# Comparing the Prediction Capabilities of Artificial Neural Network (ANN) and Nonlinear Regression Models in Pet-Poy Yarn Characteristics and Optimization of Yarn Production Conditions

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**ABSTRACT**

In the manufacture of yarn, predicting the effect of changing production conditions is vital to reducing defects in the end product. This study compares, for the first time, non-linear regression and artificial neural network (ANN) models in predicting 10 yarn properties shaped by the influence of winding speed, quenching air temperature and/or quenching air speed during production. A multilayer perceptron ANN model was created by training 81 patterns using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. The hyperbolic tangent, or TanH, activation function and logistic activation functions were used for the hidden and output layers respectively. Results showed that the ANN approach exhibited a greater prediction capability over the non-linear regression method. ANN simultaneously predicted all of the 10 final properties of a yarn; tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake based on the colour strengths (K/S), brightness, boiling shrinkage and yarn evenness, more accurately than the non-linear regression model ($R^2$=0.97 vs. $R^2$=0.92). These results lend support to the idea that the ANN analysis combined with optimization can be used successfully to prevent production defects by fine tuning the production environment.

**INTRODUCTION**

Faulty fabrics may arise during production due to changes in spinning properties, even within a single lot (Ziabicki, 1967). Faults which occur during the conversion of yarns into fabrics by weaving or knitting are difficult to detect until the fabric is colored, at which stage reversal is impossible. Such faults slow production and lead to significant costs.

The properties of polyester (PET) yarn are influenced by many interwoven factors during production including winding speed, mass transport, polymer melting temperature during extrusion and the quenching condition (quenching air temperature and speed), as well as other production parameters during the melt spinning process (Kim, 1986; Simmens, 1955; Stibal et al., 2005; K. Yildirim, 2007; Ziabicki, 1967). The physical properties are also considerably affected by the cooling process, during which disoriented molecules form chains and settle in a defined pattern. Filament properties are affected by the cooling rate, the feed fineness of the filament and stress induced during spinning. The crystallization ratio also plays a critical role in yarn production during spinning, second in importance only to the cooling rate (Simmens, 1955). Crystalline size and morphology are also affected during the spinning process.

Small changes in the conditions of yarn production can lead to large variation in the properties of the final yarn produced, which may result in an unacceptable product and consequently increased production costs (Kothari, 2000). Management of even small changes in the conditions during spinning is critical to obtain an acceptable product at minimal cost.

During production, the yarn characteristics can be obtained by testing. In real time, this information can be used to predict and control the characteristics of the yarn to be produced. If necessary, required changes can be made during production and as a result, faults may be minimized or prevented altogether. In order to construct a real time decision support system for yarn production, it is vital to obtain accurate estimations of the yarn properties under different conditions, or the perfect production conditions can be estimated for a yarn having desired yarn properties.

Multivariate regression tools for predicting physical characteristics of a yarn are the most common methods used in the estimation of yarn properties obtained under various production conditions (Üreyen & Kadoglu, 2006; Kenan Yildirim, Ulcay, & Kopmaz, 2009). Studies which compare multiple regression models to artificial neural network (ANN) models are becoming more prevalent because ANN models are better estimators than the classical methods, and particularly when compared with multiple regression (Cheng & Lam, 2003; De Weijer, Buydens, Kateman, & Heuvel, 1992; Ethridge & Zhu, 1996; Majumdar & Majumdar, 2004; Ucar & Ertugrul, 2002). For example, (Majumdar & Majumdar, 2004) reported that the prediction power of the ANN model was an improvement over the regression model with correlation coefficients of r = 0.938 and r = 0.731 for the ANN and the regression models respectively. Similarly (Cheng & Lam, 2003) also showed that ANN models (r = 0.98) are much better predictors of yarn properties than regression models (r = 0.71). In brief, ANN is gaining a positive reputation in the textile industry as an efficient tool to construct decision support systems for fault-free yarn production.

Yildirim et al.,(2009) used non-linear regression models to estimate the tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, boiling shrinkage and yarn evenness using the same data in this study. As the ever increasing number of comparative studies in the literature indicates this approach is acceptable, however there are some disadvantages of non-linear regression models as compared to ANN in estimation of yarn properties during production. The main disadvantages are; 1) only one dependent variable can be used each time in the model construction for different response variables, 2) some explanatory variables must be excluded from the model, e.g. if variables are correlated then only one needs to be included in the model, 3) variables considered to be unimportant may need to be removed from the regression model in order to improve the predicting power of a certain response. Inversely, artificial neural network analysis is robust in predicting ten response variables simultaneously. Moreover, all explanatory variables are included in the ANN model because the ANN approach can use all information, searching for patterns among variables, in contrast to classical statistical approaches. Non-linear regression for example, includes or excludes variables to or from the model depending on their statistical significance as determined by means and variance.

As a result non-linear regression models poorly predicted the outcomes of yarn evenness and brightness with or without heat draw knitting condition (HDK) and hence were not estimated in the report by Yildirim et al., (2009). Moreover, in the same study, averages of the replicate measurements of the same response variables were used in the estimation. These are the major shortcomings of the regression model in its application to yarn production. Since small changes in the winding speed, quenching air temperature and quenching air speed leads to identifiable faults in the final yarn product, models with a highly accurate predictive capability are needed. ANN is a suitable candidate, with distinct advantages over non-linear regression models in decision support systems in the fault-free production of yarns.

Artificial neural network approaches have become highly attractive in engineering due to their ability to offer significant prediction power in linear and non-linear complex systems (Jain, Mao, & Mohiuddin, 1996). ANNs are densely interconnected, adaptive and simple processing units that can carry out massive computations for data processing and knowledge presentations (Hecht-Nielsen, 1987; Schalkoff, 1997). The information processing characteristics of ANNs, such as non-linearity, high parallelism, robustness, fault and failure tolerance, learning, the ability to handle imprecise and fuzzy information, and their ability to generalize, are unique and make ANNs a very attractive tool in engineering (Basheer & Hajmeer, 2000). Moreover, De Weijer et al., (1992) also suggested that the optimization technique combined with the ANN can determine the best yarn production conditions. The coupled approach may therefore completely remove the possibility of producing faulty yarns.

De Weijer et al.,(1992) used ANN to predict ten mechanical yarn properties from five initial physical yarn structures. Solving of the quantitative structure activity relationship (QSAR) training algorithm was used in training and the transfer function was sigmoid, resulting in a successful ANN for use in real world problems. Developments in the ANN techniques and more sophisticated ways of training and testing methods, including activation functions, may further improve refinement of the prediction capacity, which is vital in detecting small but significant changes in conditions during yarn production. Moreover, a model with fewer input parameters could also improve the response speed during yarn production. In brief, new training algorithms together with new activation functions may result in more accurate predictions, in less time.

The aim of this study is to develop an effective approach, based on artificial neural networks, to simultaneously predict tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, boiling shrinkage and yarn evenness, and compare it to the predictions made by the multiple regression model. To accomplish this goal, a full factorial experimental design was implemented to determine the effects of winding speed, quenching air temperature and quenching air speed on the yarn properties. The prediction performance of the non-linear regression and artificial neural network approaches are compared by correlation analysis. The results presented here show that multilayer perceptron ANN may be used more efficiently and accurately than non-linear regression models in application to yarn production.

## METHODS

### Experimental System

150 Denier 96 filaments semi-dull and 150 Denier 72 filament semi-dull partially oriented yarn (POY) polyethylene terephthalate (PET) yarn, using a cross-flow type quenching system (*Figure 1*), were produced in a local PET yarn manufacturer, KORTEKS. In the spinneret system 180g coarse metal sand (0.85-1.20mm) and 80g thin metal sand (0.25-0.35mm) were used.

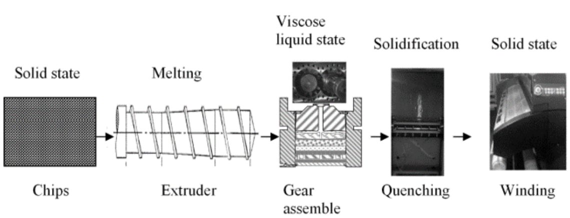


FIGURE 1. Extruder melt spinning process.

### Input Parameters

Winding speed, quenching air temperature and quenching air speed were used as input parameters in the non-linear regression model and the artificial neural network model. For each input variable three different levels, relevant to the production environment, were tested to observe and measure their effects on physical yarn properties Winding speed was measured at 2600 m/min, 3200 m/min and 3800 m/min, quenching air temperature at 17˚C, 22˚C and 27˚C and quenching air speed at 0.3 m/s, 0.5 m/s and 0.7 m/s.

### Output Parameters

The physical yarn properties (tensile strength, tensile strain, draw force, crystallinity ratio, K/S, K/S without HDK, brightness, brightness without HDK, boiling shrinkage and yarn evenness) were measured under varying levels of winding speed, quenching air temperature and quenching air speed to determine the quality of yarn produced. These ten dependent variables were predicted by the non-linear regression models and the ANN model.

Tensile strength and tensile strain properties of yarn were measured by Testometric Universal Tester (M250) with 250 kgf load cell (method ISO2062). Fifteen test specimens were used for each sample. One of the principal components of the physical yarn structure is crystallinity, size and orientation of crystals. Crystallinity ratio was measured using Perkin Elmer Sapphire II model Differential scanning calorimeter (DSC) as described by Sichina, (2000) and Kong & Hay, (2002). Two test specimens were used for each sample.

Boiling shrinkage was measured by an apparatus (method TS8288) specifically designed for this purpose at the reference laboratory belonging to the Turkish Scientific and Technological research council of Turkey (TUBITAK-Butal). Six test specimens were used for each sample.

The Textechno Dynafil ME device developed by Textechno and Lawson-Hemphil was used to measure draw force. The measurements were carried out at constant stress on the yarn moving continuously. Measurement is carried out by applying a load via a pendulum on the yarn between two gadgets. Some of the load was offset by the extension of the yarn and the rest was measured by transducer as draw force. Three test specimens were used for each sample.

Filament yarn evenness was measured by Zellweger USTER Tester (UT-3/C). Three test specimens were used for each parameter. Percent U value was used as yarn evenness level, using the following formula; where WS is winding speed, QT is quenching air temperature and QS is quenching air speed.

$$\begin{aligned}\text{Yarn Evennes} &= -3.163562823 + 9.78673\cdot 10^{-4}\cdot \\ &WS + 8.366483739\cdot QS - 1.993519\cdot 10^{-3}\cdot \\ &WS\cdot QS + 1.51657453\cdot 10^{-1}\cdot QT - 3.3009\cdot 10^{-5}\cdot \\ &WS\cdot QT - 2.92500096\cdot 10^{-1}\cdot QS\cdot QT - 5.6944\cdot 10^{-5}\cdot \\ &WS\cdot QS\cdot QT.\ (R^2 = 0.50)\end{aligned} \tag{1}$$

After converting yarn to fabric by knitting with a Lawson Hemphill Fiber Analysis Knitter (FAK) in heat draw knitting condition (HDK), brightness was determined using HunterLab Colorquest Sphere II model spectrophotometer (Method TS 12552). K/S ratio was determined from the reflectance at 700nm. Another fabric sample was prepared without HDK and both brightness and K/S were measured and named as K/S without HDK and brightness without HDK. Three test specimens were used for each parameter.

$$K/S\text{ without HDK conditioning} = 7.03991 - 1.261 \cdot 10^{-3} \cdot WS - 6.670734 \cdot QS + 1.421 \cdot 10^{-3} \cdot WS \cdot QS - 1.90342 \cdot 10^{-1} \cdot QT + 4 \cdot 10^{-5} \cdot WS \cdot QT + 2.71944 \cdot 10^{-1} \cdot QS \cdot QT - 5.6 \cdot 10^{-5} \cdot WS \cdot QS \cdot QT.\ (R^2 = 0.62) \quad (2)$$

$$\text{Brightness without HDK conditioning} = -7.140732 + 2.931 \cdot 10^{-3} \cdot WS + 15.422594 \cdot QS - 2.672 \cdot 10^{-3} \cdot WS \cdot QS + 4.52417 \cdot 10^{-1} \cdot QT - 7.8 \cdot 10^{-5} \cdot WS \cdot QT - 6.88611 \cdot 10^{-1} \cdot QS \cdot QT + 1.19 \cdot 10^{-4} \cdot WS \cdot QS \cdot QT.\ (R^2 = 0.64) \quad (3)$$

## Artificial Neural Network Analysis

The artificial neural network analysis (ANN), a highly popular feed forward multilayered perceptron model (Gibbs et al., 2006), was conducted using R (Version 3.2.5) statistic programming software. The model was a three layer neural network structure with 3 input nodes, 3-10 hidden nodes determined by the trial and error scheme, and 10 output nodes; tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, boiling shrinkage and yarn evenness (*Figure 2*). The same set of variables (winding speed, quenching air temperature and quenching air speed) were used as inputs in both analyses; ANN and multiple regression analysis.

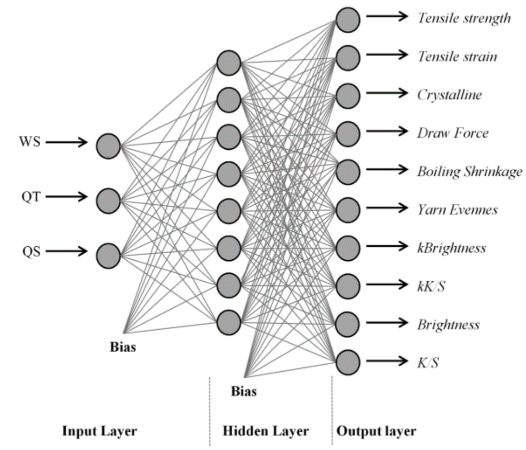


FIGURE 2. Schematic of feed-forward multilayer perceptron model. WS is the winding speed, QT is the quenching air temperature and QS is the quenching air speed.

Twenty thousand searches were carried out to determine the best network using the multilayer perceptron ANN configured as described below. Training and testing of each network was accomplished with two different subsets of the data in every network and the data was used once for each process. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm was used in training. This method is a reliable and quick iterative approach to solve unconstrained nonlinear optimization problems (Dai, 2013; Geem, 2006).

Excitation of individual processing units arranged in a layer depends upon the importance (weights) of their connections between different layers. A simple illustration is given in *Figure 3*. In this type of network hidden layers, of which there can be more than one, are packed between input and output layers.

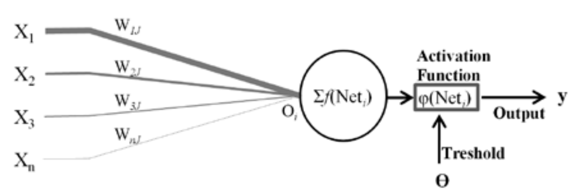


FIGURE 3. The mathematical model of an artificial neuron

As demonstrated in *Figure 2*, a neuron is connected with all inputs $(x_1, x_2 x_3 \ldots x_n)$. A weight $(Wj)$ is the connection between a neuron and input. The sum of all weights is fed through a non-linear block.

$$\text{Net}_j = \sum\nolimits_{j}^{n} W_{ij} x_i \tag{4}$$

The non-linear block is termed as the activation function and it uses input values to determine the output activity of the neuron. Then the sum of all inputs to a unit in a layer is;

$$\text{Net}_j = \sum_{i=1}^{n} W_{ij} x_1 \tag{5}$$

$$O_i = f(\text{Net}_j) \tag{6}$$

All four types of activation functions were tested to determine which one functions best in the network; Logistic function;

$$O_i = f(\text{Net}_j) = \frac{1}{1+e^{(\text{Net}_j - \theta_j)/\theta_o}} \tag{7}$$

Identity function:

$$f(x) = x \tag{8}$$

TanH function;

$$f(x) = tanH(x) = \frac{2}{1+e^{-2x}} - 1 \tag{9}$$

Exponential function;

$$f(x) = e^{-2x} \tag{10}$$

In this paper, the logistic activation function was selected as the best for the output layer function and tanH was selected as the best activation function for the hidden layers. Function $f$ generates values between 0 and 1. The value of $\theta$ determines the threshold and $\theta_o$ determines its abruptness.

For the learning process, two patterns, the observed and the output patterns, are compared. The network is given the observed pattern and the network produces its own pattern with weights and thresholds. Then the output pattern is compared to the desired pattern and an error value at a given layer is obtained;

$$e_k = t_k - O_k \tag{11}$$

Where $t_k$ is the observed output and $O_k$is the obtained output from the network. The total error function can be calculated using the following equation:

$$E = 0.5 \sum_{k=1}^{n} (t_k - O_k)^2 \tag{12}$$

Thus the learning process can be described as a process of minimizing the total error. If the error, sum of square error, at a given time for a network is significant, then the weights are adjusted to compensate for that error. Eventually it is expected that precision will improve and the answer will approach the true value. For more information about the procedure consult Singh et al. (2001).

The parameters related to learning, testing and validation are presented in *Table I*. The experimental data consisted of 81 patterns. A randomly selected seventy percent of the patterns were used in the training process and the rest was randomly assigned to the testing (15%) and the validation (15%) processes. The results obtained were compared by the means of statistical methods, standard deviation, mean squares of error, and correlation tests.

TABLE I. Prediction capabilities and comparisons of non-linear regression and artificial neural network analysis.

| | Percent Explaine | | Standard Deviation | | MSE | | StDev | MSE |
|---|---|---|---|---|---|---|---|---|
| Factor | Regression | ANN | Regression | ANN | Regression | ANN | Observed | Observed |
| Tensile Streng | 0.92 | 0.92 | 0.25 | 0.27 | 0.05 | 0.07 | 0.27 | 0.07 |
| Tensile Strain | 0.96 | 0.96 | 28 | 31.51 | 504.31 | 966.6 | 31.04 | 938.06 |
| Crystalline | 0.85 | 0.92 | 5.16 | 4.63 | 14.67 | 20.88 | 4.88 | 23.2 |
| Draw Force | 0.96 | 1 | 103.26 | 103.39 | 8311.78 | 10407.53 | 101.49 | 10029.73 |
| Boiling Shrinka | 0.88 | 0.96 | 6.98 | 8.09 | 29.79 | 63.69 | 7.94 | 61.45 |
| Yarn Evenness | 0.71 | 0.77 | 0.16 | 0.17 | 0.01 | 0.03 | 0.18 | 0.03 |
| kBrightness | 0.96 | 0.98 | 3.75 | 3.66 | 8.92 | 13.06 | 3.64 | 12.87 |
| kK/S | 0.94 | 0.98 | 0.12 | 0.116963 | 0.01 | 0.01 | 0.12 | 0.01 |
| Brightness | 0.71 | 0.94 | 0.81 | 0.88 | 0.29 | 0.76 | 0.92 | 0.82 |
| K/S | 0.69 | 0.94 | 0.22 | 0.23 | 0.02 | 0.05 | 0.24 | 0.056 |

kBrightness and kK/S = brightness after heat draw knitting conditioning (HDK) applied, Brightness and K/S: no HDK applied.
StDev: standard deviation.

**Optimization to Estimate Optimum Yarn Production Conditions**

The trained ANN model was reconstructed using its weights in Microsoft Excel (MSE), then using the MSE Visual Basic macro environment together with MSE solver, the optimum pattern for the highest tensile strength when tensile evenness less than one was determined. Generally, the optimization conditions were selected according to the range of experimental data which the ANN was trained on.

**Non-Linear Regression Analysis**

Non-linear regression analysis was carried out using SPSS (Version 21) statistical analysis package. The same set of input variables (winding speed, quenching air temperature and quenching air speed) as that of neural network model was used in the analysis. Moreover the same set of output variables; tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, dye uptake (K/S) without HDK, brightness without HDK, boiling shrinkage and yarn evenness were also predicted using both analyses and compared to each other. The results of the non-linear analysis were published previously by (K. Yildirim, 2007). The aim of this analysis was to validate the best statistical prediction, comparing the non-linear analysis to the predictions of the ANN model. General non-linear regression;

$$y' = c + b_1x_1 + b_2x_3 + \cdots + b_nx_n \tag{13}$$

where y' is each of the output variables, c is regression constant, $x_1$ to $x_n$ are the input variables and $b_1$ to $b_n$ are partial regression coeffcients. The prediction equation is given below was designed by Yildirim et al., (2009).

$$Y_i = a_i + b_i \cdot (\mathrm{WS}) + c_i \cdot (\mathrm{QS}) + d_i \cdot (\mathrm{WS} \cdot \mathrm{QS}) + e_i \cdot (\mathrm{QT}) + f_i \cdot (\mathrm{WS} \cdot \mathrm{QT}) + g_i \cdot (\mathrm{QS} \cdot \mathrm{QT}) + h_i \cdot (\mathrm{WS} \cdot \mathrm{QS} \cdot \mathrm{QT}) \tag{14}$$

where $Y_i$ are the yarn properties ($i$ = 1, tensile strength; $i$ = 2, tensile strain; $i$ = 3, draw force; $i$ = 4, crystallinity ratio; $i$ = 5, K/S; $i$ = 6, brightness; $i$ = 7, boiling water shrinkage; $i$ = 8, yarn evenness, $i$ = 9, K/S without HDK; $i$ = 10, brightness without HDK),

**RESULTS AND DISCUSSIONS**

Tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, boiling shrinkage and yarn evenness under the influence of winding speed, quenching air temperature and quenching air speed during yarn production were modeled and predicted by applying non-linear regression models and ANN models (3:8:10 network type; *Figure 3*). Training, testing and validation performances of 0.97, 0.95 and 0.94 respectively, were significant, and better than the mean Pearson's correlation coefficient (0.92) from non-linear regression. In the regression model the main effects, including the interactions between the variables were included in the analysis. For more information about the multiple regression approach consult Yildirim et al., (2009). Latter reports excluded yarn evenness, K/S without HDK conditioning and brightness without HDK conditioning because the level of variance explained by prediction values from non-linear regression models constructed for these parameters were low. It was therefore concluded that the prediction by the non-linear regression models cannot be relied upon to estimate yarn evenness. However, using ANN models an improved prediction of yarn evenness under the given conditions during production was carried out in this study (*Table I, II*). In the random search for the best neural networks, the best 10 networks had TanH function for hidden activation layer and logistic activation function was selected for the output layer (*Table II*). The most of the best networks (4) also had 3-8-8 neural network model (three input layers-eight hidden layers and eight output layers)

A full factorial design applying a real world problem was implemented to predict the effects of winding speed, quenching air temperature and quenching air speed on tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, boiling shrinkage and yarn evenness. Each output, or dependent variable, in the regression model was predicted separately, whereas a simultaneous 10 factor output prediction was carried out using the ANN model. In addition, a computer program (PETPOY_ann01) was created from the weights of the network structure for use in the yarn production. The predictions made by both ANN and non-linear regression models were close to the measured data although the ANN model represented the observed data more appropriately (0.97) than the non-linear regression model (0.92), except for predictions of tensile strength and tensile strain where predictions were statistically the same in both analyses (P>0.05; *Figure 4*).

TABLE II. The best 10 networks of 5000 runs after a network search. For the hidden layer, 3 to 10 neurons were randomly assigned. Identity, logistic, tangent, exponential activation functions were used for the hidden and output layers.

| Net. name | Training perf. | Test perf. | Validation perf. | Training error | Test error | Validation error | Hidden activation | Output activation |
|---|---|---|---|---|---|---|---|---|
| MLP 3-10-8 | 0.97 | 0.94 | 0.91 | 39.9 | 128.77 | 156.97 | Tanh | Logistic |
| MLP 3-8-8 | 0.96 | 0.96 | 0.93 | 81.5 | 146.91 | 104.04 | Tanh | Logistic |
| MLP 3-8-8 | 0.97 | 0.91 | 0.92 | 33 | 67.34 | 74.06 | Tanh | Logistic |
| MLP 3-10-8 | 0.97 | 0.94 | 0.92 | 57 | 144.76 | 72.09 | Tanh | Logistic |
| MLP 3-9-8 | 0.96 | 0.95 | 0.94 | 45.4 | 80.57 | 49.75 | Tanh | Logistic |
| MLP 3-10-8 | 0.97 | 0.94 | 0.93 | 45.7 | 92.93 | 88.77 | Tanh | Logistic |
| MLP 3-8-8 | 0.96 | 0.96 | 0.94 | 74.8 | 140.68 | 78.88 | Tanh | Logistic |
| MLP 3-8-8 | 0.96 | 0.93 | 0.91 | 53.5 | 103.4 | 133.05 | Tanh | Logistic |
| MLP 3-10-8 | 0.96 | 0.95 | 0.92 | 39.4 | 93.79 | 74.52 | Logistic | Exponential |
| MLP 3-8-10 | 0.97 | 0.95 | 0.94 | 55.1 | 128.26 | 116.55 | Tanh | Logistic |

Perf: performance

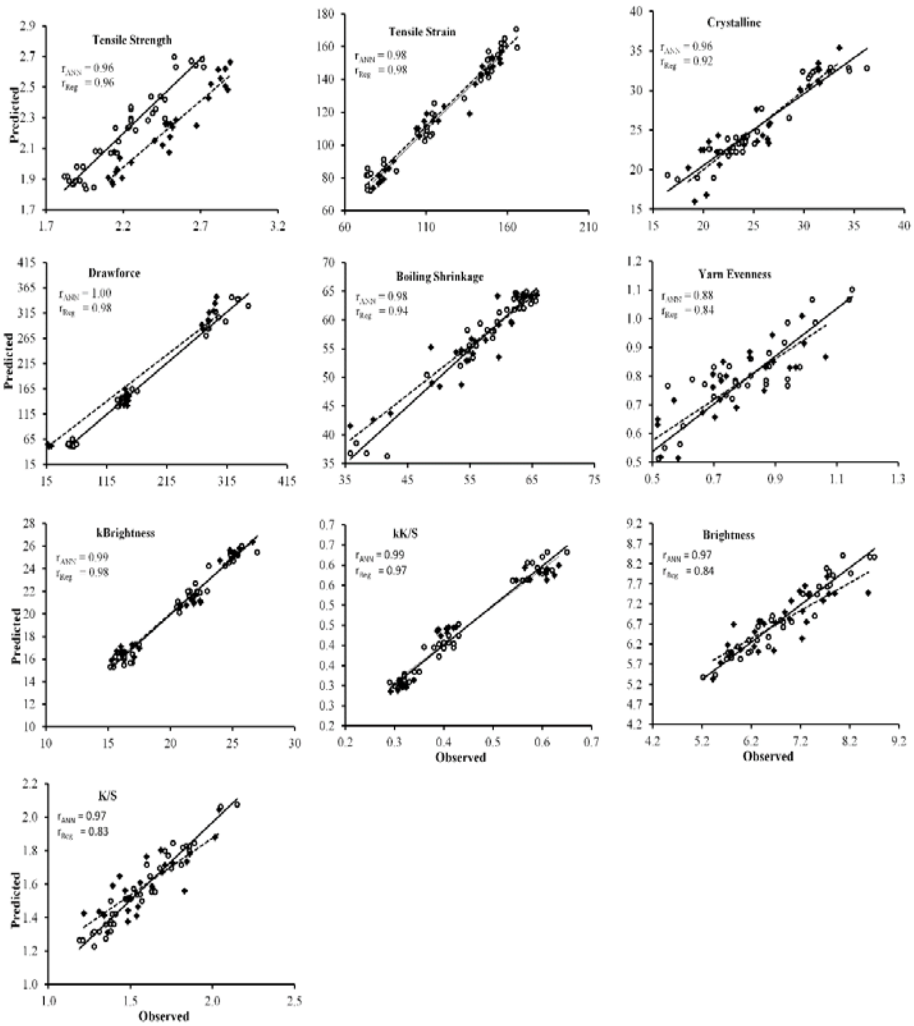


FIGURE 4. Correlations of predicted outputs and observed outputs in the analyses of non-linear regression and ANN. Dotted lines represent linear fitting for nonlinear observed and predicted data, and straight lines represent the fit between observed and expected outputs generated by the artificial neural network model predictions. In the neural network models winding speed, quenching air temperature and quenching air were used as input parameters and tensile strength, tensile strain, draw force, crystallinity ratio, K/S, K/S without HDK, brightness, brightness without HDK, boiling shrinkage and yarn evenness were used as output parameters.

The ANN model described here explained more than 90% of variance in mechanical yarn properties, except yarn evenness (*Table I*). Generally these values are an improvement over those reported by De Weijer et al.,(1992). None of the variances were explained over 80% by the ANN reported in the latter study. Though both ANNs were similar in structure, training (QSAR vs BFGS) and activation functions (sigmoid vs logistic), including the error decay is a point of difference. It should be noted therefore that though both models are ANNs, the innate structures are totally different. Four different activation functions were tested using the ANN model and none produced results comparable to the logistic activation function with minimal residual error. That is, the compiling of the ANN structure differently also changes its prediction capabilities, and its ability to recognize sophisticated patterns. With the developments in ANNs in the future, more accurate predictions may also be obtained with the same set of data used in the training, test and validation processes.

Standard deviations and mean squared errors of the predicted values by ANN were in line with the standard deviations and mean squared errors of the observed data. On the basis of three input parameters, the ANN model outlined here successfully predicts the yarn mechanical properties comparing to the five input parameters of the ANN model reported by (De Weijer, et al., 1992). Interestingly, the standard deviations were similar in predictions of the ANN and non-linear regression models. However the mean square errors (MSQE) of predictions from the non-linear regression method were mostly lower than that of the ANN. This occurs because the average of non-linear observed measurements under the same conditions was used as an input instead of the point predictions which the ANN model carried out.

Brightness and K/S predictions made by non-linear regression were lower than the predictions made by ANN model, though not different statistically (chi-square=1, P = 0.25 with 95%CI). But even a minor improvement such as this is well received in field applications.

**Optimization**

Optimization techniques are needed to look backward at the process and solve the issues which lead to faulty products. Back estimation of the best conditions for a fault free PETPOY yarn production is rare in ANN studies. De Weijer et al., (1992) drew attention to the importance of optimization using an ANN model to estimate yarn production factors from the end product features, which is the yarn properties. In this study Microsoft Excel (MSE) and its Visual Basic macro environment were used to program and solve in MSE. The ANN model was reconstructed in the MSE environment using the weights of hidden and output layers. In the optimization process, tensile strain was tested in the range 75 to 155, and tensile strength was maximized, while yarn evenness was estimated. Tensile strength decreased gradually as tensile strain increased (*Figure 6*). Yarn evenness increased sharply as tensile strain increased from 135 to 155. Optimization indicated that the best tensile strain is 95 where tensile strength is in the higher range and tensile evenness in the lower range. Being able to back calculate production conditions during the production process by experimenting with the first products is highly desirable and faulty yarn production can effectively be prevented. All yarn properties can be assigned to different ranges during the optimization procedure and the principal production parameter, in this case tensile strength, can be maximized or, if desired, minimized. This approach removes trial and error approach and selects the best possible parameters for the yarn production. Draw force (200), boiling shrinkage (64) and crystallinity (30) were all relatively constant.

**Other Specifications of the ANN**

Five thousand runs of the ANN network search were carried out to gain insight into the error decay and the best hidden and output activation functions leading to better networks. Error decay occurred close to the lowest levels (0.02) after roughly 200 cycles (*Figure 5*). Generally, the tangent activation function for the hidden layer and the logistic activation function for the output layer produced the best networks, as indicated by the lowest validation error (94) and high mean validation performance (0.93) (*Table III*). The lowest mean validation performance was obtained from exponential function.

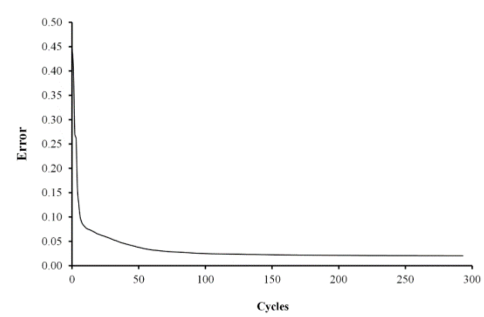


FIGURE 5. Error decaying accomplished by error back propagation.

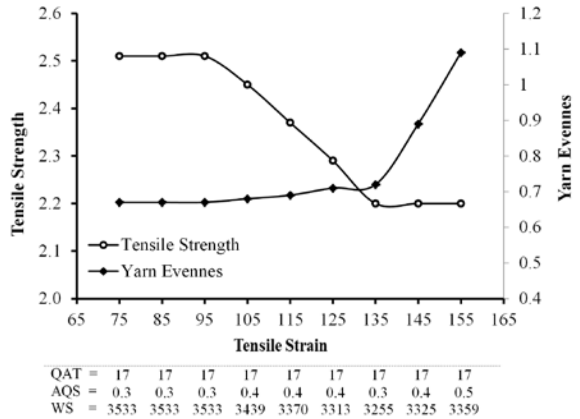


FIGURE 6. The relationship between tensile strength, tensile strain and yarn evenness established by optimization. Average draw force was 200, boiling shrinkage 63 and crystallinity 30.

TABLE III. Output activation functions and their performances during a run of 5000 different artificial neural network search.

| | Logistic | Exponential | Identity | Tangent |
|---|---|---|---|---|
| n | 1269 | 1236 | 1253 | 1242 |
| Mean training | 0.9 | 0.9 | 0.9 | 0.9 |
| Mean testing p | 0.9 | 0.9 | 0.91 | 0.92 |
| Mean Validatic | 0.93 | 0.92 | 0.93 | 0.93 |
| Training error | 113 | 152 | 161 | 272 |
| Test error | 115 | 130 | 127 | 283 |
| Validation erro | 94 | 153 | 188 | 311 |

Global sensitivity analysis showed that winding speed was the principal factor (106.7) in predicting each of 10 response variables as compared to quenching air temperature (4.7) and quenching air speed (2.48). However, as non-linear regression analysis indicated the inclusion of these two parameters improved the prediction capabilities of both models, explaining more of observed variation when included in the models.

## CONCLUSION

During yarn production, winding speed is the dominant factor affecting the yarn properties; tensile strength, tensile strain, draw force, crystallinity ratio, dye uptake (K/S), brightness, boiling shrinkage and yarn evenness. BFGS algorithms were successfully used to minimize error with 8 neurons in the hidden layer. All 10 yarn properties were simultaneously predicted by the ANN model and a program was constructed for use during the yarn production. The predicted values by both ANN and non-linear regression analysis were close to the observed values though prediction by ANN (0.97) was more accurate than that of the non-linear regression (0.92). The ANN model is recommended over the non-linear regression model because small changes in winding speed, quenching air temperature and quenching air speed are precisely predicted. This offers the potential to prevent or minimize production expense and lost time that may occur due to faulty yarns.


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