values and maintain a simple and compact structure. The number of hidden layers and the number of nodes assigned to each of these layers, as well as the number of iterations, determines the performance of the model. Best artificial neural network design was determined using a trial-and-error method (Farhadi, 2019).

Without any explicit mathematical equation connecting inputs and outputs, feedforward neural networks can be employed. Also, any continuous function may be approximated using a feedforward network with a hidden layer or layers without taking into account the number of sigmoidal hidden nodes. ANNs have a great ability for creating relationships between inputs and outputs.

The number of hidden layer nodes has a significant impact on a network's performance. The ANN performance can be affected by both too few and too many neurons in the hidden layer. Under fitting occurs when there are too few neurons in the hidden layer, whereas overfitting occurs when there are too many neurons in the hidden layer. As a result, the optimal number of neurons in the hidden layer must be chosen. The flowchart for development of ANN models is shown in Fig. 4.5.

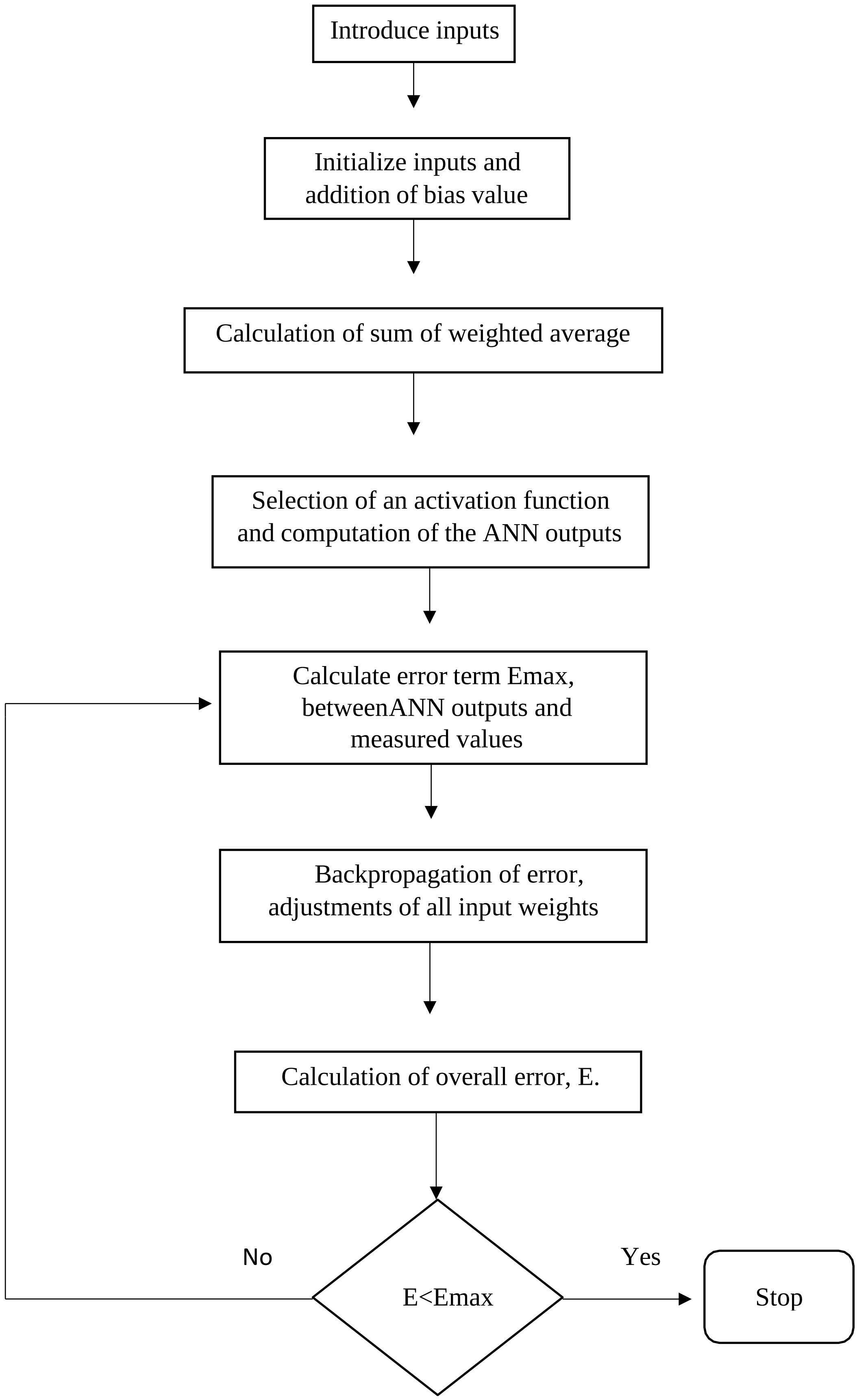


Fig. 4.5 Flowchart for the development of an ANN model.

4.3.5 Model Validation

Model validation is used to test the predictability behavior of the developed model for unseen data. In some cases, this model validation will include confirming that whether the developed model is predicting the values which is close to training dataset or not. For validation of this developed model, experimental datasets were collected from the laboratory, those datasets were also used for prediction. The model's simulated data is compared to real-world data points. Validation plots like correlation plots or residual plots can also be used to compare two sets of data. For goodness of fit, the results are submitted to qualitative and quantitative examination.

The data preprocessing methods were applied to the dataset to obtain better results. The model were evaluated by metrics like R^2, MSE and MAE and RMSE.

CHAPTER 5
RESULTS AND DISCUSSION

This chapter deals with the results obtained while implementing the developed ANN model for predicting the Soil Compaction after passing the 13.6-28 tractor tyre. A detailed description of the obtained results has been discussed in this chapter under the following main headings.

5.1. Training of Soil Compaction Prediction model

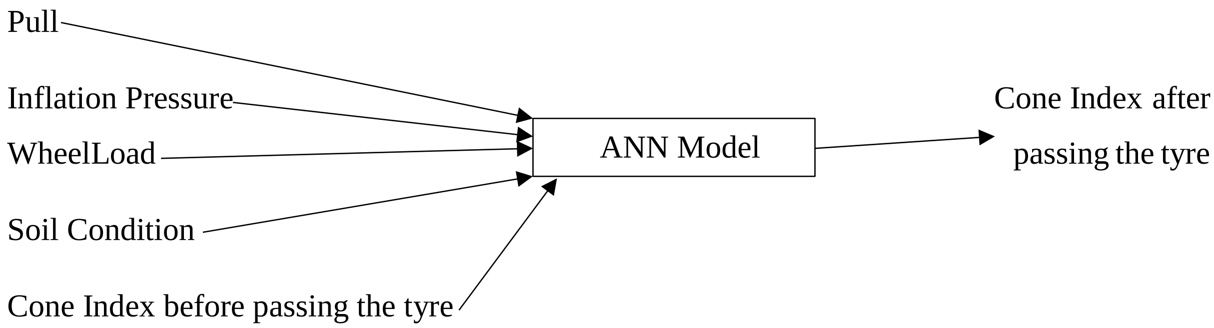


Fig.5.1. Basic Structure of ANN model to predict Soil Compaction.

Gradient Descent model was developed to achieve the objective of this study for the prediction of Soil Compaction. Out of all 220 sets of data, 176 sets were used for training and 44 sets were used for testing the developed model. Descriptions of the developed Gradient Descent model are presented in table 5.1.

Table 5.1. Description of the model

Name of the Model	**Input Parameters**	**Output Parameter**
Soil Compaction Prediction Model	Pull (N), Inflation Pressure (Psi), Soil Condition, Wheel Load (kg), Cone Index before passing the tyre (kpa).	Cone Index after passing the tyre (kpa).

The metrics used for evaluating the developed model were Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MSE) and Mean Square Error (MSE).

1) Mean Absolute Error (MAE) = $\frac{1}{N}\sum_{i=1}^{N}|Yi - Yi'|$

2) Mean Squared Error (MSE) = $\frac{1}{N}\sum_{i=1}^{N}(Yi - Yi')2$

3) Root Mean Squared Error (RMSE) = $\sqrt{MSE}$ = $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Yi - Yi')2}$

4) Coefficient of Determination = R^2 = 1 - $\frac{\sum(Yi - Yi')2}{\sum(Yi - Y'')}$

Where,

Y_i = Actual Data

Y_i' = Predicted Data

Y_i'' = Mean Value

5.2. Statistical analysis for selecting input parameters to predict the output

Statistical analysis was done to select the input parameters before feeding into the model for predicting soil compaction from 13.6-28 bias ply tyre. For statistical analysis Pull, Inflation Pressure, Soil Condition, Wheel Load, Cone Index before passing the tyre were selected as input variables and cone index after as output variable. In Fig. 5.2. Scattered graph was plotted to check the linearand non-linear relationship of input parameters with the output parameter. Before generalization of the ANN model for predicting soil compaction from the different size tyres, experimental data for 13.6-28 bias ply tyre were considered for training, testing and validation for ANN model development. Statistical parameters such as mean, max,min and standard deviation are shown for the input data in Table 5.2. It helps to check the data consistency, missing data and to find the outliers present in the data. Data inconsistency, missing data, outliers and noisy data affects the prediction ability of the developed model. The correlation of the selected input parameters with the output parameter has been shown in Fig.5.3. Correlation matrix helps to select the important input parameters for model training to ensure the developed model has accurate prediction ability. Pull, Inflation Pressure, Wheel Load, Soil Condition, Cone Index before passing the tyre were selected as input parameters and cone index after as an output parameter for ANNmodel development for 13.6-28 bias ply tyre. The schematic structure of developed ANN model has shown in Fig. 5.4

Fig. 5.2. Scatter plot showing the linear and non-linear relationship between input and output parameters

Table 5.2. Statistical analysis of the input data for ANN model development

	Pull	Inflation Pressure	CIbefore	Soil_Condition	Wheel Load	CIafter
Count	220.0	220.0	220.0	220.0	220.0	220.0
Mean	3099.94	16.023	852.38	0.66	1038.18	1590.17
Std	1600.26	3.433	438.99	0.667	117.804	273.57
Min	470.0	12.00	345.0	0.00	1000.00	1009.41
25%	1746.05	12.00	447.25	0.00	1000.00	1400.14
50%	3311.42	18.00	952.50	1.00	1000.00	1564.46
75%	4247.50	20.00	1075.64	1.00	1000.00	1761.95
Max	6950.33	20.00	2013.70	2.00	1400.00	2406.98

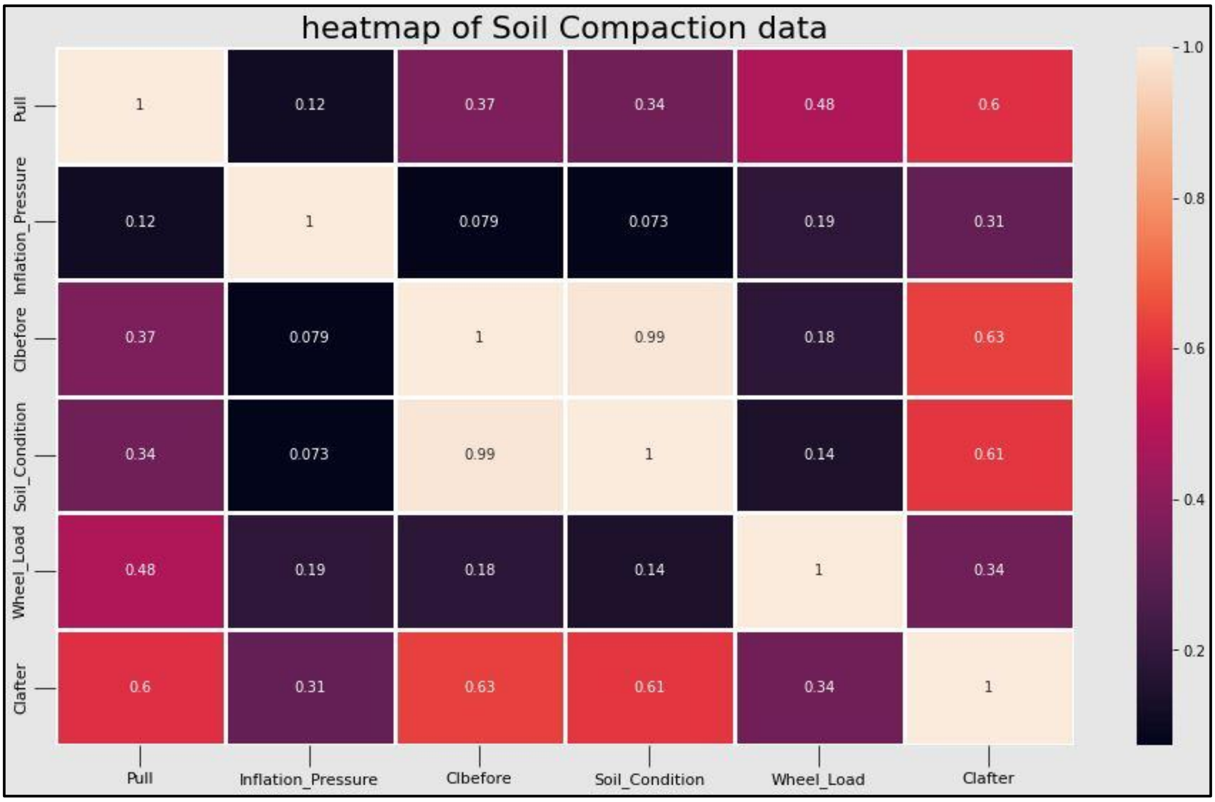


Fig. 5.3. Heatmap showing the relationship between Input and Output parameters.

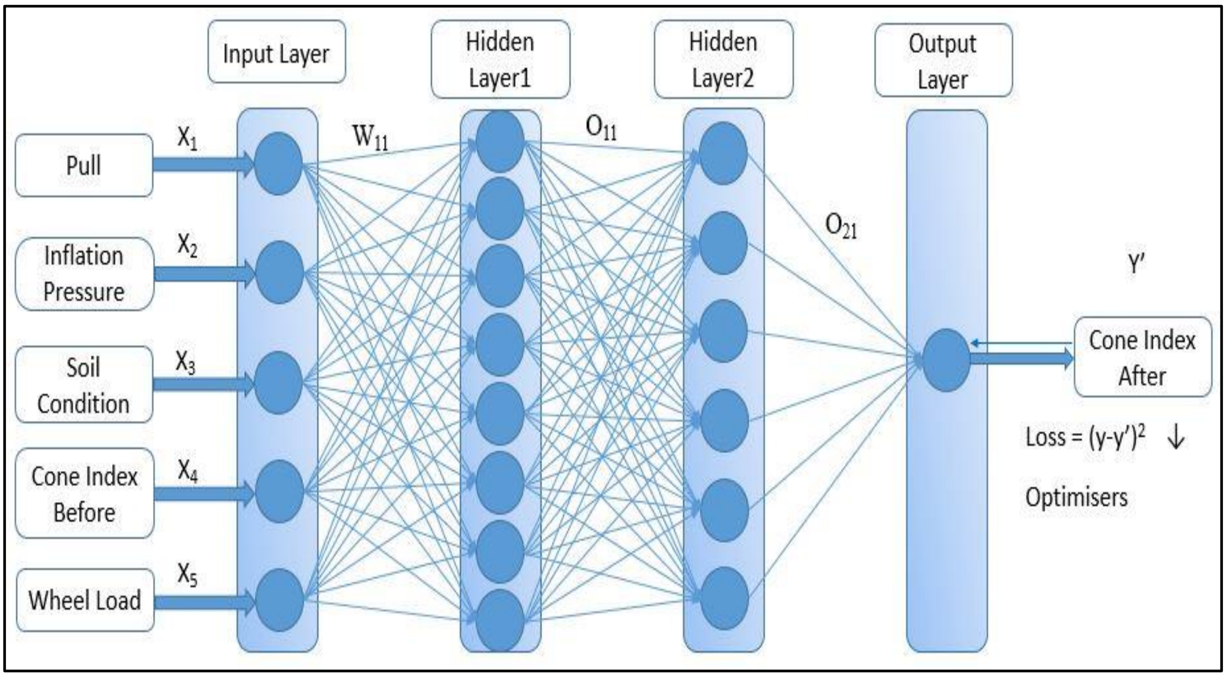


Fig.5.4. Schematic architecture of developed ANN model

5.3 Prediction of Soil Compaction using Adam Optimiser

To achieve the objective of this study, ANN model was developed in order to predict the Soil Compaction after passing the 13.6-28 bias ply tyre. The current study employed a total of 220 experimental data sets. Out of them, 176 data sets were utilized to train the model and 44 data sets for testing the model. Descriptions of the model developed are given in the following section. The developed model was evaluated in terms of MSE, MAE, RMSE and R^2.

5.4 Architecture of developed artificial neural network with the Adam optimizer.

Inputs to the model were Pull, Soil Condition, Cone Index before passing the tyre, Wheel Load, Inflation Pressure and Cone index after passing the tyre was the output with the 5-8-6-1 artificial neural network structure. To develop this soil compaction prediction model Adam optimizer was used (training algorithm) with the two hidden layers, 8 neurons in the first and 6 neurons in the second hidden layer respectively. In the first hidden layer rectilinear unit activation function was used to activate the input values from the input layer to the hidden layers, while in the second hidden layer linear activation function was used to activate the input values from the hidden layer to the output layer. Weights value was multiplied with input value and then bias values was added to transfer the input value information to the hiddenlayer through neurons. Weights and bias values taken by the model while training the model are based on the input value. Actual Cone Index after and predicted Cone Index after values on the test dataset are shown in Fig. 5.5. To train the model learning rate was taken as 0.001, learning rate plays a major role in training the model to converge the error of measured and predicted TE (%) values and also to train the model in effective time. After training the model, it was evaluated after performing 500 epochs. Firstly, while training the model forward propagation was done after calculating the error between the actual and predicted values, the developed model was validated with the experimental datasets. The actual and predicted cone index values for validation datasets are shown in table 5.3.Based on the observed error values, updation of the input weights in the backpropagation took place and MSE and MAE values got reduced.

Table 5.3. Actual and predicted cone index after passing the tyre values of 13.6-28 Bias-ply tyre.

Predicted values of Cone Index after passing the tyre	Actual values of Cone Index after passing the tyre	Error
0.4691	0.4609	0.0082
0.4609	0.3851	0.0742
0.5081	0.5441	0.0360
0.4602	0.5621	0.1019
0.4060	0.1694	0.2366
0.4459	0.2380	0.2079
0.4192	0.5405	0.1213
0.4698	0.3011	0.1687
0.4560	0.5013	0.0453
0.5389	0.5960	0.0571
0.4726	0.2380	0.2346
0.4514	0.0970	0.3544

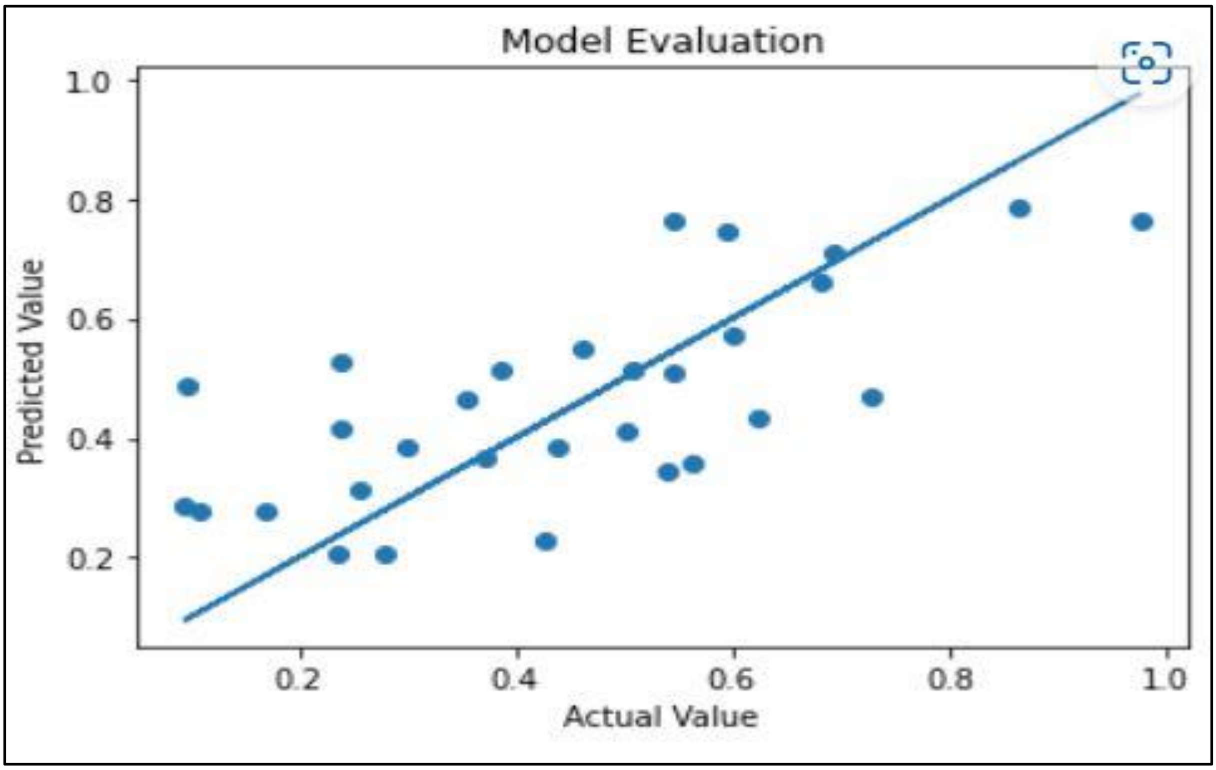


Fig 5.5. Graph showing the Actual and Predicted values (R^2 = 0.955)

Table 5.4 shows the evaluated results performed on the test and train dataset in terms of R^2, Mean Square Error, Mean Absolute Error and Root Mean Square Error using Gradient Descent Algorithm in ANN. Values of R^2 were 0.97 for training dataset while 0.95 for test dataset. Values of Mean Square Error for the train dataset and test dataset were 0.295 and 0.394 respectively. Values of Mean Absolute Error for the train dataset and test dataset were 0.462 and 0.519 respectively. Values of Root Mean Square Error for the train and test dataset were 0.588 and 0.628 respectively.

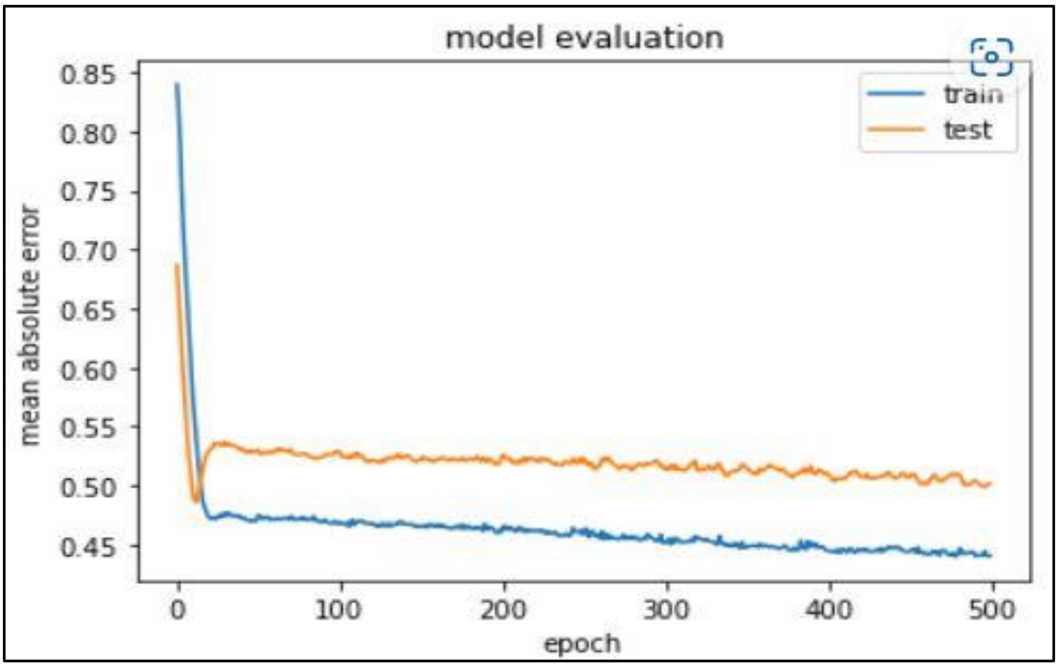
Table 5.4. Values of Coefficient of Determination (R^2), Mean Square Error, Mean Absolute Error, and Root Mean Square Error for Prediction of Soil Compaction using Gradient Descent Algorithm in ANN.

S.No.	R^2		Mean Square Error		Mean Absolute Error		Root Mean Square Error	
	Training Data	Testing Data	Training Data	Testing Data	Training Data	Testing Data	Training Data	Testing Data
1.	0.97	0.95	0.295	0.394	0.462	0.519	0.588	0.628

5.5 Model Validation

In order to validate the model, Graphs were plotted b/n Mean Square Error and Mean Absolute Error with the number of Epochs.

The below figure shows that the mean square error and mean absolute error values are decreasing i.e. approaching 0, with the increase in the number of Epochs, and also testing values are coming closer to training values as the number of epochs are increasing.



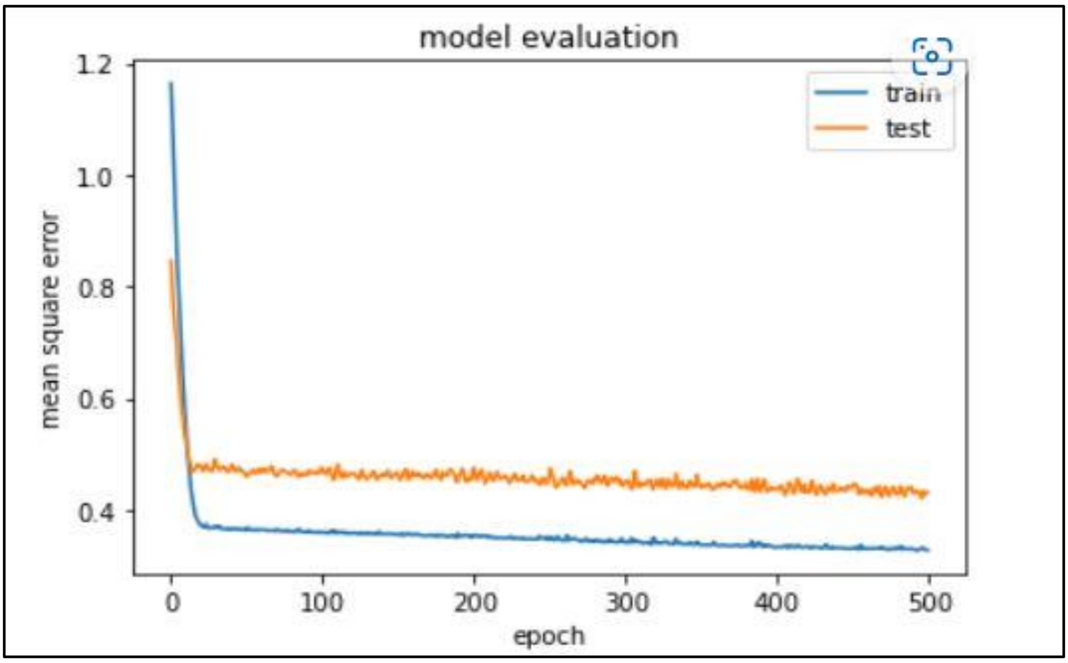


Fig. 5.6 & 5.7. With the increase in the number of epochs, MAE & MSE values are decreasing and the margin b/n train and test values are also decreasing and they are approaching towards 0.

Model 1. **Gradient Descent** method of training the model

Input layer: The network of the model has four input parameters i.e., Pull (N), Inflation Pressure (psi), Soil Conditions, Wheel Load and Cone Index before passing the tyre. The network was trained with different combinations of Pull, Inflation Pressure, Soil Condition, Cone index before and Wheel Load.

Hidden layer1: This model was trained with 8 number of neurons. To determine the number of hidden layers and the number of neurons in each hidden layer, hyper-optimization techniques were used.

Hidden layer2: This model was trained with 6 number of neurons and to determine the number of hidden layers and the number of neurons in each hidden layer, hyper-optimization techniques were used.

Activation Functions: ReLU and Linear activation functions were used in each hidden layer respectively.

Optimisers: Adam Optimiser is used to compile the model and to obtain the desired result. The number of iterations performed on the model were 500.

Output layer: Cone Index after passing the tyre was kept in the output layer. The model was successfully predicting the Cone Index after with the desired accuracy.

Learning rate: The network was trained with the different learning rate. It was found that there was little effect on changing of these values. However, learning rate should be taken small. Therefore, learning rate was taken as 0.001.

5.6. Details of the Developed Model:

Model: 1

Network type	: Feedforward and Backpropagation
Total number of Layers	: 4
Hidden Layers	: 2
Number of nodes in the input Layer	: 5
Number of neurons in the first hidden Layer	: 8
Number of neurons in the second hidden Layer	: 6
Number of nodes in the output Layer	: 1
Activation function	: ReLU, Linear
Optimizers	: Adam
Learning Rate	: 0.001
Learning Rule	: Gradient descent
Number of iterations performed (epochs)	: 500

CHAPTER 6

WORK PLAN

Phase - I

6.1 Review of Literature	Completed
6.2 Data Collection	Completed
6.3 ANN Model Development	Completed
6.4 Test and Validation of the Developed Model	Completed

Phase - II

6.5 Addition of more input parameters in the Developed ANN Model	To be Completed
6.6 Test and Validation of newly Developed Model	To be Completed
6.7 Model Deployment in AWS Cloud Platform	To be Completed
6.8 Formulation of Empirical Equation b/n Input and Output Parameters	To be Completed

CHAPTER 7

CONCLUSIONS

- The Developed Model is predicting High-Accuracy Results as it has predicted the Cone Index after the Testing Set with an R^2, MSE, RMSE, and MAE values as 0.955, 0.394, 0.628, and 0.519 respectively.
- In General ReLU and Linear are the most consistent Activation functions that provide good Predictions. The In case of Optimisers, Adam is the best in terms of Efficiency and Accuracy.
- Two hidden layers with eight and six neurons respectively is capable of predicting the Soil Compaction accurately. The performance of the ANN gets worse with the increase in the number of neurons per hidden layer.
- Results of this model have shown that deep ANN is a useful technique for the prediction of the Soil Compaction parameters as the best predictions can be achieved using multiple hidden layers.

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APPENDIX-A

Importing the python Libraries

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

%matplotlib inline
```

Importing the dataset from the file location

```
data = pd.read_excel('D:\\M.Tech Project\\13.6-28.xlsx')

data.head()
```

Replacing the categorical values in Soil Condition column to numerical values

```
data['Soil_Condition'].replace({'Soft Soil':0,'Medium Soil':1},inplace = True)

col_to_scale = ['Pull','Inflation_Pressure','CIbefore','CIafter']
```

Data Standardization

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

data[col_to_scale]=scaler.fit_transform(data[col_to_scale])

data
```

Dividing the whole dataset in to x and y dataset

```
x = data.iloc[:,0:4]

y = data.iloc[:,4]
```

Dividing the whole dataset in to train and test dataset

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2, random_state = 15)
```

```
x_train.shape

x_test.shape

from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

from math import sqrt

import tensorflow as tf

from tensorflow import keras
```

Model Development

```
model = keras.Sequential([

    keras.layers.Dense(8, input_shape=(5,), activation = 'relu'),

    keras.layers.Dense(6,activation = 'linear'),

    keras.layers.Dense(1,activation = 'linear'),

])

model.compile(optimizer = 'adam',

              loss = 'mse',

              metrics = ['mae','mse'])

model.fit(x_train,y_train)

model.evaluate(x_test,y_test)

predictions = model.predict(x_test)

root_mean_squared_error = sqrt(mean_squared_error(y_test,predictions))

root_mean_squared_error

r2_score(y_test,predictions)

model_history = model.fit(x_train,y_train,validation_split = 0.2,epochs=100)

print(model_history.history.keys())
```

Summarizing history for evaluation

```
plt.plot(model_history.history['mae'])

plt.plot(model_history.history['val_mae'])

plt.title('model evaluation')

plt.ylabel('mean absolute error')

plt.xlabel('epoch')

plt.legend(['train','test'],loc = 'best')

plt.show()
```

Summarizing history for accuracy

```
plt.plot(model_history.history['mse'])
plt.plot(model_history.history['val_mse'])
plt.title('model evaluation')
plt.ylabel('mean square error')
plt.xlabel('epoch')
plt.legend(['train','test'],loc = 'best')
plt.show()
```