Journal of Science and Technology – Engineering and Technology for Sustainable Development
Volume 36, Issue 2, April 2026, 104–110

Predicting Fabric Consumption for Jeans Using Artificial Neural Network

Nguyen Thi Le[1], Nguyen Nhat Trinh[2*], Tran Thi Hong Nhung[1], Tran Thi Bich[1], Mai Thi Nga[1], Nguyen Thi Linh Vi[1], Le Thi Hoai Thu[1], Nguyen Hoa Trung[1]
[1]Hanoi University of Industry, Ha Noi, Vietnam
[2]Hanoi University of Science and Technology, Ha Noi, Vietnam
[*]Corresponding author email: trinh.nguyennhat@hust.edu.vn

Abstract

Fabric consumption is a critical factor in industrial garment manufacturing, as fabric cost constitutes a substantial portion of total product cost. In the study, a systematically constructed dataset of jeans markers under multiple conditions was developed, and an Artificial Neural Network (ANN) model was proposed to predict fabric consumption based on fabric width, the number of garment components, and the number of garments per marker. The dataset was normalized and partitioned into two subsets: 70% for model training and 30% for testing. A four-layer feedforward ANN architecture with two hidden layers comprising 10 and 5 neurons, respectively, was employed, utilizing a unipolar sigmoid activation function and trained via the backpropagation algorithm. The evaluation results demonstrated high predictive accuracy, with a Mean Absolute Error (MAE) of 0.01, Root Mean Square Error (RMSE) of 0.02, and a coefficient of determination (R^2) of 0.9296 on the test dataset. The close alignment between actual and predicted fabric consumption confirmed the model's effectiveness. Compared with traditional linear models such as Bayesian Model Averaging (BMA), the ANN model exhibited superior capability in capturing nonlinear relationships among input variables. These results highlight the strong potential of ANN for practical applications in textile and apparel production, offering a fast and reliable approach for fabric planning.

Keywords: Artificial Neural Network, fabric comsumption for jeans, marker layout, prediction.

1. Introduction

Fabric consumption is a crucial factor in the garment manufacturing industry, directly affecting production costs, product pricing, and overall business efficiency. In addition to determining the required amount of raw materials, fabric consumption is also associated with the amount of waste generated and the sustainability of the production process.

In recent years, various studies have addressed this topic from multiple perspectives. Marker making plays a significant role in minimizing fabric waste and optimizing efficiency. It is closely related to fabric width, the number of garment components, and the number of garments per marker layout [1]. Digital pattern design offers substantial opportunities for saving time, resources, and fabric through more efficient marker planning [2]. Computer-Aided Design (CAD) systems have been widely applied in pattern making, grading, and marker generation [3]. Wong, W. *et al*. proposed a genetic algorithm (GA)-based optimization method to satisfy both the quantity of cut components and minimal processing time during manual fabric cutting [4]. A hybrid algorithm based on soft computing techniques, including Genetic Algorithm (GA), Simulated Annealing (SA), and a Hybrid Genetic Algorithm-Simulated Annealing approach (HGASA), was employed to optimize marker layout, showing that HGASA could reduce marker length by up to 28% [5]. Hora, S. and collaborators used a multi-objective optimization approach and found that selecting two sizes in a single marker was optimal, reducing fabric usage by up to 10% compared to layouts using 1, 3, 4, or more sizes [6]. Xu, Y. *et al*. proposed a mass customization-oriented production planning system based on mathematical optimization to construct efficient size charts and cutting plans [7]. Motahareh Kargar *et al*. developed optimization models for marker layout using computational algorithms to minimize fabric waste and production costs [8]. Muhammad *et al*. investigated methods to reduce the consumption of stretch denim made from cotton and cotton–polyester in garment development by controlling fabric shrinkage through reduced post-washing drying temperatures, without compromising denim properties [9]. Other studies have also integrated CAD technology with sizing standards to improve the accuracy of pattern making and enhance marker planning efficiency.

The relationship between marker parameters and fabric consumption has also been demonstrated in T-shirt production, where factors such as marker length, fabric spread length, number of fabric layers, and fabric roll length were found to have significant effects [10, 11]. Pham Thi Huyen *et al*. developed a multiple linear regression model to estimate fabric consumption for men's shirts based on fabric width, garment size, and marker efficiency using the Marker Making V6R2

p-ISSN 3093-3242
e-ISSN 3093-3579
https://doi.org/10.51316/jst.189.etsd.2026.36.2.13
Received: May 7, 2025; Revised: Nov 18, 2025;
Accepted: Dec 4, 2025; Online: Mar 24, 2026.

software [12]. A study on the influence of T-shirt construction on marker efficiency was conducted with the aim of minimizing material waste [13]. The influence of fabric width, the number of components in jeans, and the number of jeans per marker layout were found to be closely related to marker length, as shown by a multiple linear regression model with a significant coefficient of determination; however, this relationship was not reflected in the fabric consumption values [14]. This indicates that the relationship between fabric consumption and marker parameters may be nonlinear.

In the current context, accurate predicting of technical variables plays a particularly important role in industrial production. Traditional linear regression methods are often inadequate for capturing the complex nonlinear relationships between input and output variables in practice. As a result, the application of machine learning techniques, especially Artificial Neural Networks (ANNs), has been gaining increasing attention from the textile and apparel research community [15].

ANNs with their strong learning and generalization capabilities, have proven effective in modeling nonlinear and uncertain systems. ANNs operate based on principles analogous to the human brain, enabling them to identify complex patterns in data without requiring explicit assumptions about the mathematical form of relationships among variables [15]. Despite some related studies, research on predicting fabric consumption in jeans production - a segment with a distinctive position in the global apparel industry - remains limited. In this study, an ANN model was developed to predict fabric consumption for jeans in industrial garment manufacturing, based on fabric width, the number of garment components, and the number of products per marker layout. By constructing and training the ANN model using a systematically built, multi-condition dataset of marker layouts, the predictive results, model accuracy, and practical applicability were analyzed and evaluated. The findings provide a scientific and practical basis for improving the efficiency of denim fabric utilization and promoting sustainability in the garment industry. Furthermore, this study demonstrates the superior performance of the ANN model compared with traditional linear approaches such as Bayesian Model Averaging (BMA), highlighting its capability to capture complex nonlinear relationships. Overall, the research makes three key contributions: applying a nonlinear ANN model for accurate fabric consumption prediction, developing a systematic multi-condition dataset for model training and validation, and providing a quantitative performance comparison with linear models, offering guidance for practical application in the textile and apparel industry.

2. Methods

2.1. Experiments

Five jeans styles were selected for the study, based on *a* basic design (Fig. 1), with styles *b, c, d*, and *e* modified from style *a*. The technical patterns for all styles were developed at size 32, and grading for other sizes was performed using Lectra-Modaris V7R2.

A total of 175 experiments were conducted under controlled conditions. Fabric width (*kr*) was set at five levels: 1.50 m, 1.55 m, 1.60 m, 1.65 m, and 1.70 m. These fabric widths are commonly used in jeans manufacturing, readily available on the market, and can be ordered by manufacturers according to their specific requirements when working with fabric suppliers. The number of garment components per jeans style (*ct*) ranged from 16, 18, 20, 22 to 24 pieces, corresponding to five different design variations. Similarly, the number of products arranged on each marker (*sp*) was assigned values of 3, 4, 5, 6, and 7. Marker layouts were generated for multiple size groupings, including three sizes (30, 31, 32), four sizes (30-33 and 31-34), five sizes (30–34), and six sizes (29-34 and 30-35). All markers were automatically generated using the Marker Manager V6R2 and Marker Making V6R2 software packages to eliminate operator-dependent variation in marker efficiency. Fabric consumption for each jeans style was calculated using the following formula:

$$dm = L/sp \tag{1}$$

where:

dm is the fabric consumption per unit product (m),

L is the marker length (m),

sp is the number of products on the marker.

Based on the experimental results, the dataset used in this study was constructed with four variables: *kr*, *ct*, *sp*, and *dm*, in which *kr*, *ct*, and *sp* are input (independent) variables, while the fabric consumption for jeans (*dm*) is the output (dependent) variable. All variables are continuous and were validated for completeness and consistency prior to analysis.

2.2. Data Normalization

To ensure that the input variables are on the same scale and to accelerate the convergence of the artificial neural network (ANN) model, the data were normalized to the range [0,1] using the min-max scaling method, according to the following formula [16]:

$$x' = \frac{X - Xmin}{Xmax - Xmin} \tag{2}$$

where, x′ is the normalized value, *X* is the original value, *Xmin* and X*max* are the minimum and maximum values of each variable, respectively.

2.3. Data Splitting

The dataset was divided into training and testing sets. The training set accounted for 70% of the total samples and was used to develop the ANN model. The remaining 30% of the data formed the testing set, which was used to evaluate the model’s generalization capability and predictive performance. The splitting was performed randomly using a fixed seed (*set.seed = 123*) in R software to ensure result reproducibility.

2.4. Artificial Neural Network Model Configuration

A four-layer feedforward ANN model was constructed using the *neuralnet* package in R with the following architecture: the input layer consisted of 3 neurons (*kr, ct, sp*), and the output layer included 1 neuron (*dm*). The first hidden layer contained 10 neurons, and the second hidden layer consisted of 5 neurons. The unipolar sigmoid function was employed as the activation function:

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

This function enables the modeling of nonlinear relationships between input variables and intermediate layers within the network. At the output layer, a linear function was applied (*linear.output = TRUE*), meaning no additional nonlinear activation was used, which is appropriate for a regression problem aiming to predict the continuous value of the variable *dm*. The built-in backpropagation algorithm in the neuralnet package was employed to train the ANN. The training process was terminated either when the Sum of Squared Errors (*SSE*) reached a predefined minimum threshold or when the maximum number of iterations was completed.

The choice of the sigmoid activation function for the hidden layers allowed the model to effectively capture the nonlinear dependencies between inputs and outputs, while maintaining a linear output layer ensured that the network was suitable for continuous-value regression tasks.

2.5. Model Evaluation

The accuracy of the ANN model was assessed using the following performance indicators.

- *Mean Absolute Error (MAE):* Represents the average absolute difference between the predicted and actual values.
- *Root Mean Squared Error (RMSE):* Reflects the standard deviation of the residuals, indicating the dispersion of prediction errors.
- *R^2 (Coefficient of Determination):* Measures the proportion of variance in the dependent variable that can be explained by the independent variables in the model.

The predicted values from the model, originally generated from normalized data, were rescaled back to their original scale before calculating these metrics to ensure accurate evaluation of the ANN's performance.

3. Results and Discussion

After normalizing the dataset - including the input variables (*kr, ct,* and *sp*) and the output variable (*dm*) - the data were split into two subsets: 70% for training and 30% for testing. An ANN model was constructed with an architecture comprising two hidden layers, in which the first layer contained 10 neurons and the second layer contained 5 neurons, utilizing a unipolar sigmoid activation function and a linear output for continuous prediction.

The training results indicated that the forward and backward propagation processes converged after 625 learning cycles, achieving a total error *SSE* of 0.22. The final ANN structure is illustrated in Fig. 1, where the connections among neurons in the input, hidden, and output layers are clearly visualized.

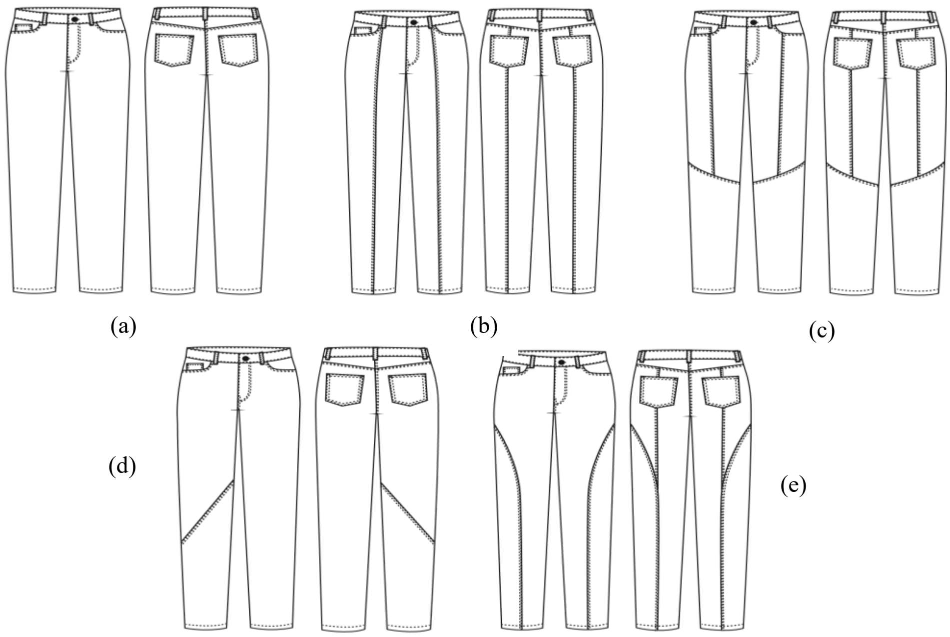

Fig. 1. Five styles of jeans selected for the experiment

Journal of Science and Technology – Engineering and Technology for Sustainable Development
Volume 36, Issue 2, April 2026, 104–110

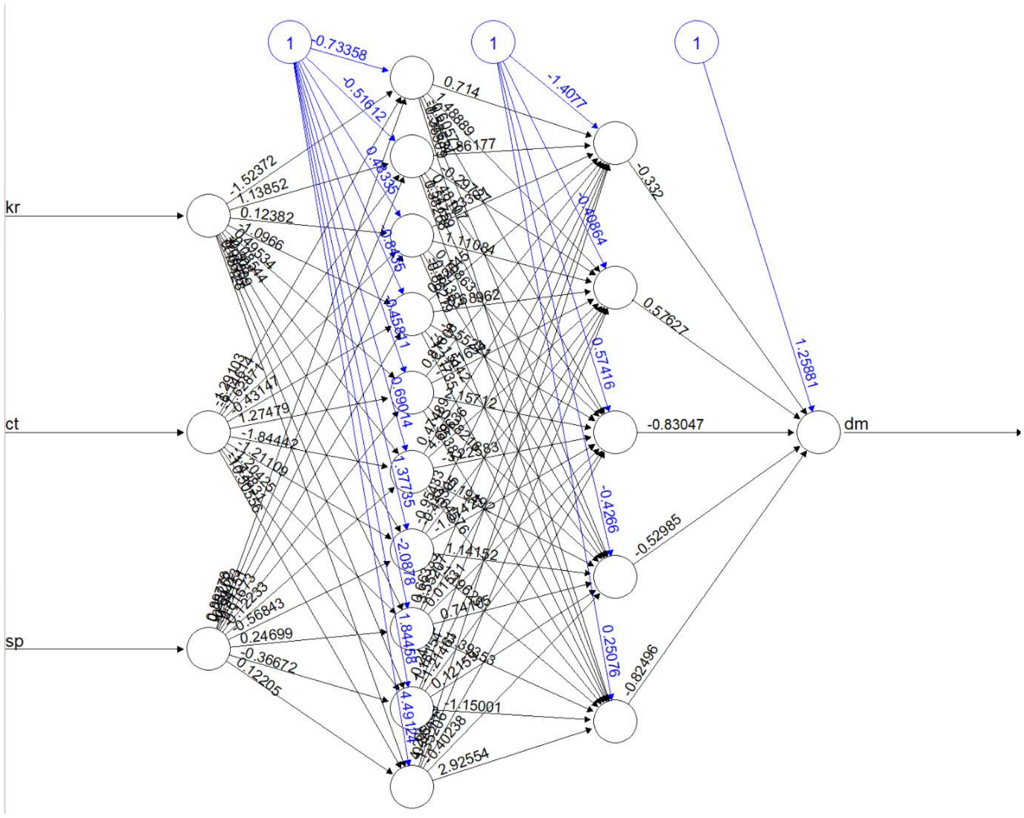

Fig. 2. Diagram of the ANN model for predicting fabric consumption for jeans

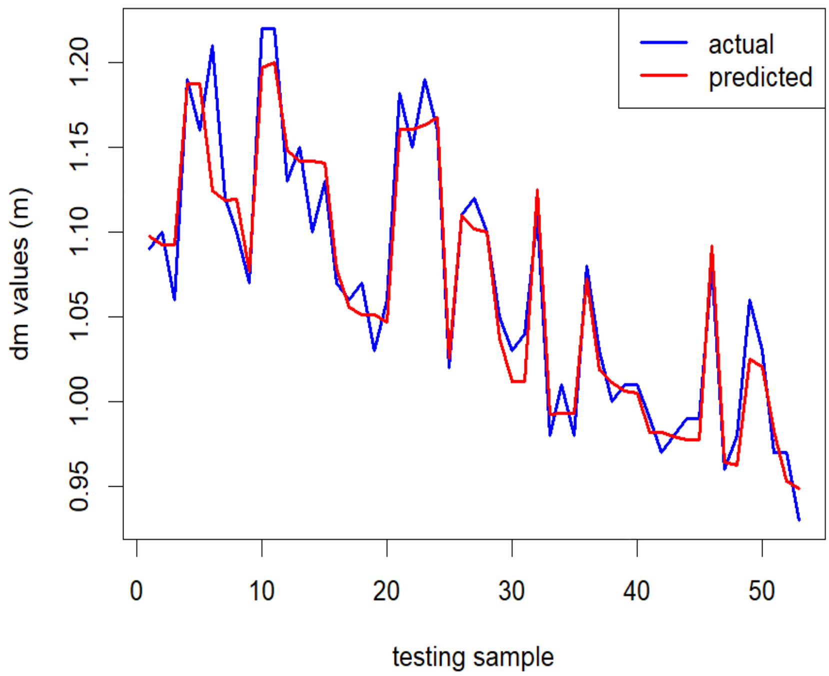

Fig. 3. Predicted and actual fabric consumptions for jeans on the test set

The prediction results on the training set, after converting the predicted and actual values back to the original scale, the error metrics of the ANN model obtained are as follows: *MAE = 0.01; RMSE = 0.02,* $R^2 = 0.9259$. The predicted results on the test set are presented in Table 1.

Fig. 3 presents the scatter plot between actual values (*dm_actual*) and predicted values (*dm_predicted*) on the test set, showing a linear relationship with a coefficient of determination R^2 equal *0.9296*. The data points are concentrated around the 45° diagonal line, indicating a high level of agreement between the forecasted and actual values. Evaluation on the test set yielded error metrics of *MAE* equal *0.01*, *RMSE* equal *0.02, and* R^2 equal *0.9296*. These values demonstrate that the ANN model established has strong predicting capability on the test set, with very small errors. This indicates that 92.96% of the variation in the fabric standard for jeans (*dm*) can be explained by the ANN model based on the three input variables *kr, ct, and sp*.

The comparison between the training and test sets shows equivalent errors, indicating that the model does not suffer from overfitting and has good generalization capability. Moreover, the high R^2 values on both datasets demonstrate that the ANN has successfully learned the underlying relationship between the input and output variables, effectively modeling the nonlinear relationships. Importantly, the nonlinear ANN model achieves very high accuracy on the systematically constructed, multi-condition dataset, highlighting its effectiveness in handling diverse marker layouts and complex variations in fabric consumption. The ANN model proves to be superior to conventional linear models in capturing complex relationships, thanks to its ability to represent the natural nonlinearity in the data.

Table 1. Predicted and actual results for fabric consumption for jeans on the test set

Marker	Actual fabric consumption (m)	Predicted fabric consumption (m)	Error (m)	Marker	Actual fabric consumption (m)	Predicted fabric consumption (m)	Error (m)
1	1.09	1.09	0.00	28	1.10	1.10	0.00
2	1.10	1.09	0.01	29	1.05	1.04	0.01
3	1.06	1.09	0.03	30	1.03	1.01	0.02
4	1.19	1.19	0.00	31	1.04	1.01	0.03
5	1.16	1.19	0.03	32	1.11	1.13	0.02
6	1.21	1.12	0.09	33	0.98	0.99	0.01
7	1.12	1.12	0.00	34	1.01	0.99	0.02
8	1.10	1.12	0.02	35	0.98	0.99	0.01
9	1.07	1.08	0.01	36	1.08	1.07	0.01
10	1.22	1.20	0.02	37	1.03	1.01	0.02
11	1.22	1.20	0.02	38	1.00	1.01	0.01
12	1.13	1.15	0.02	39	1.01	1.01	0.00
13	1.15	1.14	0.01	40	1.01	1.01	0.00
14	1.10	1.14	0.04	41	0.99	0.98	0.01
15	1.13	1.14	0.01	42	0.97	0.98	0.01
16	1.07	1.08	0.01	43	0.98	0.98	0.00
17	1.06	1.05	0.01	44	0.99	0.98	0.01
18	1.07	1.05	0.02	45	0.99	0.98	0.01
19	1.03	1.05	0.02	46	1.08	1.09	0.01
20	1.06	1.05	0.01	47	0.96	0.97	0.01
21	1.18	1.16	0.02	48	0.98	0.96	0.02
22	1.15	1.16	0.01	49	1.06	1.03	0.03
23	1.19	1.16	0.03	50	1.03	1.03	0.00
24	1.16	1.16	0.00	51	0.97	0.99	0.02
25	1.02	1.03	0.01	52	0.97	0.95	0.02
26	1.11	1.11	0.00	53	0.93	0.95	0.02
27	1.12	1.10	0.02				

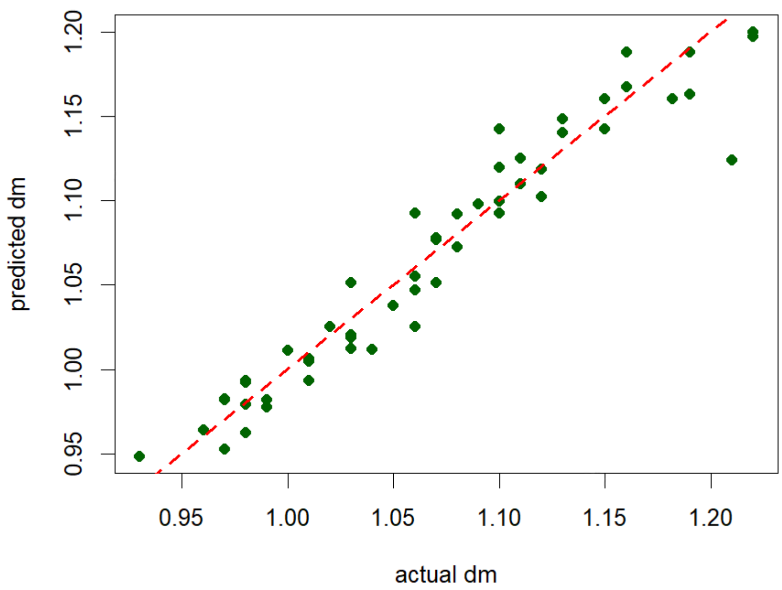

Fig. 4. Correlation between actual and predicted values of fabric consumption for jeans

An optimal linear regression model was also established using the BMA technique to predict the fabric consumption for jeans based on fabric width, number of garment components, and number of products in the marker using this experimental dataset [14]. Although BMA reduces the risk of model selection errors by averaging over highly probable models, its forecasting performance only reached *MAE* equal *0.4627, RMSE* equal *0.4685, and* R^2 equal *0.6020* [14]. These results show that the optimal linear model determined by BMA is significantly less accurate than the established ANN model. Specifically, the *MAE* and *RMSE* of the optimal multivariate linear model are approximately 46.27 and 23.42 times higher, respectively, and the R^2 is about 32.76% lower than that of the ANN model. This indicates a clearly nonlinear relationship between the variables *kr, ct, sp*, and *dm*. Therefore, the ANN model, with its ability to learn nonlinear patterns, demonstrates clear superiority over the optimal multivariate linear model determined by BMA. This performance comparison highlights one of the key contributions of this study: it quantitatively demonstrates the effectiveness of the nonlinear ANN model on the systematically constructed, multi-condition dataset and confirms its clear advantage over traditional linear approaches like BMA in predicting fabric consumption. This comparison underscores that in cases where data exhibits nonlinear structures or complex variable relationships, artificial neural networks are a more effective forecasting tool than traditional linear regression methods, even when advanced model selection techniques like BMA are applied.

Although the ANN model achieved high accuracy, the relatively small number of training samples may affect its generalization ability when applied to entirely new data. Moreover, the ANN model lacks interpretability, making it difficult to clearly explain the specific impact of each input variable on the output variable. In future studies, it would be beneficial to experiment with a larger sample size, apply techniques such as Shapley Additive Explanations values or permutation importance to assess the significance of each input variable, or compare the performance of the ANN with other machine learning models such as Random Forest, Gradient Boosting, or Support Vector Machine to obtain a more comprehensive evaluation.

4. Conclusion

In this study, an ANN model was developed to predict fabric consumption for jeans based on fabric width, the number of garment components, and the number of products in the marker. The results show that the ANN model achieved high accuracy, with a *MAE* of 0.01, *RMSE* of 0.02, and a coefficient of determination R^2 of 0.9296 on the test set. These low error metrics and the high R^2 value confirm that the model effectively learns the nonlinear relationships among variables and generalizes well across varying marker conditions.

The predicted values closely match the actual fabric consumption on the test set, demonstrating the model's accuracy and reliability. When compared with the multivariate linear regression model determined using BMA, the ANN clearly outperforms the linear approach. This finding underscores a key scientific implication: linear models are insufficient to capture the nonlinear interactions among marker parameters and fabric consumption, whereas ANNs are inherently suited to modeling datasets with complex and nonlinear variable interactions, as demonstrated in the multi-condition dataset developed in this study.

From a practical perspective, the ability to accurately predict fabric consumption has significant implications for industrial garment production. Reliable predictions support more efficient production planning, cost estimation, material budgeting, and reduction of fabric waste, thereby improving operational efficiency. The ANN-based approach thus enables manufacturers to make faster and more precise decisions, especially in contexts requiring rapid evaluation of multiple marker layout scenarios.

However, the relatively small dataset remains a limitation. Expanding the dataset and incorporating interpretability techniques such as SHAP or Local Interpretable Model-Agnostic Explanations may further enhance the practical applicability of ANN models in fabric consumption prediction. Future studies could also explore hybrid modeling frameworks or integrate production constraints to increase the robustness of predictive tools for industrial implementation.

References

[1] Khawar, M. T., Al Kashifah Razzaq, A., and Fatima, H., Digital pattern-making techniques, SDGs and Textiles, Springer, Singapore, pp. 199–224, Oct. 2024. https://doi.org/10.1007/978-981-97-7683-2_10

[2] Wong, W. K, Chan, C. K, Kwong, C. K, Mok P. Y., and W. H. Ip, Optimization of manual fabric-cutting process in apparel manufacture using genetic algorithms, The International Journal of Advanced Manufacturing Technology, vol. 27, pp. 152–158, Jan. 2005. https://doi.org/10.1007/s00170-004-2161-0

[3] Jankoska, M. and Stojanovska, R. S., Comparison of a computer-aided design and manual pattern-making, Proceedings of the Joint International Conference: 10th Textile Conference and 4th, Conference on Engineering and Entrepreneurship, Springer, pp. 461–467, Jan. 2024. https://doi.org/10.1007/978-3-031-48933-4_45

[4] Tsao, Y-C., Hung, C-H, and Vu, T-L, Hybrid heuristics for marker planning in the apparel industry, Arabian Journal for Science Engineering, vol. 46, pp. 10077–10096, Feb. 2021. https://doi.org/10.1007/s13369-020-05210-1

[5] Hora, S., Gruescu, CM., Bungau, C., Bodea, R. (2023). Optimization of Marker Design in Garment Industry on the Criterion of Utility Coefficient. In: Doroftei, I., Nitulescu, M., Pisla, D., Lovasz, EC. (eds) Proceedings of SYROM 2022 & ROBOTICS 2022. IISSMM 2022. Mechanisms and Machine Science, vol 127. Springer, Cham. https://doi.org/10.1007/978-3-031-25655-4_42

[6] Xu, Y., Thomassey, S., and Zeng, X., Optimization of garment sizing and cutting order planning in the context of mass customization, International Journal of Advanced Manufacturing Technology, vol. 106, pp. 3485–3503, Jan. 2020. https://doi.org/10.1007/s00170-019-04866-w

[7] Akhtar, S., Khan, M.Q., Jabbar, M. (2024). Introduction of Marker and Types. In: Khan, M.Q., Nawab, Y., Kim, I.S. (eds) Garment Sizing and Pattern Making. SDGs and Textiles. Springer, Singapore. https://doi.org/10.1007/978-981-97-7683-2_11

[8] Motahareh Kargar, Pedram Payvandy, Optimization of fabric layout by using imperialist competitive algorithm, Journal of Textiles and Polymers, vol. 3, no. 2, pp. 55–63, Jun. 2015.

[9] AMIR Muhammad, NAQVI Shenela, NAEEM Farhana, Investigation into shrinkage of stretchable denim fabric and its consumption in marker making by varying drying temperatures, Mehran University Research Journal of Engineering and Technology, vol. 42, no. 4, pp. 41–49, Oct. 2023. https://doi.org/10.22581/muet1982.2304.2871

[10] N.T. Le, Effect of marker parameters on fabric consumption of T-shirt in industrial garment manufacturing, no. 50, pp. 80–82, Feb. 2019. [In Vietnamese]: Ảnh hưởng của thông số sơ đồ giác tới định mức vải áo T-shirt trong may công nghiệp, Tạp chí Khoa học Công nghệ, ISSN 1859-3585, số 50, tr. 80–82, 2/2019.

[11] N.T. Le, Influence of Fabric Roll Parameters on Loss during Spreading, no. 9, pp. 73-76, Mar. 2016, [In Vietnamese]: Ảnh hưởng của thông số cuộn vải tới độ hao hụt trải vải], Tạp chí Khoa học và Công nghệ, ISSN 2354-0575, số 9, tr. 73-76, 3/2016.

[12] Pham Thi Huyen, Nguyen Thi Mai Hoa, Determine fabric consumption of products for garment production and business, International Journal of Engineering Inventions, vol. 13, iss. 4, pp. 114–119, Apr. 2024.

[13] Pham Thi Huyen, Nguyen Thi Mai Hoa, Nguyen Hoa Trung, Research the influence of the T-shirt body structure and marker performance, International Journal of Engineering Inventions, vol. 13, iss. 6, pp. 205–212, Jun. 2024.

[14] Le, N. T., Nhung, T. T. H., Bich, T. T., Nga, M. T., Vi, N. T. L., and Phuong, D. T., The Impact of marker parameters on fabric consumption for jeans, in Proceedings of the 2nd International Conference on Sustainability and Emerging Technologies for Smart Manufacturing, SETSM 2025, 22–23 Apr, Hanoi, Vietnam, Proceedings in Technology Transfer, Springer, Singapore, 2026. https://doi.org/10.1007/978-981-95-1750-3_49

[15] Nguyen Thi Le, Ngo Chi Trung, Le Huu Chien, Seam pucker prediction based on fabric structure and mechanical properties using neural network, Journal of Science and Technology, No. 65, 2008.

[16] G. Ciaburro, B. Venkateswaran, Neural Network with R, Packt Publishing, Birmingham, UK, 2017.