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Predicting Worsted Spinning Performance with Artificial Neural Network Modeling

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ABSTRACT

For a given fiber spun to a pre-determined yarn specification, the spinning performance of the yarn usually varies from mill to mill. For this reason, it is necessary to develop an empirical model that can encompass all known processing variables that exist in different spinning mills and then to generalize this information and be able to accurately predict yarn quality for an individual mill. This paper reports a method for the prediction of worsted spinning performance through the use of an artificial neural network (ANN) trained with backpropagation. The applicability of artificial neural networks for the prediction of spinning performance is first evaluated against a well established prediction and benchmarking tool (Sirolan Yarnspec™). The ANN is subsequently trained with commercial mill data to assess the feasibility of the method as a mill specific performance prediction tool. The incorporation of mill specific data results in an improved fit to the commercial mill data set, suggesting that the proposed method has the ability to predict the spinning performance of a specific mill accurately.

Introduction

Yarn properties are influenced by fiber properties, yarn specifications and operational parameters. Among the fiber properties in a top, the mean fiber diameter is regarded as the most influential factor for worsted yarns[10]. Other fiber properties including mean fiber length (Hauteur), diameter distribution and fiber strength also play an important role in influencing yarn properties and the spinning performance of that yarn. The distribution of fiber length has been demonstrated to be not as significant as previously anticipated[11]. Linear density and twist are two yarn parameters, which are required to be considered in the prediction of yarn properties and spinning performance[10]. Increasing the twist level results in an increase in yarn strength up to a maximum point beyond which yarn strength reduces[4]. Irregularity in yarn linear density influences yarn strength as it relates to the presence of thin or weak places[12]. Ring size, traveller weight and spinning speed are three operational parameters affecting yarn properties and spinning performance. As a guide, the smaller the ring size, the lighter the traveller, the slower the spinning speed, the lower the yarn tension, and therefore the reduced possibility of spinning end breaks[10].

Each spinning mill may use different raw materials, processing methodologies and equipment, which influence the quality of yarns produced. As there are many independent variables, it becomes difficult to cover the entire range of parameters with the capability of interpolating and extrapolating experimental observations or mill measurements and to take into account the interactive contribution between each independent variable. This poses a difficulty in developing a universal empirical/theoretical model that can accurately predict the yarn properties and spinning performance for different mills.

To determine the likely spinning performance and subsequent yarn properties for a given fiber and processing condition, empirical models and prediction packages have been created. A well known example is the Sirolan Yarnspec™ program developed at CSIRO, which incorporates theory and algorithms derived from fits to experimental data[10]. It predicts worsted spinning performance and resultant yarn properties when a spinning mill operates according to "world best practice", rendering it a very useful benchmarking tool. Difficulties arise when developing an empirical model that allows for dynamic variations found between different mills. Systematic differences between instruments, test speeds[11], and assumptions such as "optimal drafting settings" accumulate to deteriorate the accuracy of the empirical model. These conditions however can be utilized in the development of a mill specific model. In addition to the dynamic differences found between different mills, the continuous improvement in materials and processes can make an empirical model obsolete. It is necessary that a mill specific model is developed that can dynamically evolve with time by taking into account changes in both materials and processes. This requirement is perfectly illustrated with the continual improvement achieved in yarn evenness CV_m% from 1957 to 2001(Figure 1).

FIGURE 1. Improvement in yarn evenness (CV_m%) from 1957 to 2001 according to the 50% line of the Uster® Statistics[21].

Artificial neural networks (ANN) have been used in many engineering fields, to predict material properties. Within the textile industry alone numerous applications have been reported. For example, Ethridge and Zhu [3] applied ANN to predict the quality of rotor spun cotton yarns and compared the prediction with the traditional regression algorithms. They found that the neural networks provide a worthwhile alternative to regression techniques whenever the fiber/textile structural relationships contain significant non-linearities. Sette *et al.*[16] employed a feed-forward neural network with the backpropagation learning rule to model yarn strength and yarn elongation using machine settings and fiber qualities as inputs. Jackowska-Strumillo *et al.*[8] investigated the modeling of average force and coefficient of mass variation of cotton yarn in relation to yarn linear density and the rotational speed of the rotor through the application of hybrid neural networks.

Unlike conventional techniques which are often limited by strict assumptions of normality, linearity, and variable independence ANN's are universal approximators[2,6], which, by possessing the capacity to learn directly from the data being modeled, are able to find associations or discover regularities within a set of patterns, where the volume or variation within the data is large, or the relationships between variables are dynamic and non-linear.

Several yarn parameters are able to be predicated to a high degree of accuracy through existing linear models, for example, the theory developed by Martindale[13] and WIRA[20] to predict the number of fibers in a yarn cross-section and, the limiting irregularity for an ideal yarn with fiber variability. Modeling of these parameters through a ANN can be accomplished with a perceptron, comprising simply of an input and output layer possessing a nonlinear transfer function. On the other hand improved prediction capabilities for ends down, a multivariable parameter dependent on the interactions between yarn strength, yarn irregularity and tensions imposed by the spinning speed, traveller weight and ring size[7], may be achieved with the use of a multi layer perceptron (MLP) with the ability to solve non-linear, non deterministic relationships.

In this paper, we report on the validity of artificial neural networks as a tool for the mill specific prediction of worsted spinning performance.

DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK MODEL

We trained the models using backpropagation learning algorithm[5]. Top properties, yarn specifications and processing information were designated as the input vectors X for the input layer and can be expressed in the vector form as $X= (x_1, x_2 \ldots x_n)$. Predicted performance parameters (network outputs) are denoted Y. As shown in equation 1, the *ith* component of the input signal x_i comes out from the unit i and is transferred to the unit j of the model through the synapse weight W_{ji}. Where b_j is the bias term connected to the *jth* unit;

$$u_j = \left(\sum_{i=1}^{n} W_{ji} x_i + b_j \right) \tag{1}$$

The unit j nonlinearly transforms the total input u_j (Equation 1) by means of hyperbolic tangent transfer function which is propagated forward to the unit of the next layer as the input signal y_j (Equation 2);

$$y_j = \frac{2}{1+e^{(-2\gamma u_j)}} - 1 \tag{2}$$

where γ is the slope parameter of the ridge function set at 0.75.

The difference in the output y_j from the target output t_j was used to adjust the synapse weights according to the calculated mean squared error (MSE) as shown in Equation 3;

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(t_{ij} - y_{ij}\right)}{NP} \qquad (3)$$

where y_{ij} is the network output for dataset i at neuron j, t_{ij} is the target network output for data set i at neuron j, p indicates the number of output neurons and N refers to the number of data sets.

The ANN is trained by updating the weights using a backpropagation learning rule. The change in synapse weight w_{ji} is based on the gradient descent rule according to Equation 4;

$$\Delta w_{ji} = -\eta \frac{\partial(MSE)}{\partial\, w_{ji}} \qquad (4)$$

where η is the learning rate, set at 0.7.

Experimental

A total of 250 sets of training data were randomly generated from within Sirolan Yarnspec™. Each data set contained both the generated inputs and the corresponding Sirolan Yarnspec™ predicted outputs. Mean fiber diameter(17-28μm), diameter distribution CV_D (18-42%), Hauteur(55-85mm), fiber length distribution CV_H (24-53%), fiber bundle tenacity(6.4-15.5cN/tex), curvature(55-118deg/mm), short fiber content (5-30%), yarn count(13-61tex), twist(227-912t.p.m.), processing information (draft, spinning speed, ring size and traveller weight) served as inputs to the neural network. The number of fibers in cross-section, unevenness CV%, unevenness U%, thin places per kilometre(-50%), neps per kilometer(+200%), yarn tenacity(cN/tex), elongation at break, breaking force(gF), ends-down per 1000 spindle hours, index of irregularity, thick places per kilometer (+50%), and hairiness served as the “target” spinning performance outputs.

The input data was normalized so that it is bounded within the prescribed range of 1 and 0. Scaling of the input values *(v_i)* was carried out according to Equation 5;

$$x_i = \frac{v_i - \min(v_{1 \ldots n})}{\max(v_{1 \ldots n}) - \min(v_{1 \ldots n})} \qquad i = 1 \ldots n \tag{5}$$

where x_i is the scaled value, $min(v_{1 \ldots n})$ and $max(v_{1 \ldots n})$ are the respective maximum and minimum values within each input data array.

The first 180 data sets were used for network training, 20 data sets were set aside for cross-validation and the last 50 data sets were used for evaluating the trained network's performance (prediction). Network training was terminated based on the cross validation stop criteria. This form of stop criteria ensured that training ceases prior to the point where the test set performance would deteriorate with further training, leading to a loss in generalization[14].

Although the number of hidden layers required is problem dependent, the prediction of practical problems requires only one, at the most two hidden layers[18]. Considering that several of the outputs have been predicted with empirical models and that their relationships are deterministic, linear components may be present. It is therefore assumed that simulations based on single layer multilayer perceptron (MLP) comprising of hyperbolic tangent transfer function layer in the hidden layer and pure linear functions in the output layer would be best suited to this application. The reduced complexity of the single layer MLP will have improved generalization capabilities and require less for training compared to a larger network possessing more free network parameters [9].

In order to gauge the ability of artificial neural networks to predict the properties of a yarn at a specific mill, commercial mill datasets were added to the 250 sets of Sirolan Yarnspec™ generated data. Thirty sets of data were sourced from the previous Australian Wool Corporation (AWC) and International Wool Secretariat (IWS) Australian wool trials [1]. Twenty sets of data were added to the previously generated training exemplars. Training was optimized for the performance on the test set through the incorporation of five data sets within the cross validation set. The remaining randomly chosen five commercial data sets were set aside for testing. Fiber curvature values absent from the commercial mill dataset were acquired from Sirolan Yarnspec™ using the default curvature values which were governed by the input fiber diameter.

Results and Discussion

OPTIMISATION OF THE ARTIFICIAL NEURAL NETWORK MODEL

One of the primary aspects pertaining the design of a multilayer perceptron is the number of units in the hidden layer. To establish the appropriate number of neurons required in the hidden layer, the final network training error obtained from Equation 3 was considered along with the test performance also measured as a mean squared error difference between the network output and corresponding "target" Sirolan Yarnspec™ output.

FIGURE 2. Performance of the network as a function of the number of neurons in the hidden layer over nine training runs of 1000 epochs.

As Figure 2 indicates, a reduction in the training error occurs as the number of hidden nodes increases, consequently a network possessing a greater number of neurons in the hidden layer will achieve a smaller training error. Initially with an increase in the number of neurons the test error is reduced, however unlike the trend displayed by the training error, the test error does not continually improve, but reaches a minimum with eleven nodes in the hidden layer prior to a degradation in performance indicating a loss in genralisation[15, 19]. Importantly it can be seen in Figure 2 that the correct allocation of nodes in the hidden layer for this application is somewhat less important, as any small deviation from this optimum will not have a significant influence on the networks performance.

A shortcoming of artificial neural network is that it is very difficult to intuitively know at what point the system will over fit the data. To overcome the likelihood of over fitting from excessive training the cross validation stop criteria was evoked. From Figure 3, it can be seen that the cross validation mean squared error exponentially falls to 6.0×10^{-3} at 800 training epochs beyond which the cross validation error begins to rise. For this particular application 800 epochs represents the point where sufficient training has occurred, but prior to the over fitting of the specific solutions within the training set.

FIGURE 3. Calculated training mean squared error (MSE) and cross validation error (MSE) over 4,000 epochs.

ARTIFICIAL NEURAL NETWORK VALIDATION

The success of any given neural network depends strongly on the inputs that are presented to it[17]. For this study the inputs are predetermined based on those used within Sirolan Yarnspec. Along with the input channels used, the size of the input data set directly influences the network performance. As there are no *priori* assumptions about the data the number of data sets required tends to be generally high[15]. The effect of the number of training patterns on network performance is evaluated by testing fifty previously "unseen" sets of data from which the network test and training errors are compared.

FIGURE 4. Training and test error between the network predicted outputs and Sirolan Yarnspec™ predicted, trained over nine runs of 1000 epochs terminated after 100 epochs without improvement.

The performance of the network in relation to the number of training data sets used can be seen in Figure 4. As would be expected there is no other indication besides improved network performance with an increase in the number of data sets available for training. Table 1 summarizes the results obtained from testing. The results reported are of nine repetitions comprising of 1000 epochs terminated after 100 epochs without improvement.

TABLE 1. Linear correlation coefficient (r^2) between the network predicted output and Sirolan Yarnspec™ predicted output.

The overall performance of the model achieves a proportion of variance in common with Sirolan Yarnspec™ of over 92%. Whilst high levels of correlation between the ANN and Sirolan Yarnspec outputs is attained, a true indication of the proposed method requires the modelling of a data set that contains the random variations and noise that would be associated with a commercial data set.

MILL SPECIFIC PERFORMANCE PREDICTIONS

The optimal solutions found in the previous sections are applied to a real data set [1] in order to asses the applicability of neural networks as a mill specific prediction tool. Given the advantages provided by both the empirical and ANN models, it is possible to develop an integrated model in which the capabilities of each model are combined. Validation of the models was performed by comparing the ANN predicted outputs against the corresponding measured data and Sirolan Yarnspec™ prediction. All parameters were modeled using a single layer MLP, training was terminated after 100 epochs without improvement in the cross validation error.

FIGURE 5. Comparison between neural network predicted outputs and Yarnspec™ predicted outputs with measured "target" outputs.

The agreement between ANN and Sirolan Yarnspec™ predicted outputs against the "target" measured values, is presented in Figure 5. The ANN and Sirolan Yarnspec™ predictions are comparable, this is to be expected considering that the training was predominately based on generated training data and therefore would portray similar degrees of accuracy or limitations. This aside, the addition of twenty two sets of mill specific training data, has improved the accuracy of the ANN. Further improvements would result with the addition of more mill specific data within the existing training dataset. The predictions for tenacity and elongation are a significant improvement over the empirical model. This may be partially due to the generated fiber curvature inputs but emphasis the fact that unlike conventional empirical models neural networks possess the capacity to learn directly from the data presented, and therefore may be adapted to incorporate forthcoming experimental or mill data into the model to improve future predictions.

TABLE 2. Accuracy of mill specific predictions. Root mean squared error (RMSE), linear correlation coefficient (r^2) and bias achieved through the artificial neural network and Sirolan Yarnspec™.

The linear regression (r^2) and root mean squared errors between the actual desired values and predicted outputs of the two models for each spinning performance criteria are presented in Table 2. Predictions of yarn unevenness and number of fibers in cross section are in good agreements with the target values for both the ANN model and Sirolan Yarnspec™ in part due to the linear relationships of these parameters[13, 20]. The accuracy of the predictions for thin and thick places per kilometer and yarn tenacity can be further improved if the bias is addressed, a significant contribution to the prediction error is due solely to the presence of persistent bias. Both models underestimate the degree to which thin and thick places will develop. In the case of tenacity the opposite occurs. Nevertheless the accuracy of the ANN predictions has been significantly improved through the incorporation of mill specific data within the training patterns. Additional work is needed to accurately model the occurrence of spinning ends-down and neps. ANN is particularly suited to this form of problem. Further additions of mill specific data and further developments of the ANN simulations presented would improve the prediction of these phenomena.

Conclusions

In this paper, ANN models are presented as a tool for prediction of the worsted spinning performance. It has been demonstrated that, trained with data from a commercial mill, ANN is a suitable tool to predict worsted yarn quality for the specific mill. By learning the specific patterns found in the commercial data set improvements were found in the accuracy of prediction. As the number of mill specific data sets increase it is anticipated that further improvements in prediction accuracy shall arise.

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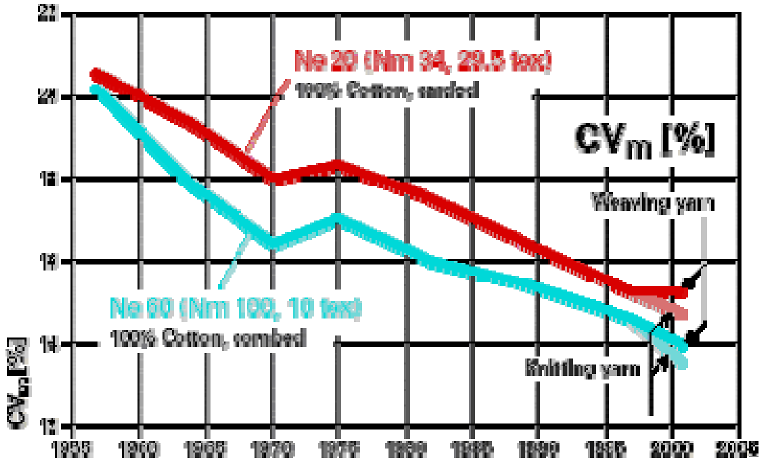

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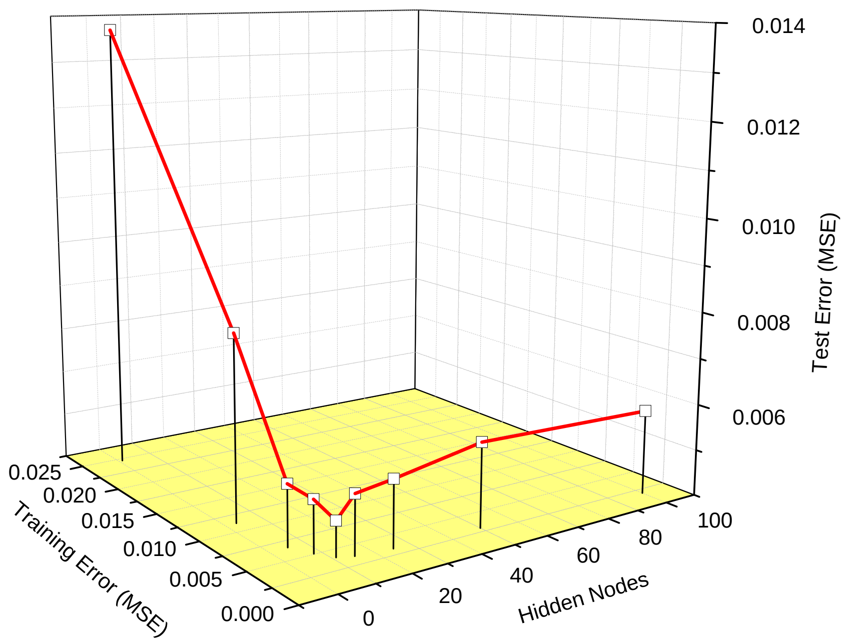

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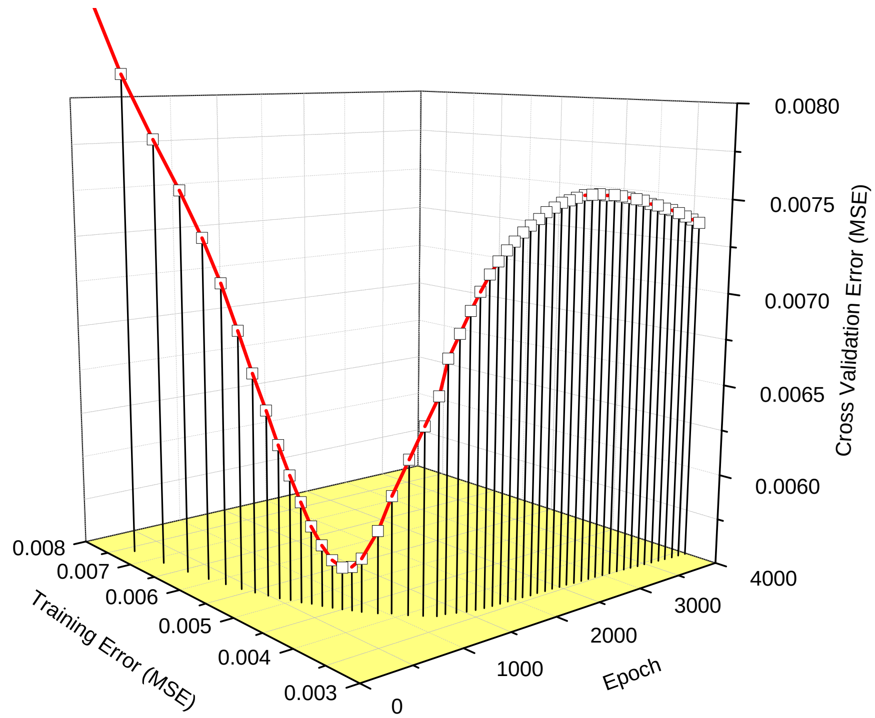

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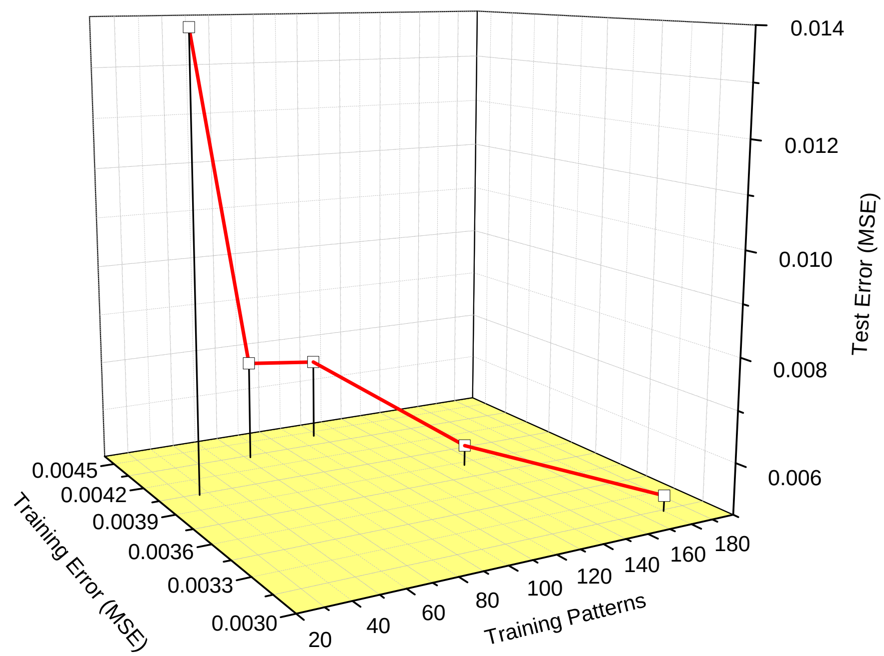

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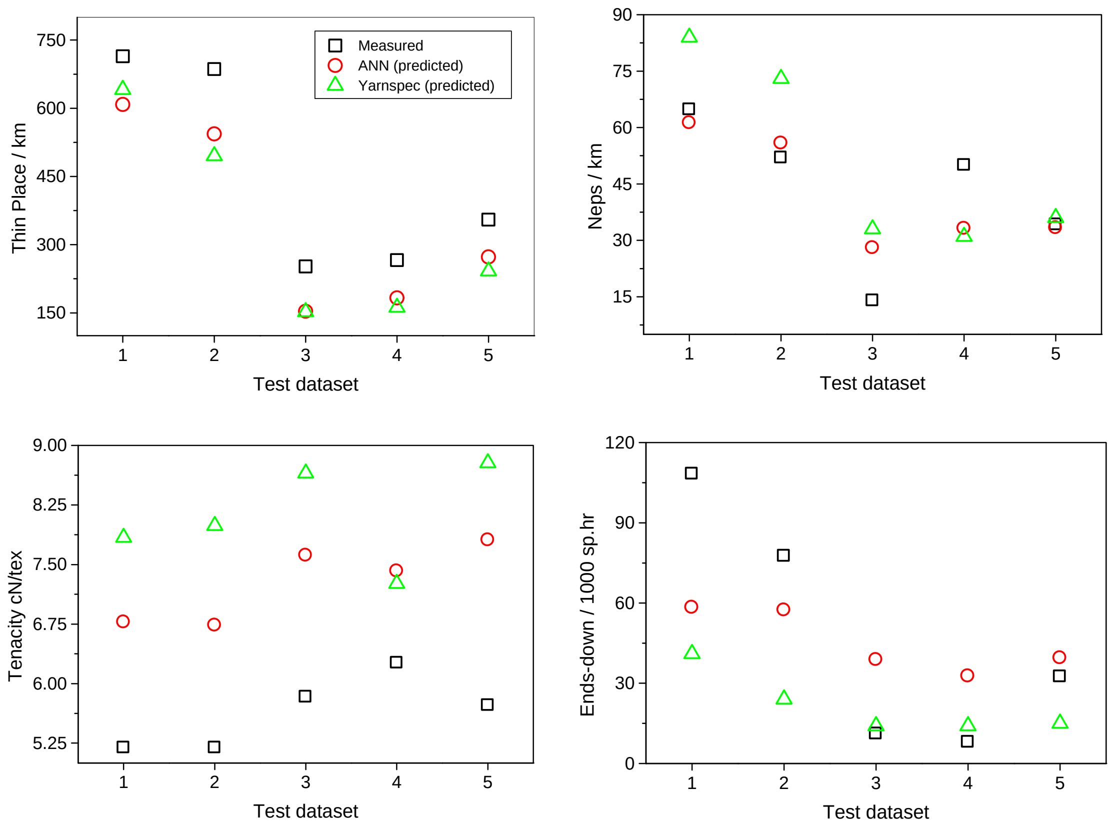

FIGURE 5. Comparison between neural network predicted outputs and Yarnspec™ predicted outputs with measured "target" outputs.

Output Parameter	Correlation Coefficient (r^2)
no. of fibers in cross-section	0.988
unevenness CV%	0.980
unevenness U%	0.982
thin places / kilometre(-50%)	0.947
neps per kilometre(+200%)	0.976
yarn tenacity(cN/tex)	0.945
elongation at break	0.966
breaking force(gF)	0.968
ends-down per 1000 sp.hr	0.965
index of irregularity	0.924
thick places / kilometre (+50%)	0.947
hairiness	0.982

TABLE 1. Linear correlation coefficient (r^2) between the network predicted output and Sirolan Yarnspec^{TM} predicted output.

Output parameter	Artificial Neural Network			Sirolan Yarnspec ™		
	r^2	RMSE	Bias	r^2	RMSE	Bias
no. of fibers in cross-section	0.918	1.482	0.302	0.895	1.814	0.380
unevenness U%	0.903	0.443	0.221	0.884	0.506	0.240
thin places / kilometre(-50%)	0.994	104.778	102.449	0.962	122.797	116.200
neps per kilometre(+200%)	0.670	10.086	0.691	0.533	17.521	8.400
yarn tenacity(cN/tex)	0.554	1.657	1.629	0.028	2.572	2.462
elongation at break %	0.596	5.935	5.280	0.067	8.396	7.480
ends-down per 1000 sp.hr	0.921	29.422	2.177	0.890	39.378	25.908
thick places / kilometre (+50%)	0.995	33.772	30.145	0.927	33.695	26.600

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