ANALYTICAL DATA FOR SEWING PRODUCTION EFFICIENCY: A MODEL BASED ON ARTIFICIAL NEURAL NETWORKS (ANNS)

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Abstract

The labor-intensive garment manufacturing sector is continually focused on meeting output goals, necessitating continuous improvements in production efficiency. Achieving targets at the lowest feasible cost is crucial for production management efficiency, especially in clothing production. The sewing component plays a vital role in enhancing the usefulness of clothing through a series of steps to produce ready-made garments. To optimize this process, we developed a model using an artificial intelligence (AI)-based method, specifically Artificial Neural Networks (ANNs), to enhance sewing production efficiency. The model focused on optimizing parameters that significantly influenced efficiency. Our results demonstrate that the ANNs model, with 1000 iterations, successfully replicates empirical data with an R-squared value of 0.98. The research introduces the novel use of an ANNs model with a five-node configuration and 1000 iterations, proving effective in optimizing sewing process parameters. This AI-based approach is a powerful tool for improving production efficiency in the garment industry, making significant theoretical and practical contributions. The findings offer substantial practical implications for practitioners in the textile industry and provide a robust framework for optimizing sewing production process parameters to achieve higher efficiency.

Keywords : Efficiency; ANNs, Sewing, Garment, Apparel

INTRODUCTION

The quality of the company's offerings, including its products, has a significant impact on its capacity to satisfy client demands. Customer satisfaction will increase with the quality of products the company offers its clients. To achieve this, the business must continue to uphold its standards and capacity, and make effective use of its resources to retain the caliber of the items it produces. One way to improve a company's capabilities is by meeting customer needs, which includes ensuring high product availability and superior product quality [1,2].

In this highly competitive environment, a company's ability to meet customer demands is crucial,

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particularly in the production process [3,4]. To remain competitive, businesses must adopt efficient production strategies, leverage advanced technologies, and continuously innovate to enhance product quality and operational efficiency.

This approach not only meets current customer expectations but also positions the company to effectively tackle future market challenges. Businesses can obtain maximum profits by spending or using the least amount of production expenses, hence efficiency in all business sectors, but particularly in production aspects, is crucial. When actual output is measured with effective capacity, it is called efficiency[6]. Manufacturing goods and services with the best possible mix of inputs to generate maximum output at the lowest possible cost is known as production efficiency.

Achieving this requires optimizing processes, minimizing waste, and continuously improving resource utilization. Implementing strategies such as lean manufacturing principles, advanced analytics, and AI-driven optimization models can further enhance production efficiency by identifying inefficiencies and streamlining operations [5] . This approach not only increases profitability but also ensures sustainable growth and competitiveness in today's dynamic business environment.

Production efficiency, a key parameter of success, plays a vital role in determining a company's financial performance [6,7]. Achieving production efficiency involves minimizing production costs while maximizing profit. This can be accomplished through an effective production process, proper production control, and the use of appropriate technology [8]. When it comes to producing things, a technically efficient corporation knows how to best mix labor and capital. To find the most effective and efficient work procedures and planning system, production control is used to research the concepts and methods. [9].

Apparel manufacturing companies currently face significant challenges in enhancing production efficiency, particularly in the sewing department. These challenges include managing the supply of raw materials, labor, facility utilization, and improving work methods [10]. Efficient management of these factors is critical to maintaining competitiveness and meeting market demands. However, achieving this efficiency is complex due to the dynamic nature of production environments and the interplay of various influencing factors.

To address these challenges, companies need to seek optimization of the right combination of parameters to improve production efficiency, especially in the sewing department. This requires conducting comprehensive optimization studies to identify the best parameter combinations that can lead to substantial improvements in productivity and cost-effectiveness [11,12]. Given the urgency and need to solve issues related to improving sewing production efficiency, AI-based modeling can be a viable solution. Artificial neural networks (ANNs) are AI models commonly used as optimization methods in industrial production processes due to their ability to handle large datasets and identify complex patterns [13–20].

ANNs can learn from historical data and make accurate predictions, making them

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particularly useful for optimizing production processes. However, this modeling has not yet been applied to the sewing production process to find the best parameter combinations for determining efficiency. The application of ANNs in this context could uncover insights that traditional methods might overlook, providing a more robust framework for decision-making.

Therefore, this study aims to provide theoretical contributions to the use of AI models in industrial settings and practical contributions by identifying the optimum combination of parameters for determining sewing production efficiency in apparel manufacturing companies. By integrating AI-based optimization methods into the sewing production process, companies can potentially achieve higher levels of efficiency, reduce operational costs, and improve overall production outcomes.

The findings of this research could pave the way for further advancements in the application of AI in manufacturing, offering a blueprint for other sectors facing similar efficiency challenges. The successful implementation of AI models can enhance decision-making processes, provide deeper insights into production dynamics, and foster innovation in optimizing resource utilization and productivity. This comprehensive approach not only addresses current inefficiencies but also prepares companies to adapt to evolving industry demands and maintain a competitive edge in the global market.

METHOD

This study employed an observational approach to gather empirical data on the production process within the sewing department. Data were collected from an apparel manufacturing company based in Bandung, West Java.

Subsequently, the research involved developing an AI-based optimization model and identifying the optimal combination of parameters based on their correlation coefficients. Figure 1 illustrates the research design. The observational approach allowed for an in-depth understanding of the current production practices and identification of key variables affecting efficiency.

The collected data were then used to train the AI model, which analyzed the relationships between different parameters and their impact on production outcomes. The model's goal was to pinpoint the parameter combinations that would maximize efficiency and productivity. The research design, as depicted in Figure 1, outlines the systematic process of data collection, model development, and validation, ensuring that the findings are robust and applicable to real-world industrial settings.

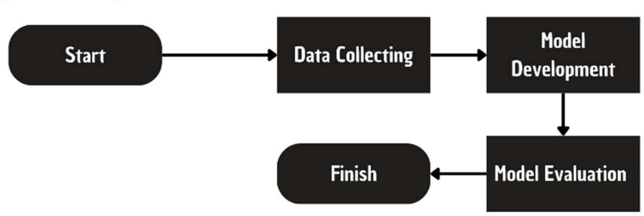

Figure 1. Research Framework

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Based on Figure 1, the research methodology begins with data collection, where relevant data is gathered from primary sources, specifically production reports in the garment industry. This data collection is conducted by professionals in the garment industry. Following this, model development uses the collected data to create predictive or explanatory models utilizing AI-based techniques, specifically artificial neural networks (ANNs). The model development process involves

several steps: dividing the data into training and testing sets, training the model with the training set, evaluating the model using various metrics, refining the model for improved accuracy, and validating it in real-world contexts to ensure its applicability and robustness.

The research concludes with the assessment of the value of the coefficient of correlation, which measures the strength of the relationship between actual data and the predictive model data using statistical techniques such as the residual coefficient from two different populations. This step is crucial as it helps identify important variables and provides deeper insights into model performance and reliability. By understanding the correlation between the predicted and actual outcomes, researchers can fine-tune the model and enhance its predictive capabilities.

These three stages data collection, model development, and correlation assessment work together to ensure that the research results are accurate, valid, and reliable. Through this comprehensive methodology, the study aims to contribute valuable insights into the use of AI models in optimizing production efficiency in the garment industry and potentially other sectors facing similar challenges.

RESULT AND DISCUSSION

1. Data Collection

The experimental data from garment industry. Table 1 shows the three process parameters as the independent variables, with piece quality serving as the dependent variable.

Table 1. Data Collection

No.	QTY ORDER	LINE	MP	SMV (MENIT)	WORKING HOUR (MENIT)	OUTPUT	TARGET IE %	% EFF
1	30290	6	46	28,7	480	520	769	68%
2	30290	6	47	28,7	480	500	786	64%
3	30290	6	48	28,7	480	550	803	69%
4	30290	6	50	28,7	480	532	836	64%
5	30290	6	48	28,7	480	520	803	65%
6	30290	6	47	28,7	480	510	786	65%
7	30290	6	44	28,7	480	500	736	68%
8	30290	6	46	28,7	480	421	769	55%
9	30290	1	60	28,7	480	499	1003	50%
10	30290	6	44	27,0	480	570	820	70%
11	30290	6	44	27,0	480	550	782	70%
12	30290	5	61	27,0	480	750	1084	69%
13	30290	6	48	27,0	480	600	853	70%
14	30290	6	47	27,0	480	500	836	60%
15	30290	2	57	27,0	480	450	1013	44%
16	30290	6	47	27,0	480	570	836	68%

DOI: texere.v23i2.07

17	30290	6	47	27,0	480	579	836	69%
18	30290	6	47	27,0	480	550	836	66%
19	30290	6	46	27,0	480	200	818	24%
20	30290	6	47	27,0	480	502	836	60%
21	30290	6	42	27,0	480	405	747	54%
22	30290	2	58	27,0	480	600	1031	58%
23	30290	1	57	27,0	480	421	1013	42%
24	30290	4	62	27,0	480	700	1102	64%
25	30290	6	40	27,0	570	550	844	65%
26	30290	6	38	27,0	540	513	760	68%
27	30290	6	41	27,0	480	265	729	36%

Table 1 presents the distribution of data influencing production efficiency, with the following variables: main power (MP) representing labor allocation, Standard Minutes Value (SMV) indicating the time required to sew a product, working hours representing the labor work time, production output corresponding to the target, process effectiveness measurement as the industrial engineering value, and sewing production efficiency.

The main power (MP) variable is crucial as it represents the allocation of labor, which directly impacts productivity. Effective labor allocation ensures that the right number of workers is assigned to tasks, balancing workload and preventing bottlenecks. The Standard Minutes Value (SMV) is another vital parameter, reflecting the time required to sew a product. It serves as a benchmark for measuring efficiency and setting realistic production targets.

Working hours denote the actual labor work time, influencing the total output. Efficient management of working hours can lead to higher productivity and better utilization of human resources. Production output is the measure of the actual production achieved against the target, providing a clear indication of the production line's performance.

Process effectiveness measurement, represented as the industrial engineering value, evaluates how well the production process is being managed and executed. This metric helps in identifying inefficiencies and areas that require improvement. Finally, sewing production efficiency is the overall measure of how effectively the sewing department converts inputs into outputs, considering all influencing factors. The statistics in Table 1 on production efficiency lead to the conclusion that the achieved efficiency fell short of the 75% efficiency objective that the corporation had previously established. This shortfall highlights several potential issues: inadequate labor allocation, suboptimal use of working hours, inefficiencies in the sewing process, or inaccuracies in the SMV estimation.

Addressing these issues involves a detailed analysis of each variable. For example, refining the SMV could help set more accurate production targets, while better labor management might improve overall efficiency. Additionally, examining the industrial engineering value can provide insights into process bottlenecks and areas for improvement.

Overall, the data from Table 1 underscores the need for comprehensive strategies to optimize production efficiency. This

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includes leveraging AI-based optimization models to identify the best parameter combinations, continuously monitoring and adjusting processes, and implementing best practices in labor management and process engineering. By doing so, companies can move closer to achieving and surpassing their efficiency goals, ultimately enhancing productivity and profitability.

- **Operator placement is inconsistent with job desk/skills**

Because the placement of operators in production activities according to their talents plays a large role in the level of output generated, placing operators in an appropriate manner is crucial to enhancing corporate productivity and efficiency.

Therefore, it would be extremely difficult to carry out continuing production operations when there are barriers in the form of placements that do not match their skills. This will lead to the level of output produced. Therefore, it will be quite difficult to carry out ongoing production operations when there are barriers in the form of placements that do not match their capabilities, leading to subpar output results.

- **Limitations of Machines**

A machine that is in operation can significantly boost a business's productivity and efficiency because the amount of output produced during production is greatly influenced by the employment of machines. Consequently, issues arising from malfunctioning machinery or needing replacement spare parts will make it extremely difficult to continue with production, leading to subpar output outcomes.

- **Production material delays**

The primary ingredients used in the production of goods are materials, sometimes known as raw materials. The manufacturing process stops when there are delays in raw materials or production materials because of poor divisional coordination, which lowers output results.

- **The products are of poor quality**.

Good or good quality goods play a major role in boosting business productivity and efficiency because quality is the primary consideration that opens up orders for goods from customers. Aside from that, the standard of items generated during production processes serves as a guide for the final product. As a result, issues arising from substandard quality of goods would pose significant challenges to the continuous manufacturing process, leading to suboptimal output outcomes.

2. Model Development

The development of the model begins with the collection of extensive datasets from sewing production, which includes gathering various operational parameters such as machine speeds, labour efficiency, material quality, and production timelines. These datasets undergo thorough preprocessing to clean the data, handle missing values, and normalize it to ensure consistency and reliability across all variables. Once prepared, the dataset is divided into training and testing sets. The training set is used to iteratively train the artificial neural network (ANN), adjusting its weights and biases to minimize prediction errors and optimize performance.

DOI: texere.v23i2.07

Different network architectures and configurations are tested during training to determine the most effective model. Techniques like cross-validation are employed to assess the model's ability to generalize to new data and prevent overfitting. After training, the model is validated using the testing set to evaluate its accuracy in predicting optimal parameter combinations for enhancing production efficiency.

This rigorous process ensures that the developed model is robust, reliable, and capable of driving significant improvements in operational performance within apparel manufacturing companies. By implementing such a comprehensive approach, companies can effectively utilize AI-based optimization to enhance their production processes, leading to higher efficiency, reduced costs, and improved overall productivity.

Moreover, this methodology can be adapted and applied to other sectors facing similar efficiency challenges, demonstrating the versatility and potential impact of AI-driven solutions in various industrial settings. The continuous refinement and validation of the model further ensure its relevance and effectiveness in addressing dynamic production environments, ultimately contributing to the long-term sustainability and competitiveness of manufacturing businesses.

A. Data Preparation

To prepare data for Artificial Neural Network (ANN) modeling, standardization and normalization are essential procedures to ensure data uniformity. Beyond aiding the ANN training process, normalization can improve the model's convergence. In this study, normalization is conducted using the X_{min}-X_{max} method, as in Eq. (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

X' represents the normalized data, where X_{min} is the smallest value in the dataset, and X_{max} is the highest value in the dataset. Table 2 shows the results of the data normalization process.

Table 2. Result Normalization Data

NO	QTY ORDER	LINE	MP	SMV (MENIT)	WORKING HOUR (MENIT)	OUTPUT	TARGET IE %	% EFF
1	30290	6	0.33	1	0	0.58	0.10	0.95
2	30290	6	0.37	1	0	0.54	0.15	0.86
3	30290	6	0.42	1	0	0.63	0.19	0.97
4	30290	6	0.5	1	0	0.60	0.28	0.86
5	30290	6	0.42	1	0	0.58	0.19	0.89
6	30290	6	0.37	1	0	0.56	0.15	0.89
7	30290	6	0.25	1	0	0.54	0.02	0.95
8	30290	6	0.33	1	0	0.40	0.11	0.67
9	30290	1	0.92	1	0	0.54	0.73	0.56
10	30290	6	0.25	0	0	0.67	0.24	1
11	30290	6	0.25	0	0	0.63	0.14	1
12	30290	5	0.95	0	0	1	0.95	0.97
13	30290	6	0.42	0	0	0.72	0.33	1
14	30290	6	0.37	0	0	0.54	0.28	0.78
15	30290	2	0.79	0	0	0.45	0.76	0.43

DOI: texere.v23i2.07

16	30290	6	0.37	0	0	0.67	0.28	0.95
17	30290	6	0.37	0	0	0.68	0.28	0.97
18	30290	6	0.37	0	0	0.63	0.28	0.91
19	30290	6	0.33	0	0	0	0.24	0
20	30290	6	0.37	0	0	0.54	0.28	0.78
21	30290	6	0.16	0	0	0.37	0.04	0.65
22	30290	2	0.83	0	0	0.72	0.81	0.74
23	30290	1	0.79	0	0	0.40	0.76	0.39
24	30290	4	1	0	0	0.90	1	0.86
25	30290	6	0.08	0	1	0.63	0.31	0.89
26	30290	6	0	0	0.66	0.56	0.08	0.95

B. ANNs Modelling

The ANN model has six input neurons, which indicate main power, SMV, working hours, output production sewing and industrial engineering (IE) value. The output layer determines the efficiency of production. Eqs. (1) and (2) can be used to express the hidden layer output (ψ_i) as well as efficiency production result (y).

$$\boldsymbol{\psi_i = w_{ij}x_j + \beta_i} \tag{1}$$

$$y_i = \varphi(\varsigma(\psi_i)) + \beta_i \tag{2}$$

Where ψ_i represents the value of the hidden layer neuron, x_{ij} denotes the input neuron, β is the bias, w_{ij} signifies the weight from the input to the hidden layer, φ is the activation function, and in this study, a sigmoid activation function is employed y represents the weight of the output neuron. In this research, ANN architecture was created that incorporates three types of nodes into a single hidden layer. These variants were used to determine the best model, which was defined by minimal evaluation criteria. Figure. 2 shows the structure of the Perceptron used in this first model. The model employed consists of three input neurons and one output neuron, as illustrated in Figure. 2. The determination of weights, as referenced in Eq. 1, can be derived through Eqs (3-7).

$$(\psi_1) = (w_{11}x_1) + (w_{12}x_2) + ((w_{13}x_3) + (w_{14}x_1) + (w_{15}x_2) + ((w_{16}x_3) \tag{3}$$

$$(\psi_2) = (w_{21}x_1) + (w_{22}x_2) + (w_{23}x_3) + (w_{24}x_4) + (w_{25}x_5) + ((w_{26}x_6) \tag{4}$$

$$(\psi_3) = (w_{31}x_1) + (w_{32}x_2) + (w_{33}x_3) + (w_{34}x_4) + (w_{35}x_5) + ((w_{36}x_6) \tag{5}$$

$$(\psi_4) = (w_{41}x_1) + (w_{42}x_2) + (w_{43}x_3) + (w_{44}x_4) + (w_{45}x_5) + ((w_{46}x_6) \tag{6}$$

$$(\psi_5) = (w_{51}x_1) + (w_{52}x_2) + (w_{53}x_3) + (w_{54}x_4) + (w_{55}x_5) + ((w_{56}x_6) \tag{7}$$

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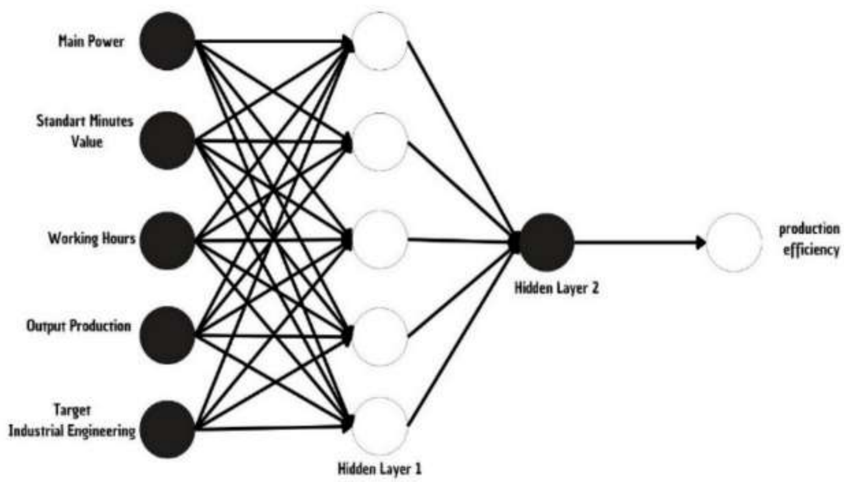

Figure 1. Architecture Model ANNs.

The neuron inputs the weighted sum into a linear function, which generates the output. The neuron's properties is characterized by this linear output function, as expressed in Eqs. (8) and (9).

$$d = \lambda(\pi_i) = \lambda(\sum\sum w_{ij}{}^{(2)}\,\varsigma(\psi_j) = (w_{11}{}^{(2)} \quad \dots \quad w_{15}{}^{(2)})_{1x5}\begin{pmatrix}\varsigma(\psi_1)\\ \varsigma(\psi_2)\\ \varsigma(\psi_3)\\ \varsigma(\psi_4)\\ \varsigma(\psi_5)\end{pmatrix}_{5x1} \quad (8)$$

$$d = (w_{11}{}^{(2)} \quad \dots \quad w_{15}{}^{(2)})_{1x5}\begin{pmatrix}\varsigma(\psi_1)\\ \varsigma(\psi_2)\\ \varsigma(\psi_3)\\ \varsigma(\psi_4)\\ \varsigma(\psi_5)\end{pmatrix}_{5x1} \quad (9a)$$

$$d = \lambda\,(w_{11}{}^{(2)} \quad \dots \quad w_{15}{}^{(2)})_{1x5}\,\varsigma\left(\begin{pmatrix}w_{11} & \dots\\ \vdots & w_{56}\end{pmatrix}_{(5x6)}\begin{pmatrix}x_1\\ \vdots\\ x_6\end{pmatrix}_{6x1}\right) \quad (9b)$$

The constants derived through the optimization process in Eqs. (8), (9a) and (9b), as well as the ANN architecture with five nodes in one hidden layer for 1000 iterations, are detailed in Eq. (10)

$$d = \lambda\,(6.21368954 \quad \dots \quad -5.18853431)_{1x5}\,\varsigma\left(\begin{pmatrix}-2.10523182\mathrm{e}-01 & \dots\\ \vdots & -2.29048877\mathrm{e}+00\end{pmatrix}_{(5x6)}\begin{pmatrix}x_1\\ \vdots\\ x_6\end{pmatrix}_{6x1}\right) \quad (10)$$

The result of the mapping is measured based on three different ANN models, with six nodes in the hidden layer, and 1000 iterations for the model. Table 3 shows the optimized results for the ANNs architecture model.

DOI: texere.v23i2.07

Table 3. Result of ANNs model.

Actual	Model
68%	67%
64%	64%
69%	67%
64%	63%
65%	65%
65%	65%
68%	67%
55%	55%
50%	50%
70%	69%
70%	68%
69%	66%
70%	68%
60%	61%
44%	44%
68%	67%
69%	67%
66%	66%
24%	26%
60%	61%
54%	56%
58%	59%
42%	42%
64%	65%
65%	65%
68%	68%
36%	33%

3. Model Evaluation

A. Value of coefficient correlation

The coefficient of determination, commonly referred to as R-squared or R^2, is a statistical measure that assesses the extent to which a theoretical model corresponds to the actual observed data. In this context, R^2 indicates the proportion of variance in the dependent variable that can be explained by the independent variables in the model. The R^2 value ranges from 0 to 1, with a score of 1 indicating that the model fully accounts for the variation in the data, while a value of 0 suggests that the model does not explain any variation and the results are due to random error. Eq.(11) demonstrates the R^2 calculations for the developed model techniques.

$$R^2 = \frac{SSR}{SST} = 0.98 \qquad (11)$$

When ; SST sum of squared regression, SST total variation in the data.

The Artificial Neural Network (ANN) model can be used to optimize efficient sewing production settings. The ANN-based model, which was built over 1000 iterations with a five-node architecture on one hidden layer, showed superior performance, with a coefficient of determination (R^2) of 0.98. This indicates that the model effectively explains 98% of the variance in the actual data on sewing

DOI: texere.v23i2.07

production efficiency. The type of architecture and complexity of the nodes and hidden layers used had a significant impact on the variability of the ANN model validation results. Figure. 3 shows the spread of actual data received from the garment industry compared to the model results, to clearly highlight the optimization model. These findings can help in the development of standard parameter indices to optimize production efficiency.

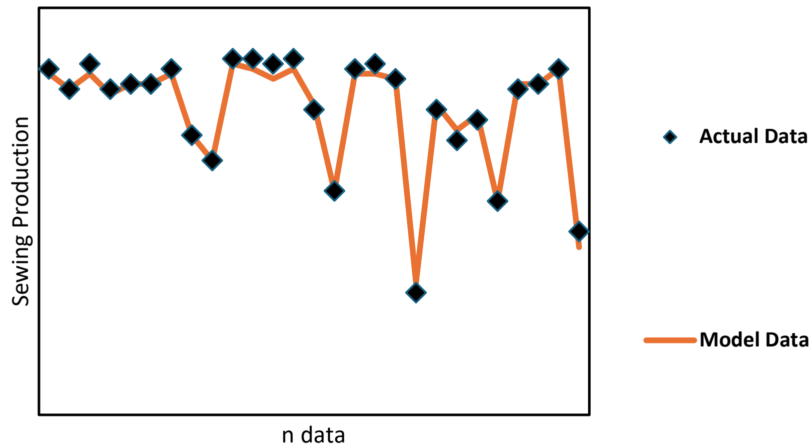

Figure 2. Data Distribution Model Against Actual

The optimization process also emphasizes that the production process must consider parameters aimed at enhancing production efficiency, thereby increasing the company's profits. It is crucial to identify and fine-tune these parameters to ensure the highest possible efficiency levels, leading to cost savings and better resource utilization. The optimization model derived from AI-based ANN modeling indicates that the sewing production process can optimize its parameter combinations with a correlation coefficient of 0.98. This high correlation suggests a very strong predictive relationship, indicating that the ANN model is highly effective in identifying the optimal combinations of production parameters.

Problem solving and improvement efforts can be undertaken by applying this model to optimize the process. By doing so, companies can systematically address inefficiencies and continuously refine their production methods. The model provides a data-driven approach to decision-making, allowing managers to base their strategies on reliable predictions and insights generated by the ANN. This reduces the reliance on trial-and-error methods and enhances the precision of process adjustments.

Figure. 3 also demonstrates that the data model accurately replicates the actual data. This validation is essential as it confirms the model's reliability and accuracy in real-world applications. The ability of the model to replicate actual production data means that it can be trusted to guide significant process improvements and drive efficiency gains. The visual representation in Figure 3 helps stakeholders understand the model's effectiveness and reinforces

DOI: texere.v23i2.07

confidence in adopting AI-based optimization techniques. In summary, leveraging AI-based ANN modeling for optimizing sewing production parameters not only addresses existing inefficiencies but also sets a foundation for sustained operational excellence and profitability.

CONCLUSION

In conclusion, this study successfully developed an optimization model to improve the parameters affecting production efficiency in the sewing process in the garment industry. The ANN model, using five nodes and 1000 iterations, showed superior performance in optimizing these parameters, with a high correlation coefficient of 0.98. Analysis of the optimization results shows that the ANN-based model is highly effective in predicting efficiency when setting sewing production parameters by explaining almost 98% of the actual data. These findings have significance for practitioners in the garment industry in providing a valuable framework for optimizing sewing production process parameters to improve production efficiency. In order to increase production efficiency, the garment manufacturing faced many challenges.

These included creating a standard operating procedure (SOP) for routine and sporadic machine maintenance schedules, allocating operators according to their job desk and skill, ensuring the quality of the products after they are sewn, and then fostering strong departmental or divisional collaboration.

Some suggestions for enhancements include examining and maintaining production machinery on a regular and recurring basis, rather than just when they are brought in for damage, to prevent production from stopping because of malfunctioning machinery. implies that businesses should be mindful of their workers' general well-being. It is desired that businesses will always combine their current raw material supply to ensure that there are never any shortages during manufacturing. Moreover, applying Artificial Neural Networks (ANNs) to address the complexity of production efficiency offers a new perspective on mathematical modelling in garment manufacturing.

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