Optimisation of combed yarn properties based on yarn number and machine jaw range using artificial neural networks

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ABSTRACT – REZUMAT

Optimisation of combed yarn properties based on yarn number and machine jaw range using artificial neural networks

The need for natural clothing is increasing day by day. To meet this demand, the apparel industry is developing new systems to enhance production and raw material usage. Using healthy products is essential for a healthy life, which increases the need for natural raw materials. Cotton is the ideal natural raw material for a renewable and sustainable production line. Despite the growing production, it cannot fully meet the demand. Therefore, new systems are being developed to improve the quality of cotton production. The foundation of the textile industry is yarn, and yarn production lines consist of systematically operated machines. These production systems include carded, combed, and open-end methods. In combed production, high-quality and long fibres are used to produce yarns with counts such as Ne 30 or Ne 50. In combed yarn production, fibre length and ratio can be adjusted through machine settings. Lap feeding cylinder gaps in combed yarn machines are critical for this adjustment. In this study, experimental results were obtained using 4 different yarn counts produced from the same blend and 5 different combed feeding jaw settings. These results were optimised using artificial neural networks. In the analysis, yarn count and combing cylinder gap were used as input data, while the physical properties of the yarn were used as output data.

Keywords: *combed yarn, natural raw materials, fibre length, artificial neural network, optimisation*

Optimizarea proprietăților firelor pieptănate pe baza numărului de fire și a intervalului fălcii de fixare al mașinii, utilizând rețele neuronale artificiale

Nevoia de îmbrăcăminte naturală crește pe zi ce trece. Pentru a satisface această cerere, industria de îmbrăcăminte dezvoltă noi sisteme pentru a îmbunătăți producția și utilizarea materiilor prime. Utilizarea produselor calitative este esențială pentru o viață sănătoasă, ceea ce crește nevoia de materii prime naturale. Bumbacul este materia primă naturală ideală pentru o linie de producție regenerabilă și durabilă. În ciuda producției în creștere, acesta nu poate satisface pe deplin cererea. Prin urmare, se dezvoltă noi sisteme pentru a îmbunătăți calitatea producției de bumbac. Baza industriei textile este dată de fire, iar liniile de producție a firelor constau în mașini operate sistematic. Aceste sisteme de producție includ metode de cardare, pieptănare și open-end. În producția de fire pieptănate, se utilizează fibre de înaltă calitate și lungi pentru a produce fire cu finețe Ne 30 sau Ne 50. În producția de fire pieptănate, lungimea și raportul fibrelor pot fi ajustate prin setările mașinii. Distanțele dintre cilindrii de alimentare în mașinile de filare a firelor pieptănate sunt esențiale pentru această ajustare. În acest studiu, rezultatele experimentale au fost obținute utilizând 4 tipuri de finețe produse din același amestec și 5 setări diferite ale fălcilor de fixare a mașinilor de filare a firelor pieptănate. Aceste rezultate au fost optimizate utilizând rețele neuronale artificiale. În analiză, finețea firelor și distanța dintre cilindrii de pieptănare au fost utilizate ca date de intrare, în timp ce proprietățile fizice ale firului au fost utilizate ca date de ieșire.

Cuvinte-cheie: *fire pieptănate, materii prime naturale, lungimea fibrei, rețea neuronală artificială, optimizare*

INTRODUCTION

Ready-to-wear products designed to meet the growing demand for clothing in the 21st century are often questioned in terms of quality due to their mass-production nature. While the apparel industry has made significant advancements by improving existing production systems, these innovations have also led to a shift in raw material usage, moving from natural fibres to artificial fibres to boost production. Despite the availability of artificial fibres, consumer preference remains inclined toward natural fibres due to their perceived health benefits and sustainability.

In the production of natural fibres like cotton, optimising machinery and production settings plays a critical role in reducing waste and improving efficiency. Each type of yarn requires distinct machine settings tailored to its specific production parameters. These settings are influenced by the quality and properties of the raw cotton used [1, 2].

Different types of defects arise in various yarn production systems, including carded, combed, and open-end spinning. Among these, the combed cotton production line stands out for its ability to produce fine and high-quality yarns. This system utilises long fibres, selected through precise fibre scanning, to manufacture thin-count yarns. The combing system,

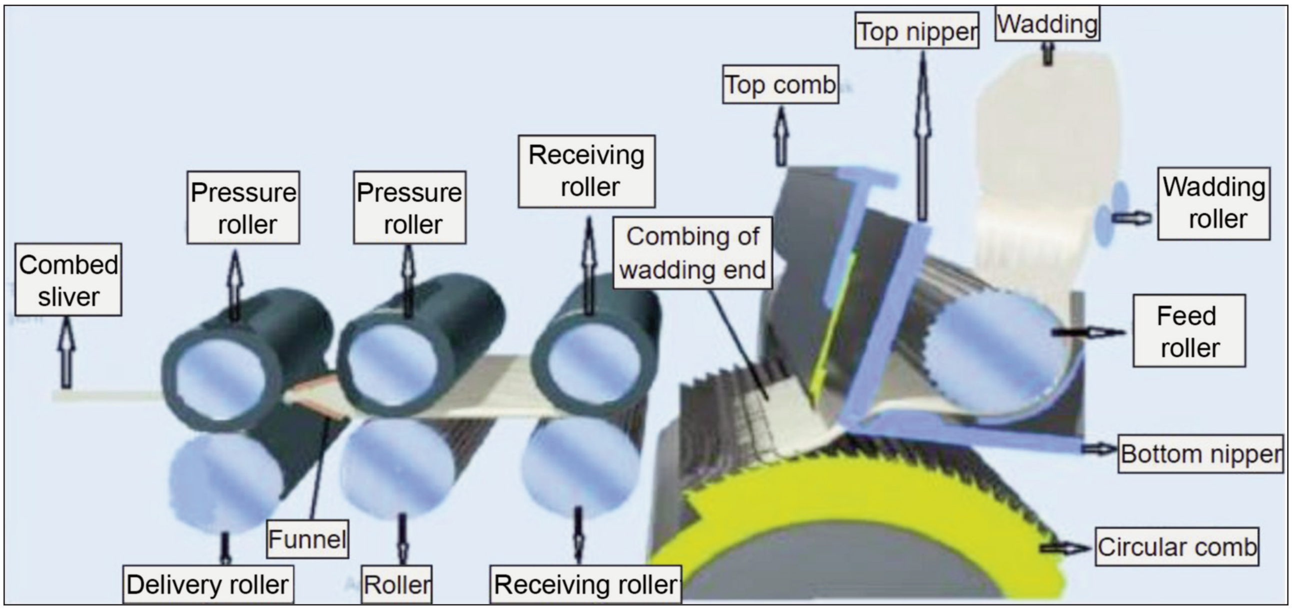

Fig. 1. Combing machine technological scheme [1]

particularly the comber machine, is integral to this process. It performs crucial functions such as cleaning, short fibre removal, fibre parallelisation, and drafting. These operations ensure the production of superior-quality yarns with minimal waste.
The comber machine is a cornerstone of combed yarn production, with its operational mechanism depicted in figure 1. Its advanced functionalities make it a vital component in the production of fine yarns, reinforcing its importance in modern textile manufacturing [1].
In the comber machine, fibres held in a pendulum-like position between the fibre jaw and the feeding roller are pulled and sorted during the combing process. The feeding roller operates with precise control, stopping at specific angles to adjust the jaw distance in both positive and negative directions, effectively performing the fibre scanning task. This dynamic adjustment ensures the separation of short fibres and enhances the quality of the output yarn.
Each adjustment in the machine settings, particularly during yarn number changes, impacts the resulting yarn parameters. Therefore, extensive tests are conducted at every stage to predefine and optimise these parameters. Based on the test results, the machine settings are fine-tuned to meet the desired quality standards.
The setting of the machines, like drafting and twisting, has a significant impact on yarn strength and its elongation. Üstüntağ investigated the optimisation of these parameters and determined the twist coefficient that provided the best overall result [3]. These results correlate with Jiang et al.'s studies using generalised regression neural networks to estimate yarn unevenness, which revealed that as optimisation algorithms become more complex, ANNs continue to optimise yarn production more efficiently [4]. Alongside this, the use of AI also corroborates the experimental results on the impact of yarn structure and count on the physical properties of yarns [5, 6].
In addition, ANNs were useful for exercising control over the quality of production of yarns, and various possibilities are found for their use in this area. In this specific area, for instance, Farooq et al. showed that using resilient backpropagation neural networks successfully predicted yarn quality through a variety of input parameters, thus improving production conditions [7]. In the same way, Ghanmi et al. showed the achievement of accurate predictive performance of ring-spun yarn quality using hybrid neural networks [8].
The need for a multidimensional approach is more apparent in research centred on core-spun yarns because the interaction of core and sheath structures affects the properties of the yarn, such as strength and uniformity [9]. This complexity can more effectively be modelled with ANNs, and various yarn characteristics can be simulated and optimised.
The quality parameters of yarns produced under varying settings can be predicted using advanced mathematical modelling systems. Among these systems, artificial neural networks (ANNs) have emerged as a robust tool due to their ability to analyse and interpret complex datasets with diverse characteristics. ANNs, like other artificial intelligence methods, excel at identifying patterns and making predictions across numerous fields, including aviation, aerospace, automotive, defence, sound and signal detection, robotics, manufacturing, optimisation, and control engineering.
One of the primary reasons for the widespread adoption of ANNs in engineering applications is their capability to address problems that are difficult or impossible to solve using classical methods. By leveraging sample data with distinct features and forms, ANNs provide an efficient and versatile approach to solving

complex problems, making them a valuable asset in modern textile manufacturing and beyond [10–12].

MATERIAL AND METHODS

In this study, yarn was produced by adjusting the feed roller gap to five distinct positions on the combing machine within the combing production line. The adjustments were applied to four different yarn counts – Ne 18, Ne 20, Ne 30, and Ne 40 – obtained from the same cotton blend. The physical properties of the produced yarns were analysed through comprehensive testing. The results of these tests were subsequently compared to predictions made using an artificial neural network (ANN) model to evaluate its accuracy and effectiveness.

The feed roller gap settings used were –1, 0, 1, 1.5, and 2, and a total of eight physical properties were examined for each yarn sample. Before testing, all yarn samples were conditioned for 24 hours under standard atmospheric conditions (20±2°C temperature and 65±2% relative humidity) in accordance with TSE 240 standards [13].

Yarn count was determined using the skein method with a spinning reel. Twist values were measured under the same standard atmospheric conditions using a Zweigle brand yarn twisting device, following the twisting and re-twisting method outlined in TSE 247 [14]. Unevenness values were evaluated using the USTER Tester III, a capacitive measurement system, under TSE 628 standards. Measurements included parameters such as % U (percentage unevenness), thin places (–50%), thick places (+50%), and neps (+200%). The material entry speed was maintained at 400 meters per minute during the tests [15].

The strength and elongation properties of the yarns were measured using the USTER TENSOJET device according to TSE 245 standards [16]. A constant elongation rate of 5 meters per minute was applied during these measurements. A total of 40 measurements were taken for each feed roller setting, with 10 measurements performed for each of the four yarn counts, resulting in 200 measurements overall.

The data collected from these tests were meticulously analysed, and the results for each yarn count are summarised in table 1. This systematic approach provided insights into the impact of feed roller adjustments on yarn properties, offering a robust foundation for validating predictions made using ANN models.

The artificial neural network (ANN) model used in this study was implemented using the Pythia program. ANNs are computational modelling tools widely recognised in various fields of engineering and science for their ability to effectively address complex, nonlinear problems. These models draw inspiration from the functioning of biological nerve cells in the human brain, providing a robust algorithmic foundation for processing and analysing data.

An artificial neural network consists of interconnected units known as artificial neurons or nodes. These nodes are simple processing elements capable of

Table 1

PHYSICAL PROPERTIES OF YARNS

Data no	Yarn count	Machine setting	Twist T/″	% U	Thin places	Thick places	Neps	Hairiness, H	Strength (g)	Strength %CV	Elongation (%)
1	18	–1	15.11	6.49	3.10	6.00	7.80	5,98	662.36	5.15	6.48
2	18	0	15.19	6.46	4.40	7.20	5.70	6,51	666.10	5.31	6.25
3	18	1	15.09	6.55	6.80	11.20	11.50	6,02	632.39	5.47	5.98
4	18	1.5	15.04	6.49	7.10	9.90	12.20	5,50	518.38	5.51	6.09
5	18	2	14.99	6.98	6.90	13.00	17.00	6,04	481.15	5.54	5.47
6	20	–1	16.05	6.55	5.60	7.30	8.20	6,09	558.72	7.04	6.05
7	20	0	16.13	6.67	3.20	6.00	12.10	6,23	554.22	7.14	6.04
8	20	1	16.21	7.38	6.20	8.20	14.20	6,19	550.65	7.26	5.80
9	20	1.5	16.00	6.84	5.10	8.10	8.50	6,15	408.43	7.20	5.52
10	20	2	16.10	7.54	6.50	11.30	25.70	6,33	422.18	7.37	5.54
11	30	–1	20.19	6.92	6.50	17.00	64.20	5,77	347.61	7.10	4.89
12	30	0	20.27	7.53	5.70	16.90	38.00	5,63	348.44	7.05	4.75
13	30	1	20.12	8.63	6.60	18.60	46.30	5,67	350.31	7.34	4.89
14	30	1.5	20.07	7.81	5.00	18.80	39.90	4,78	313.31	7.25	5.43
15	30	2	20.22	8.52	5.50	21.00	52.00	5,71	322.15	7.28	5.01
16	40	–1	25.15	10.21	13.90	25.10	85.30	5,54	248.39	8.94	5.21
17	40	0	25.22	9.86	9.40	30.90	90.30	5,28	253.48	9.25	4.80
18	40	1	25.12	10.09	8.00	32.10	73.50	4,92	269.44	9.24	4.91
19	40	1.5	25.30	10.08	6.40	23.60	58.30	4,50	265.98	9.18	5.29
20	40	2	25.20	10.30	6.80	20.90	64.00	5,34	261.00	9.23	5.25

performing largely parallel computations, enabling efficient data processing and pattern recognition. The structure of an ANN is designed to mimic the architecture and functionality of biological neural networks, leveraging connections between neurons to process input data and generate meaningful outputs. The architecture of an ANN typically comprises three primary layers: the input layer, which receives raw data; one or more hidden layers, where the actual computations and data transformations occur; and the output layer, which produces the result. Each layer is interconnected by weighted connections, which are adjusted during the learning process to minimise errors and optimise performance. The learning mechanism involves algorithms such as backpropagation, which iteratively update these weights to improve accuracy and reliability.

This biologically inspired approach allows ANNs to excel in modelling complex systems, identifying intricate patterns, and making predictions even with incomplete or noisy data. Applications of ANNs span diverse domains, including image recognition, speech processing, control systems, robotics, manufacturing, optimisation, and predictive modelling.

In this study, the Pythia program was employed to develop and train an ANN for predicting yarn properties based on input variables such as machine settings and yarn count. Figure 2 illustrates the conceptual similarity between a biological nerve cell and an artificial neural network, emphasising how ANNs emulate the fundamental principles of biological neural systems to achieve their computational capabilities.

Artificial neural network (ANN) modelling can be implemented through custom-developed programs or by utilising various specialised software tools and add-ins, such as those designed for Microsoft Excel. These tools simplify the modelling process by offering user-friendly interfaces and pre-configured algorithms tailored to specific types of neural networks. In this study, Pythia 1.02, a software developed by Runtime Software, was employed to conduct the ANN modelling. Pythia 1.02 is specifically designed to support feedback multilayer sensor models, making it a suitable choice for the research objectives. The software leverages the Levenberg-Marquardt algorithm, a widely recognised optimisation technique known for its efficiency in training neural networks by minimising errors. Additionally, the model utilises a Sigmoid transfer function, a crucial component for introducing non-linearity into the system, enabling the ANN to model complex patterns and relationships in the data. For this study, the Sigmoid function parameters were set as c = 4 and T_i = –1.5, allowing for precise calibration of the transfer function's slope and position. The Pythia program's interface, illustrated in figure 3, provides a comprehensive yet intuitive platform for designing, training, and analysing neural network models. Its features facilitate the adjustment of model parameters, visualisation of training progress, and evaluation of performance metrics. The Sigmoid transfer function employed in the study is mathematically represented in equation 1, which defines its role in transforming the input signals into outputs that contribute to the model's decision-making process

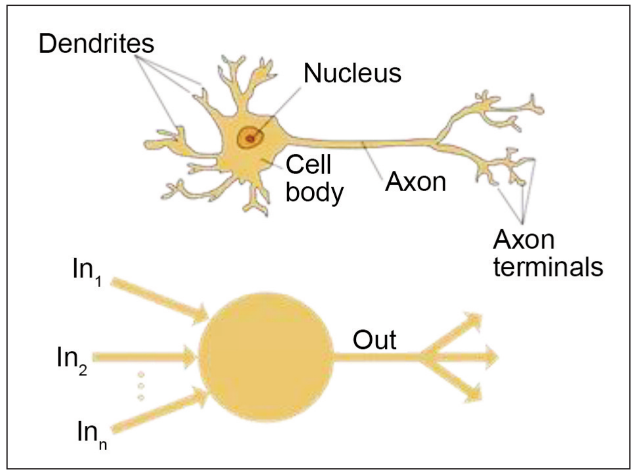

Fig. 2. Nerve cell and a simple artificial neural network

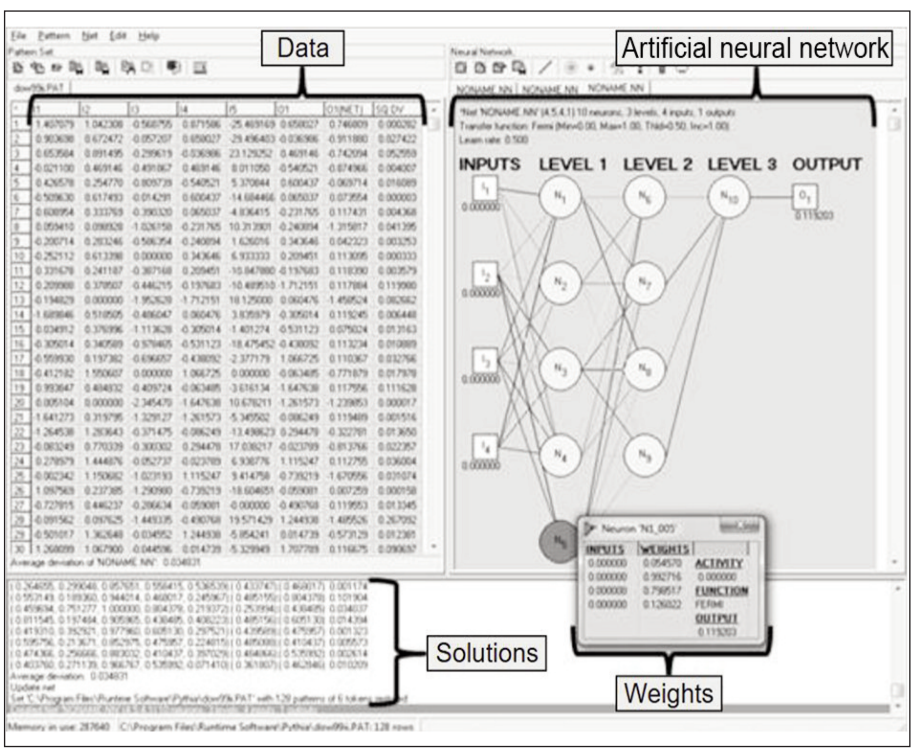

Fig. 3. Interface of the Pythia Program used for the artificial neural network solution

[17–20]. This function is integral to the feedback multilayer architecture, enhancing the network's ability to generalise and adapt to diverse input scenarios. By leveraging Pythia 1.02, the study not only ensured robust and reliable ANN modelling but also benefited from the software's streamlined workflow, which significantly reduced the complexity and time required for model development and analysis.

$$y_i = f(z_i, T_i, c) = \frac{1}{1 + e^{-c(z_i + T_i)}} \quad (1)$$

A neural network operates through two primary phases, commonly referred to as the Training Phase and the Reproduction Phase. During the training phase, the network is exposed to a dataset comprising inputs and their corresponding desired outputs. The primary objective of this phase is to minimise the error or deviation between the network's predicted outputs and the actual outputs by optimising the network's parameters, such as weights and biases. This optimisation is achieved using iterative learning algorithms, which adjust the parameters to improve the network's performance.

Once the training phase is complete, the network enters the reproduction phase. In this phase, the network's parameters remain fixed, and it is used to process new input data to predict or estimate the corresponding output. This phase demonstrates the network's ability to generalise learned patterns from the training data to unseen data, which is a critical aspect of artificial neural networks (ANNs).

In the Pythia software, the structure and configuration of the neural network can be easily customised. Users can specify the desired number of input and output nodes based on the problem at hand. The data required for training can be imported into the program's "Pattern Set" section either by copying and pasting directly or by uploading a file. After the data transfer, the software prompts the user to define the number of output nodes, enabling flexible adaptation to various datasets. Once this configuration is complete, the user can initiate the networking process.

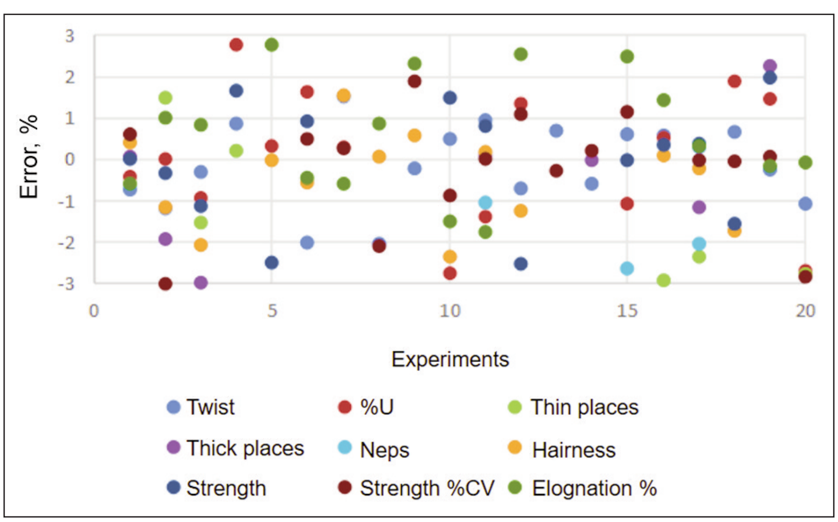

Fig. 4. Error graph occurring in artificial neural network data

The topology of the ANN in Pythia is defined as INPUTS (G) - HIDDEN LAYERS (GK) - OUTPUTS (D), which can be represented in shorthand notation as G-GK1-GK2-GK3…-GKN-D. For instance, consider a dataset with three inputs and two outputs. If the user specifies a topology of 3-2-5-3-2, the first number represents the number of input nodes, while the subsequent numbers denote the number of neurons in each hidden layer. The number of neurons in the final hidden layer corresponds to the number of output nodes. Effectively, the last hidden layer neurons function as outputs. In this example, the network consists of four layers, and the total number of neurons in the hidden layers and outputs is 2 + 5 + 3 + 2 = 12, where the final two neurons represent the two outputs.

For the current study, an ANN with a topology of 2-6-9-8-9 was designed to handle a dataset comprising two input variables and nine output variables. This network includes four layers and a total of 32 neurons, distributed across the layers as follows: 6 in the first hidden layer, 9 in the second, 8 in the third, and 9 in the final hidden layer, which also serves as the output layer.

The performance of the model was evaluated by comparing the outputs predicted by Pythia to the actual values, with the results presented in figure 4. The analysis revealed an error margin of ±3%, indicating a high degree of accuracy. Given that the task involved estimating nine output values based on two input variables, an error rate of 3% is considered acceptable and demonstrates the reliability and applicability of the model. This level of precision underscores the suitability of the Pythia software for constructing and training artificial neural networks for complex predictive modelling tasks.

To mathematically reproduce the results obtained through the artificial neural network (ANN), it is essential to determine the weight coefficients used in the Sigmoid function defined in equation 1. These weight coefficients play a crucial role in the computational process of the neural network, as they govern the strength of the connections between neurons in successive layers. Specifically, for each neuron in each layer, the number of weight coefficients corresponds to the number of neurons in the preceding layer.

In the case of the input layer, the number of weight coefficients for each neuron equals the total number of input variables. These coefficients represent the influence of each input variable on the neuron's output. Similarly, for hidden and output layers, the coefficients are calculated based on the number of neurons in the immediately preceding layer.

For this study, the weight coefficients for the ANN were generated using the Pythia software, resulting

Table 2

WEIGHT COEFFICIENTS CALCULATED IN AN ARTIFICIAL NEURAL NETWORK										
Layer	Neuron	1	2	3	4	5	6	7	8	9
1	1	–1.975436	–3.304375							
1	2	0.917336	–1.493784							
1	3	–0.964339	–0.355952							
1	4	–3.855961	–0.574815							
1	5	–0.717976	–0.701802							
1	6	–0.685916	–0.676397							
2	7	–0.455567	–6.376816	–0.915245	–0.539521	–0.704509	–2.373251			
2	8	1.263206	–1.175547	–5.465372	–6.374568	–5.710916	–5.470427			
2	9	0.993879	–2.106173	0.354421	1.932337	3.201756	2.009222			
2	10	3.693220	–12.36576	0.737505	5.19373	1.57856	0.85751			
2	11	4.743962	–3.552935	–6.936252	–5.495812	–5.494661	–7.226669			
2	12	–0.013889	0.901521	–11.97177	–10.56661	–12.80283	–11.99614			
2	13	–9.539616	–4.277408	0.026468	1.908465	1.134271	1.724469			
2	14	–3.374830	–0.383755	–2.463115	–1.982897	–2.990539	–3.062944			
2	15	–0.622525	–8.737184	–1.292008	–0.440332	–1.191800	–0.508064			
3	16	0.788359	–3.920467	0.427467	8.235882	–1.864157	–6.477185	–9.239868	–2.066066	3.505495
3	17	1.269854	–0.045228	–0.383782	1.164789	0.339000	–1.348221	0.092236	0.448676	–1.151577
3	18	2.038355	–1.448557	–1.849511	1.399077	–3.989047	0.253506	–4.534108	2.774514	3.098728
3	19	4.452354	–2.584293	1.054378	–0.845092	–1.596711	–5.729222	–1.656045	–0.642605	3.266479
3	20	–0.572861	–1.967473	–6.152833	–0.705612	1.793678	1.151936	–2.405619	–5.162993	–0.930477
3	21	0.726511	1.149204	–2.495070	–1.822240	0.671769	5.151226	0.003265	0.060201	–1.224241
3	22	–2.180354	–2.203089	0.833990	3.960603	–0.155722	–1.060682	–0.892994	–1.619960	–2.581570
3	23	–2.325955	0.701559	–1.954277	–0.254894	–1.468134	–0.103564	–0.572754	–2.100381	–0.785084
4	24	–1.195267	0.551559	–3.087801	0.426245	1.437288	3.655280	–0.463852	2.793774	
4	25	–0.174748	0.756523	–1.540473	0.821151	–1.837228	3.024875	–1.830760	–1.897849	
4	26	0.772637	1.605489	–0.920176	–0.172195	2.184985	0.459433	–0.946581	1.089862	
4	27	1.600520	2.861688	2.038323	–2.461917	–1.304598	0.800450	–1.899195	0.170927	
4	28	0.638565	3.286466	0.662980	–2.297918	4.931860	0.711646	–1.567963	0.168045	
4	29	–2.465545	2.326171	3.539940	1.061798	0.756865	–0.477453	2.460634	–2.991679	
4	30	–0.971837	0.908059	0.732549	0.616447	–1.202303	–0.699542	2.372659	0.055733	
4	31	–2.555997	0.244255	–1.840284	2.985291	1.499405	3.125452	–0.421809	0.497417	
4	32	–0.838692	1.435933	–4.152856	1.596498	1.964948	0.649681	1.180128	–3.419045	

in a total of 210 weight coefficients. These coefficients were derived as part of the training phase of the neural network, where the model optimised its parameters to minimise error and improve predictive accuracy. By incorporating these coefficients into the Sigmoid function, the ANN can mathematically estimate key output variables for any given input data.

The calculated outputs include several critical textile parameters: Twist, U% (Unevenness Percentage), Thin Places, Thick Places, Neps, Hairiness, Strength, Strength% CV (Coefficient of Variation), and Elongation Percentage. These parameters are essential for evaluating the quality and performance of yarn, providing valuable insights for both production processes and quality control.

By utilising the weight coefficients and the Sigmoid function, it is possible to predict these outputs accurately for any combination of yarn count and machine settings. This approach not only ensures precision but also eliminates the need for exhaustive experimental trials, thereby saving time and resources in the textile manufacturing process. The integration of ANN modelling with tools like Pythia demonstrates the potential of artificial intelligence in solving complex industrial problems and optimising operations.

CONCLUSION

In this study, the physical properties of yarn produced from the same fibre blend were examined across four different yarn counts. Additionally, the combing machine feed roller jaw spacing was adjusted at five distinct intervals, resulting in a comprehensive dataset that reflects variations in yarn quality under different machine settings and fibre processing conditions. These experimental data served as the foundation for developing an artificial neural network (ANN) model using the Pythia software.

The ANN model was designed with a topology of 2-6-9-8-9, representing a network with four layers and a total of 32 neurons. The structure includes two input nodes, which correspond to the independent variables (yarn count and combing machine jaw spacing), and nine output nodes, which represent the dependent variables or target properties of the yarn. These output variables are Twist, U% (Unevenness Percentage), Thin Places, Thick Places, Neps, Hairiness, Strength, Strength% CV (Coefficient of Variation), and Elongation Percentage. The hidden layers of the network are composed of 6, 9, and 8 neurons, respectively, with the final hidden layer directly feeding into the output layer. The Sigmoid function was employed as the transfer function for all neurons in the network, facilitating the transformation of input data into meaningful output predictions.

The training and testing of the model revealed an error margin of ±3% between the predicted values generated by the ANN and the actual experimental data. This low error rate indicates a high level of accuracy and demonstrates the robustness of the model. For a dataset involving two input variables and nine output variables, an error margin of this magnitude is considered highly acceptable and validates the model's predictive capability.

The ANN's weight coefficients, totalling 210, were generated during the training process using the Pythia software. These coefficients define the strength and influence of connections between neurons in adjacent layers. By applying these coefficients in the Sigmoid function, it becomes possible to accurately estimate the nine output variables for any combination of yarn count and machine settings. This predictive capability significantly enhances operational efficiency by enabling the optimisation of production parameters without the need for extensive experimental trials.

Overall, the use of the ANN model in this study highlights its potential as a powerful tool for understanding and predicting complex relationships between input variables and output properties in textile manufacturing. The integration of machine learning techniques, such as artificial neural networks, with advanced software like Pythia provides valuable insights into the interplay between machine settings, material characteristics, and final product quality, paving the way for more efficient and precise process control in the industry.

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