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Prediction of Tractor Power Take-Off Performance using Artificial Neural Network

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ABSTRACT

Prediction of tractor PTO performance can lead to simulation and optimization of tractor performance, allowing optimum setting of different parameters as well as enhancing decision-making of manufacturer in the design of new tractor. Twenty different parameters were selected as input for PTO performance prediction. The data used as input to train the network were collected from 141 tractor test reports tested between 1997-2013 at Central Farm Machinery Training and Testing Institute, Budni. A Back propagation artificial neural network (ANN) was developed using Neural Network Toolbox in Matlab software. A Matrix of 1704×20 and 1704×1 was used as input for PTO prediction in ANN. The optimum structure of neural network was determined by a trial and error method and 30 different structures were tried. For prediction ANN model with 2 hidden layers having 40 and 35 neurons in first and second layer, respectively gave highest performance. Regression coefficient and MSE for this model was 0.996 and 1.080.

Key Words: Artificial neural network, Performance, Power, Prediction, Tractor, Transmission.

INTRODUCTION

Agricultural mechanization has been accepted as the essential input for increasing agricultural productivity and advancing industrialization of the rural sector (Almaliki *et al*, 2016). Farm machines have played a paramount role in increasing the agriculture production and have grown into an ample industry in India. The application of tractor for agricultural activities which swept India during the last twenty years has eased the problem of farmers in almost all the field operations. The key purpose of tractors is to be interfaced with suitable implements that provide power, tractive effort to move the implements through the field and control its implements. It is necessary that one must have the proper understanding of how the tractor power can be used, and tractor-implement systems can be optimized. The correct field machines operation is crucial for any system to be reasonably profitable. Thus, efficient operation of farm tractors includes: (a) maximizing fuel efficiency of the engine and mechanical efficiency of the drive train, (b) maximizing attractive advantage of traction devices and (c) selecting an optimum travel speed for a given tractor-implement system (Grisso *et al,* 2008). Therefore, prediction model for tractor performance is vital for farm machinery operators and manufacturers alike.

The modeling techniques used in mechanization processes are quite important to provide an accurate and workable use of power resources. Among many others, one of the most prevalent techniques for modelling and forecasting behavior of nonlinear systems is soft computing. It is a technology is an interdisciplinary research field of computational science. At present, various techniques are being used in soft computing such as statistics, machine learning (ML), neural network (NN) and fuzzy

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logic for exploratory data analysis (Carman, 2008). In recent years, the methods of artificial intelligence (AI) have extensively been used in different areas including agricultural applications (Safa *et al,* 2009; Douik and Abdellaoui, 2008; Kashaninejad *et al,* 2009). The application of soft computing to AI is studied collectively by the emerging discipline of computational intelligence (CI) for example, artificial neural networks (ANN). Artificial Neural Networks (ANN) is becoming a common tool for modeling complex input- output dependencies (Samarasinghe, 2007). The plus point of using neural networks is that it can be able to use some prior unknown information hidden in the data (but they are not able to extract it explicitly). The ANN mimics the learning process of a human brain. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. In addition, inherently noisy data do not seem to create a problem, as ANN's are tolerant to noise variations.

Already numerous researchers focused on AI for modeling of different component of agricultural systems (Cakmak and Yıldız, 2011; Zarifneshat *et al,* 2012; Çay *et al,* 2013; Aghbashlo *et al,* 2012; Khoshnevisan *et al,* 2013; Young *et al,* 2013; Safa and Samarasinghe, 2013). Aghbashlo *et al* (2012) developed a supervised ANN and mathematical models for determining the exegetics performance of a spray drying process. Cakmak and Yıldız (2011) used ANN to determine the drying rate of seedy grapes. Input parameters used for the ANN model were the moisture content, the hot air temperature and the hot airflow rate. The structure of the ANN model with one hidden layer was determined considering different neuron numbers at the hidden layer. Based on error analysis results, they concluded Levenberge-Marquardt optimization technique was the most appropriate method for prediction capability of transient drying rates. Developments of prediction equations for tire tractive performance have been the focus of much research. Artificial Neural Networks (ANNs) have been accepted as a potentially useful tool for modeling complex non-linear systems and widely used for prediction (Nayak *et al*, 2004). Many researchers have reported the proper ability of ANN versus regression method such as study done by Rahimi and Abbaspour (2011). Roul *et al* (2009) successfully applied ANN representation predicting the draught requirement of tillage implements under varying operating and soil conditions. A neural network is adjusted for a definite task such as model distinguishing and data classification during a training process. Extensive aptitude of this approach for accurate estimations of complicated regressions contributes more advantage compared to classical statistical techniques. ANN was applied to predict the traction performance parameters (Taghavifar and Mardani, 2013), prediction of tractor noise level (Emam, 2012), prediction of combine harvester performance (Gundoshmian *et al*, 2010), prediction of tractor fuel consumption (Ajdadi and Gilandeh, 2011), predicting tire tractive performance (Çarman and Taner, 2012). However, so far, the studies related to prediction of tractor PTO performance using ANN have not been carried out. Such a model would specifically aid simulation and optimization of tractor performance, allowing optimum setting of different parameters as well as enhancing decision-making of manufacturers for improvement in tractor performance.

MATERIALS AND METHODS

Data Collection

Data required to train the ANN was taken from 141 tractor test reports for tractors tested between 1997 and 2013 at the Central Farm Machinery Training and Testing Institute (CFMT&T), Budni (MP). CFMT&T conducts tractor testing according to the codes of Organization for Economic Co-operation and Development (OECD) and Bureau of Indian Standards (BIS). The size of the data sample were important because an ANN cannot create the accurate relationship without enough example's

Table 1. Selected input parameters.

Sr. No.	Variable	Sr. No.	Variable
1.	Number of cylinders	11.	Engine to PTO speed ratio
2.	Stroke	12.	PTO speed*
3.	Bore	13.	Engine speed*
4.	Capacity	14.	Fuel consumption*
5.	Compression ratio	15.	Specific fuel consumption*
6.	Rated speed	16.	Specific energy*
7.	Number of friction plate	17.	No load maximum engine speed*
8.	Size of friction plate	18.	Equivalent crankshaft torque at maximum power*
9.	Reduction through final drive	19.	Maximum equivalent crankshaft torque*
10.	PTO to rpm speed ratio	20.	Engine speed at maximum equivalent crankshaft torque*

** Under natural and high ambient condition*

datasets. The selection of tractors for data collection was such that it covered wide power range (18.6 kW to 44.7 kW) from 16 major tractor manufacturers *viz.,* Ace, Deutz-Fahr, Eicher, Escort, Farmtrac, FNH, Force motors, HMT, Indofarm, John Deere, Mahindra, Powertrac, Preet, Same, Sonalika, Swaraj, Standard and TAFE.

Selection of input parameters

Performance of tractor PTO power is important component of tractor performance and predicting the power-take off performance of tractor would specifically aid simulation and optimization of tractor performance, allowing optimum setting of different parameters as well as enhancing decision-making for manufacturers for improvement in tractor performance. PTO power of tractor depends on many factors which makes it more complex to predict the PTO power considering the entire factor affecting it.

The selection of input variables was very critical in order to find the optimal function in ANNs. Keeping in mind the parameters measured during the PTO testing and also those used in previous studies, 20 important parameters affecting the performance for tractor PTO power were selected, under natural and high ambient conditions (Table 1).

The output parameter of the ANN model was tractor PTO power.

Artificial neural network model

Modelling of an ANN was based on the principles of the error back-propagation algorithm. The error back-propagation algorithm showed learning rule that consisted the adjustment of the network weights and polarizations, based on the error found in the output. Accuracy was achieved through the continuous update of the weights and polarizations in each interaction in the opposite direction of the function gradient at the current point *i.e.,* proportionally to the negative of the derivative of the square error in relation to the current weights. Therefore, it is a deterministic supervised training algorithm, which implemented the method of the descending gradient in the sum of the square errors. In order to find out an optimal configuration of neural network model, it is necessary to test many different ANN prototypes/models. Determination of the best number of neurons in the hidden layers is a substantial step in the multilayer neural network. Increased number of hidden layers decreases the modelling error. In order to find the best model which can predict well, 30 ANN configurations with different numbers of hidden layers (one or two hidden layer) and different numbers of neurons for each of the hidden layers were used. Back propagation algorithm with Levenberg–Marquardt training algorithm was chosen to build the prediction models. Tangent sigmoid and linear transfer function was used in hidden layer and output layer, respectively. In order to determine the number of optimal neurons in hidden layers, neurons increased to assess the variation of model performance. Initially adopted weights and biases of neurons in ANN were randomly chosen.

All the parameters that are measured during the tractor testing and specified in testing reports related to power-takeoff shaft are selected as input. The input variables were selected are number of cylinder, stroke, bore, capacity, compression ratio, rated speed, number of friction, size of friction plate, reduction through final drive, PTO to rpm speed ratio, engine to PTO speed ratio, PTO speed, engine speed, fuel consumption, specific fuel consumption, specific energy, no load maximum engine speed, equivalent crankshaft torque at maximum power, maximum equivalent crankshaft torque and engine speed at maximum equivalent crankshaft torque PTO power as output parameter required for training the network is tabulated from 141 tractors test reports of different tractors thus making a matrix of input and output dataset. For training of network, the input matrix 20×1704 and output matrix 1×1704 was fed to network.

Training of ANN

One of the key difficulties in the training of multilayer neural networks with error back-propagation training algorithm was the definition of the parameters. Selecting the training parameters of the algorithm was a process that demanded great effort, since small alterations in these parameters led to huge differences in both training time and the obtained generalization.

Preliminary trials indicated that two hidden layer networks yielded better result than one hidden layer network. For simple nonlinear problems, one hidden layer of neuron may be sufficient. However, for highly nonlinear problems involving many input variables, a large number of neurons may be necessary to correctly approximate the desired input-output relationship. Selecting number of neurons is an art more than science. When the number of hidden neurons is less than required, errors increase and correlation between inputs and outputs become weak; and when the number of hidden neurons is more than required, problem of over learning sets in (Kermanshahi and Iwamiya, 2001). In training function, *trainlm* was practiced that updates weight and bias values according to the Levenberg Marquardt optimization, and is typically considered as the fastest back-propagation algorithm which is highly recommended as a first-choice supervised algorithm (Taghavifar, 2015). Performance of network with Levenberg Marquardt (LM) training algorithm is best considering the criteria's as coefficient of determination and mean square error. Moreover, tan-sigmoid activation functions ('*transig'*) for hidden layers and the linear activation functions ('*purelin'*) for the output layer were most suitable after initial trails. The parameter learning rate showed great influence during the process of neural network training. A very low learning rate made the process very slow, while a very high learning rate caused oscillations in the training, which prevented the convergence of the learning process. In general, its value varies from 0.1 to 1.0; however, for the training of this neural network, a pre-fixed value of 0.1 was adopted as higher values did not allow the convergence of the process on the MSE surface. The input data of 20 parameters was tabulated, making a matrix of 1704×20 for input and 1704×1 for output. This data were divided into three distinct training, testing and validation sets. The training set was the largest

Table 2. Neural network performance for different neurons arrangements in different hidden layers for prediction of tractor PTO performance.

Model number	NH_1	NH_2	MSE			R^2			
			Trg.	Validation	Testing	Trg.	Validation	Testing	All
1	15	0	0.610	12.164	95.987	0.997	0.942	0.736	0.928
2	20	0	10.613	11.308	12.811	0.997	0.994	0.986	0.981
3	25	0	3.561	9.880	8.733	0.983	0.955	0.956	0.974
4	30	0	0.273	0.115	104.738	0.998	0.995	0.714	0.931
5	35	0	14.370	35.948	20.970	0.943	0.816	0.887	0.909
6	40	0	1.336	2.383	9.171	0.933	0.907	0.959	0.987
7	45	0	9.787	2.878	8.375	0.997	0.993	0.991	0.995
8	50	0	38.573	22.856	5.961	0.871	0.791	0.856	0.834
9	55	0	18.467	27.756	31.960	0.977	0.934	0.899	0.900
10	60	0	50.021	38.978	107.892	0.854	0.871	0.882	0.859
11	65	0	45.827	64.819	67.381	0.901	0.895	0.845	0.827
12	70	0	30.867	50.976	40.789	0.879	0.832	0.814	0.801
13	20	20	38.637	75.967	96.599	0.789	0.818	0.801	0.799
14	25	20	34.320	45.342	117.230	0.864	0.821	0.825	0.824
15	25	25	41.342	55.341	34.123	0.793	0.732	0.746	0.757
16	30	25	28.239	20.238	17.238	0.947	0.923	0.956	0.928
17	30	30	18.239	13.390	451.23	0.878	0.819	0.811	0.799
18	35	30	32.238	5.185	11.239	0.915	0.898	0.899	0.889
19	35	35	4.381	6.231	8.352	0.998	0.961	0.993	0.991
20	**40**	**35**	**0.572**	**1.080**	**1.029**	**0.997**	**0.994**	**0.994**	**0.996**
21	40	40	5.239	4.123	7.349	0.998	0.908	0.771	0.947
22	45	40	15.239	8.675	9.718	0.992	0.965	0.950	0.982
23	45	45	20.349	10.980	9.998	0.922	0.916	0.929	0.923
24	50	45	33.453	45.234	23.234	0.995	0.992	0.996	0.989
25	50	50	12.129	34.123	65.734	0.916	0.937	0.984	0.910
26	55	50	9.978	8.281	37.987	0.878	0.846	0.831	0.825
27	55	55	17.987	19.987	28.412	0.901	0.970	0.929	0.884
28	60	55	10.098	9.870	48.976	0.854	0.745	0.798	0.815
29	60	60	20.976	19.976	80.679	0.950	0.840	0.887	0.894
30	65	60	35.089	7.987	50.981	0.989	0.891	0.919	0.933

** NH_1 and NH_2 was number of neurons in hidden layer 1 and hidden layer 2 respectively* set used by the network to learn patterns present in the data. The testing set was used to evaluate the generalization ability of a supposedly trained network. A final check on the performance of the trained network was made using validation set. The function used to divide data was divider and which divided data into three sets randomly such that 70% of the data were assigned to the training set, 15% to the validation and 15% to the test set. Prior to the utilization of data set for model development, the inputs and target output were normalized or scaled linearly between 0 and 1 in order to increase the accuracy, performance and speed of ANN by using the equation given below.

RESULTS AND DISCUSSION

Performance analysis

In order to find the best model that can predict well, 30 ANN configurations with different numbers of neurons on both hidden layers were developed, trained and generalized (Table 2). Back propagation algorithm with Levenberg–Marquardt training algorithm was chosen to build the prediction models. Tangent sigmoid transfer function was used in the hidden layer, and linear transfer function for the output layer. The results obtained from the 30 ANN models with their characteristics are shown in table 2. Among them, the best model (No. 20) which was composed of an input layer with 20 input variables, two hidden layers with 40 and 35 neurons in each layer, and an output layer with one output variable (20-40-35-1 structure).

During the training process the network weights were adjusted so as to minimize the error between the actual output and the predicted output from the network. The neural network with 35 neurons in each hidden layer outperformed other networks in terms of mean square error and coefficient of determination. The network performed as many validation checks till the MSE value stopped to decrease further. During training, the progress was constantly updated in the training window and the gradient reached its lowest value before completion of all 6 validation checks, thus stopping further training of network.

The network architecture which was selected, contains 2 hidden layers (40 and 35 neurons) with tangent sigmoid transfer function and output layer with linear transfer function. Levenberg–Marquardt training algorithm was used as it is best suited for large amount of data to be analyzed for prediction problems.

Best ANN model was selected based on the coefficient of determination and MSE value. There are four values (training, validation, testing and overall network) of R^2 at different stages which is shown in Fig. 1. All values of R^2 must be close to one for the best fit of predicted and actual outcome. The model number 20 was selected as the best one due to the highest regression coefficient value (R^2 = 0.996) and the lowest values of MSE for all three phases i.e. training (0.572), validation (1.080) and testing (1.029). Figure 2 shows the regression plot shows the correlation between the output's values of the network and the targets values.

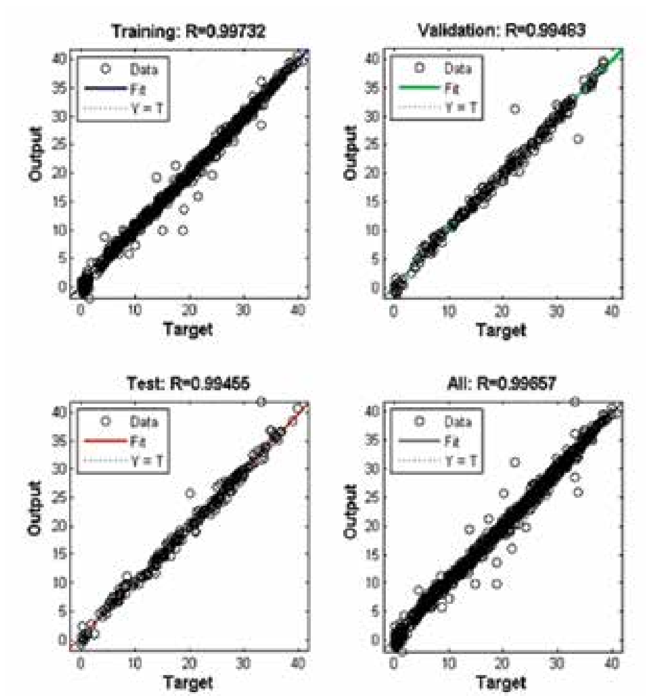

Fig1: Regression analysis of network at training, testing phase and overall performance.

The regression analysis of the network as shown is figure showed regression coefficient of the network at different stages. The four plots represent the training, testing data, validation and final data. The regression coefficient was 0.997, 0.994, 0.994 and 0.996 at training, validation, testing and overall network, respectively.

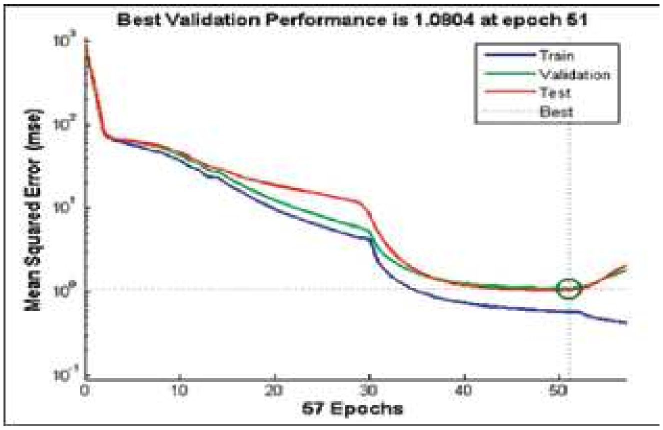

Fig.2: Performance curve of best suited neural network

Figure 2 showed the mean square error graph of all the three stages i.e. training, testing and validation. The training was ended when there was convergence on the MSE surface, in which the value of 1.0804 was achieved. The time taken to complete the training was 51 s. Out of total of 57 epochs, the best result was at 51 epochs, thus ceasing the network to train further.

CONCLUSION

This study represents an effective model for predicting tractor PTO power using artificial neural network models. Back propagation neural networks with 30 different network configurations were developed to select the best model for predicting the PTO power. The ANN with Levenberg–Marquardt training algorithm with two hidden layers having 40 neurons in first and 35 neurons in second hidden layer, presented better accuracy in simulation compared to others. Results showed that the neural network can learn the relationships between the input variables and PTO power very well. There is no previous research related to prediction of PTO power of tractor using 20 input parameters. Finally, it can be claimed that the ANN model can be suggested to predict PTO power of tractor engines because of fast, accurate and reliable results effectively.

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