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A Novel Mathematical Model for Quality Optimization of Textile Products During Shipment

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ABSTRACT

The process of shipping products in the textile industry is essential as it determines the effectiveness of the business. However, non-ideal shipping can result in damage to the shipped products. Therefore, this study aims to develop a mathematical model to optimize the shipping process by assessing the textile product damage rate against environmental parameters such as humidity and temperature and shipping parameters such as shipping duration. The model developed using the Response Surface Methodology (RSM) statistical approach is based on linear and nonlinear models. The results showed that the linear model had a better coefficient of determination as a model validation parameter, with a coefficient of determination of 0.83. This value shows the effectiveness of optimizing the shipping process as a monitoring effort to determine the damage to textile products against several parameters that affect it. The results of this study have implications for the field of textile science, especially regarding the dynamics of distribution or logistics, as well as the application of mathematical applications in the textile field. In addition, the practical implications of this research are expected to be used as a monitoring effort for the textile industry to determine the impact of environmental parameters and shipping duration on the products they ship.

1. INTRODUCTION

The evolving dynamics of the textile industry make maintaining product quality key to business success in this sector (Chan et al., 2024; Harsanto et al., 2023). The challenges to quality degradation faced by textile manufacturers occur during the production and shipping phases (Köksal et al., 2017; Patwary, 2020; Warasthe et al., 2022). Shipping often involves uncontrollable environmental conditions, such as temperature and humidity fluctuations and shocks, which can be detrimental to product quality (Moazzem et al., 2022; Yue, 2023). Therefore, developing a mathematical model to optimize product quality during shipping is crucial to improving efficiency and reducing losses.

The development of this mathematical model is based on the principles of optimization theory and uses computer simulation and is equipped with validation methods such as correlation coefficients to mean absolute percentage error (MAPE) (Abdullah et al., 2023; Chicco et al., 2021; Jadhav et al., 2015; Masruroh & Prasetyorini, 2015; Putra et al., 2017; Putra & Mohamad, 2022; Suprayogi & Paillin, 2018; Suprayogi & Ramdhani, 2015). The approach used is response-based, allowing analysis of other variables' influence (Putra & Mohamad, 2023; Setiawati & Kusnadi, 2021). This method of model building has been widely used in various sectors because it can provide predictions of responses from an impact on the problem under study (Mohd Rozalli et al., 2014; Mourya et al., 2024; Sakhi et al., 2020; Setiawati & Kusnadi, 2021).

Various relevant variables regarding product quality in the delivery process must be addressed. It aims to provide preventive measures and analyze the impact during the distribution process. In the distribution process of a textile product, humidity and temperature determine the quality of textile products in terms of material (Marolleau et al., 2017). Temperature and humidity that are too low or high and do not match the characteristics of the material can quickly damage a textile product. Several things must also be considered because they impact the textile products being shipped in addition to temperature and humidity during the shipping process. One of them is the duration of delivery. Goods that are too long in the distribution process will make the quality of textile products poor (Jerath et al., 2017).

This method has been widely used in manufacturing fields, one of which is the research of Putra and Mohamad (2023). However, in product delivery, it significantly optimizes the possibility of damage to products during delivery and ensures that product quality is explicitly maintained well for textile commodities, which has never been done. Therefore, this research is the first to form a mathematical model to optimize these needs. Through careful analysis, the model can provide recommendations on the parameters that should be set and monitored in real time to maintain product quality during shipping. Thus, manufacturers can implement appropriate preventive measures and reduce potential losses due to damage to textile products during shipment.

This research aims to design an innovative mathematical model that specifically addresses the challenge of maintaining the quality of textile products during shipping. The model considers various factors affecting product quality, such as environmental conditions and delivery time. This research is also the first to explicitly build a model that considers the optimization of the shipping process and considers various related variables, such as temperature and humidity, that impact product quality. Product quality is measured based on the level of damage during the shipping process. The results of this study are expected to positively impact textile industry players, especially manufacturers, to more effectively plan delivery strategies that minimize the risk of product damage.

2. RESEARCH METHODS

This study used a response approach using Responses Surface Methodology (RSM). The research flow is shown in Fig. 1.

2.1. Data Collection

This research uses three independent variables and one dependent variable. The three dependent variables are temperature in centigrade, humidity in (%), and shipping duration in (days), which affect one independent variable, the textile product damage rate (%). Data requirements and variable constructs can be shown in Table 1.

Sample data was collected from a textile company in Central Java that assessed product damage from shipments in January 2024. The collected data will be preprocessed to assess data bias and adjust for model-building needs using a statistical-based model.

Table 1. Specification of Model

Construct	Attribute	Function
Degree of damage product (y)	%	Dependent Variable
Humidity (x_1)	%	Independent Variabel
Temperature (x_2)	Celcius	
Delivery Duration (x_3)	Days	

2.2. Data Adequacy Test

This study tests the collected data for adequacy to ensure that the model meets the minimum requirements. The data sufficiency test is conducted by comparing the ideal data sufficiency value (N'), calculated using Eq (1), with the measured data (N). This study adopts the data sufficiency test calculation from (Heldayani & Yuamita, 2022).

$$\left[N' = \frac{\frac{k}{s}\sqrt{N(\sum x^2)-(\sum x)^2}}{(\sum x)^2} \right] \tag{1}$$

where k represents the confidence level (95%=2), s is the degree of confidence, and x is the observation data. The test data is considered sufficient if N' ≤ N. However, if N' > N, the data is deemed insufficient, in such cases, additional data must be collected, and after the new collection, the data sufficiency test should be performed again to determine whether the newly collected data meets the sufficiency criteria.

2.3. Model Development

The study presents a mathematical model based on Response Surface Methodology (RSM), which utilizes statistical techniques to explore relationships between multiple independent variables and a response variable. The novelty of the mathematical model offered in this study lies in its specific architecture, which integrates three independent variables for model development (Fig. 2). This model is tailored to the unique context of the study, distinguishing it from the general RSM formula.

The main difference from the general RSM formula is how data distribution and the nature of the problem influence the model. In this study, the model accounts for nonlinear relationships, which is crucial when the data exhibit non-linearity, unlike the traditional linear

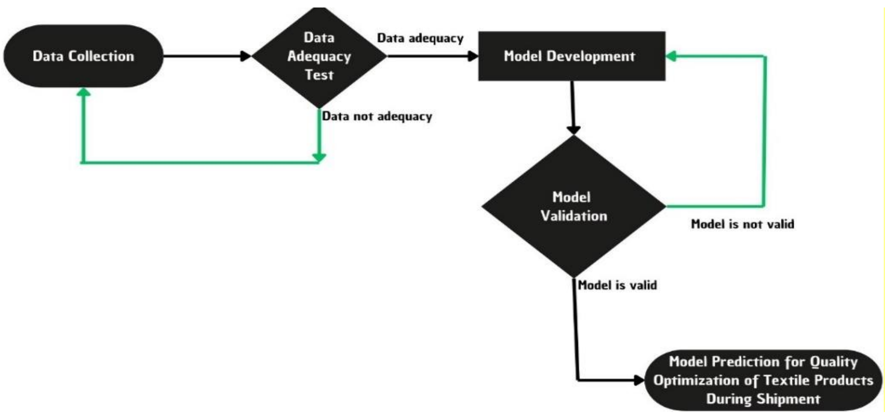

Fig.1. Research Framework

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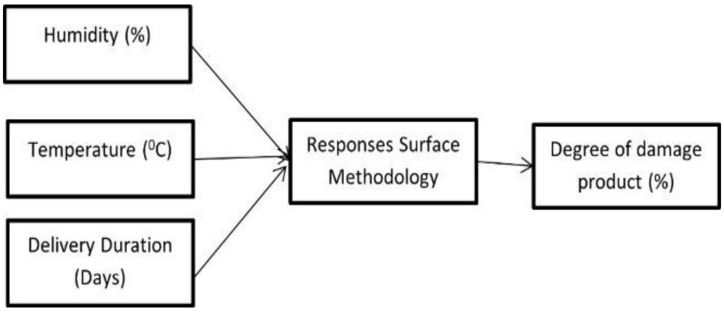

Fig. 2. Model RSM Framework

approach commonly used in general RSM. It ensures the model is better suited for more complex real-world problems than the standard linear RSM model.

2.3.1. Model Responses surface methodology linear

The Response Surface Methodology (RSM) linear model used in this study was developed based on three independent variables: humidity (x_1), temperature (x_2), and delivery duration (x_3). These variables influence the degree of damage product (y). The following equation represents the RSM linear model (Eq. 2).

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \epsilon \tag{2}$$

The independent variables are x_1, x_2, x_3. A_0 is the regression model constant, A_1 is the regression model constant for x_1, A_2 is the regression model constant for x_2, and A_3 is the regression model constant for x_3. ϵ is the regression model error.

The Value of Eq. (3) can be determined by modeling it as illustrated in Eqs. (2) and (3). The difference between the experimental data ($\hat{y}$i) and (yi) model model is defined as the error(ϵ), which is as follows. The Value of Eq. (1) can be determined by modeling it as illustrated in Eqs. (3) and (4).

$$\sum_{i=1}^{n} y_i = a_0 + a_1 \sum x_{i1} + a_2 \sum x_{i2} + a_3 \sum x_{i3},, \tag{3a}$$

$$\begin{aligned} y_1 &= a_0 + a_1 x_{11} + a_2 x_{12} + a_3 x_{13}, \\ &\vdots \\ y_n &= a_0 + a_1 x_{n1} + a_2 x_{n2} + a_3 x_{n3}, \end{aligned} \tag{3b}$$

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & \dots & x_{1k} \\ 1 & \iddots & \vdots \\ 1 & \dots & x_{nk} \end{pmatrix} \begin{pmatrix} a_0 \\ \vdots \\ a_k \end{pmatrix} \tag{4a}$$

$$y_i = x_{ik}a_{k,} \tag{4b}$$

$$y = Xa \tag{4c}$$

The difference between the experimental data ($\hat{y}$i) and (yi) model model is defined as the error(ϵ).

$$\sum_{i=1}^{n} (\hat{y}_i - y_i) = \epsilon \tag{5}$$

Eqs. (6) and (7) we used to find a for model:

$$a = (X^TX)^{-1}X^Ty, \tag{6}$$

with,

$$y = Xa = X(X^TX)^{-1}X^Ty \tag{7}$$

Eq (8) can be utilized to solve the linear equation formed by Eq (2), resulting in the formulation presented in Eqs (8) to (10).

$$y_1 = a_0 + a_1x_1 + a_2x_2 + a_3x_3\epsilon \tag{8}$$

$$\vdots$$

$$y_n = a_0 + a_1x_1 + a_2x_2 + a_3x_3\epsilon \tag{8}$$

Eq. (8) can be converted into matrix form as in Eq. (9).

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_1 & x_2 & x_3 \\ 1 & x_1 & x_2 & x_3 \\ 1 & x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} \tag{9}$$

The coefficients a_0, a_1, a_2, a_3 in Eq. (9) are obtained through the parameter optimization technique outlined in Eq. (10). This optimization technique uses the Least Squares method to determine the values of (a). The process involves solving for the partial derivatives of the error function concerning (a) to locate the minimum point. From Eq. 10, each constant a is sought as the optimization constant of a problem modeled using a linear-based statistical model.

$$a = (X^TX)^{-1}X^Ty, \tag{10}$$

2.3.2. Model Responses Surface Methodology Nonlinear

In this study, the RSM model nonlinear multiple regression is built around three independent variables: humidity (x_1), temperature (x_2) and delivery duration (x_3), both of which influence the degree of damage product (y). The fundamental equation of the RSM model's nonlinear multiple regression is as follows (Eqs. 11).

$$y_i = a_0{x_1}^{a_1}{x_2}^{a_2}{x_3}^{a_3} + \epsilon \tag{11}$$

$$\sum_{i=1}^{n} y_i = a_0 + a_1 \sum x_{i1} + a_2 \sum x_{i2} + a_3 \sum x_{i3,} \tag{12a}$$

$$\begin{aligned} y_1 &= a_0 + a_1 x_{11} + a_2 x_{12} + a_3 x_{33}, \\ &\vdots \\ y_n &= a_0 + a_1 x_{n1} + a_2 x_{n2} + a_3 x_{n3} \end{aligned} \tag{12b}$$

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & \dots & x_{1k} \\ 1 & \iddots & \vdots \\ 1 & \dots & x_{nk} \end{pmatrix} \begin{pmatrix} a_0 \\ \vdots \\ a_k \end{pmatrix} \tag{13a}$$

$$y_i = x_{1k}a_{k,} \tag{13b}$$

$$y = XA \tag{13c}$$

Eqs. (12 and 13) we used to find a for model:

$$a = (X^TX)^{-1}X^Ty, \tag{12}$$

With,

$$y = Xa = X(X^TX)^{-1}X^Ty \tag{13}$$

Eq (13) can be utilized to solve the nonlinear equation formed by Eq (9), resulting in the formulation presented in Eqs (14) to (20).

$$y = a_0 x_1^{a_1} x_2^{a_2} x_3^{a_3}, \quad (14)$$
$$\ln y = \ln(a_0 x_1^{a_1} x_2^{a_2} x_3^{a_3}), \quad (15)$$
$$\ln y = \ln a_0 + a_1 \ln x_1 + a_2 \ln x_2 + a_3 \ln x_3,, \quad (16)$$
$$Y_i = A_0 + A_1 X_1 + A_2 X_2 + A_3 X_3, \quad (17)$$
$$Y_1 = A_0 + A_1 x_1 + A_2 x_2 + A_3 x_3 \epsilon \quad (18)$$
$$Y_n = A_0 + A_1 x_1 + A_2 x_2 + A_3 x_3 \epsilon \quad (18)$$

Eq. (18) can be converted into matrix form as in Eq. (19).

$$\begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix} = \left(\begin{pmatrix} 1 & X_1 & X_2 & X_3 \\ 1 & X_1 & X_2 & X_3 \\ 1 & X_1 & X_2 & X_3 \end{pmatrix} \begin{pmatrix} A_0 \\ A_1 \\ A_2 \\ A_3 \end{pmatrix} \right) \quad (19)$$

The values A_0, A_1, A_2, A_3 in Eq. (18) are derived using the parameter optimization method described in Eq. (20). The optimization method employs the least squares approach to determine the values of (a), which involves solving the partial derivative of the error function concerning (A) to find the minimum point. To get a_0, a_1, a_2, a_3 from the nonlinear equation, the conditions are as follows (Eq.21). Value of a_0, a_1, a_2, a_3 which has been successfully calculated and is used as a constant for nonlinear equations to optimize a problem.

$$A = (X^T X)^{-1} X^T y, \quad (20)$$
$$= \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} \exp(A_0) \\ A_1 \\ A_2 \\ A_3 \end{pmatrix} \quad (21)$$

2.4. Model Validation

The coefficient of determination, known as R-squared or R2, is a statistical metric used to assess how well a theoretical model fits the observed data (Putra & Mohamad, 2023; Samura et al., 2024). It is the most frequently used method in analyzing how well a predictive model has been built. In this context, R^2 measures the proportion of variation in the dependent variable that the independent variables in the model can explain. R^2 values range from 0 to 1, where 1 indicates that the model perfectly describes the variation in the data, and 0 indicates that the model explains nothing, attributing it entirely to random error. Eq (22) illustrates the calculation of R^2 for the two models developed.

$$R^2 = \frac{((n \sum y_{theory}) - (\sum y_{actual} x \sum y_{actual} x y_{theory}))}{\sqrt{((n\, x \sum y_{theory}{}^2) - (\sum y_{theory})^2)}\ x \sqrt{((n\, x \sum y_{actual}{}^2) - (\sum y_{actual})^2)}} \quad (22)$$

3. RESULTS AND DISCUSSION

3.1. Data Collection

Data is taken from one of the textile companies engaged in textiles and apparel. The 10 sample data that have been collected are tested for data adequacy. If the data adequacy test results state that the sample is insufficient, then the data collection is repeated. This result of the adequacy test is shown in Table 2, and the final data is shown in Table 3.

Table 2. Result from Data Adequacy Test.

Variable	N (Actual)	N' (Ideal)	Decision
Degree of damage product (y)	10	19.2	rejected (repeat data collection)
Humidity (x_1)	10	19.7	rejected (repeat data collection)
Temperature (x_2)	10	19.11	rejected (repeat data collection)
Delivery Duration (x_3)	10	17.48	rejected (repeat data collection)

Table 3. Final Data Collect

Degree of Damage Product (y) (%)	Humidity (x_1) (%)	Temperature (x_2) (Celcius)	Delivery Duration (x_3) (Days)
2.5	60	23	5
4.0	70	21	7
6.5	80	20	10
8.0	90	25	14
3.5	50	30	3
5.0	65	19	8
7.0	75	22	12
6.0	85	28	9
3.0	55	21	6
2.5	60	22	11
3	60	24	6
7.5	80	20	13
8	92	18	14
9	98	18	14
5	66	28	5
4	72	25	5
4.5	75	25	5
6	75	25	7
7	60	30	12
8	83	19	14

3.2. Data Adequacy Test

Data sufficiency testing is performed based on equation (1), shown in the previous section. If the result is N'>N, the data must be collected again. Measurement of data sufficiency is carried out on each variable used. Table 2 shows the results of the data sufficiency test that has been carried out.

Table 4. Result from Data Adequacy Test (After Reply Collecting)

Variable	N (Actual)	N' (Ideal)	Decision
Degree of damage product (y)	20	4.15	Accepted
Humidity (x_1)	20	3.52	Accepted
Temperature (x_2)	20	3.23	Accepted
Delivery Duration (x_3)	20	8.13	Accepted

Table 2 explains that the data collection of 10 samples that have been done for each variable has not met the data sufficiency. Then, the data collection is repeated according to the N' value obtained for each variable. This missing data collection adds 10 new data samples so that the N (actual) sample data totals 20 and is tested again for data adequacy (Table 4).

Based on the results of the data sufficiency test, it

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is concluded that the data from the new data collection has met the data sufficiency test and can be used as a model formation as a prediction tool and experimental design and optimization of the delivery process that has an impact on product quality with the percentage of damage as a reference.

3.3. Model Development

In this section, two model developments in response surface methodology, linear and nonlinear, will be discussed. The selection of these two RSM models is due to differences in data distribution to find optimal modeling in solving the problem of damage degree (%).

3.3.1. Model RSM linear

Eq 1 shows the general linear model and explains that a matrix calculation can obtain the constant a. Eqs (23-25) shows the matrix calculation based on the data collected in the previous section.

$$y_1 = a_0 + a_1x_1 + a_2x_2 + a_3x_3\epsilon$$
$$\vdots$$
$$y_{20} = a_0 + a_1x_1 + a_2x_2 + a_3x_3\epsilon \quad (23)$$

Eq. (6) can be converted into matrix form as in Eq. (24).

$$\begin{pmatrix} y_1 \\ \vdots \\ y_{20} \end{pmatrix} = \begin{pmatrix} 1 & 60 & 23 & 5 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 83 & 19 & 14 \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} \quad (24)$$

$$a = (X^TX)^{-1}X^T, y \quad (25a)$$

$$a = \begin{bmatrix} 20 & 1451 & 463 & 180 \\ 1451 & 108547 & 33175 & 13707 \\ 463 & 33175 & 10993 & 4037 \\ 180 & 13707 & 4037 & 1886 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 1 & 1 \\ 60 & \vdots & 83 \\ 23 & \vdots & 19 \\ 5 & \dots & 14 \end{bmatrix} \begin{bmatrix} 2.5 \\ \vdots \\ 8 \end{bmatrix} \quad (25b)$$

$$= \begin{bmatrix} 6.39 & -0.04 & -0.15 & -0.01 \\ -0.04 & 0.00 & 0.00 & -0.00 \\ -0.15 & 0.00 & 0.00 & 0.00 \\ -0.01 & -0.00 & 0.00 & 0.01 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 60 & \vdots & 83 \\ 23 & \vdots & 19 \\ 5 & \dots & 14 \end{bmatrix} \begin{bmatrix} 2.5 \\ \vdots \\ 8 \end{bmatrix} \quad (25c)$$

$$= \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} -6.15 \\ 0.08 \\ 0.12 \\ 0.30 \end{pmatrix} \quad (25d)$$

Then, Eq. (26) is derived to assess the degree of damage product results.

$$y = -6.15 + 0.08x_1 + 0.12x_2 + 0.30x_3 \quad (26)$$

Once the values of a_0, a_1, dan a_2, a_3 have been determined, Eq. (26) can be utilized for prediction calculations, as shown in Table 5.

3.3.2. Model RSM Nonlinear

Eq (11) shows the general nonlinear model and explains that obtaining the constant, a can be done through matrix optimization. Eqs (27-30) show the matrix calculation based on the data collected in the previous section.

$$Y_1 = a_0 + a_1x_1 + a_2x_2 + a_3x_3\epsilon$$
$$\vdots$$
$$Y_{10} = a_0 + a_1x_1 + a_2x_2 + a_3x_3\epsilon \quad (27)$$

Eq. (11) can be converted into matrix form as in Eq. (28)

$$\begin{pmatrix} Y_1 \\ \vdots \\ Y_{20} \end{pmatrix} = \begin{pmatrix} 1 & 4.09 & 3.1 & 1.6 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 2.9 & 2.6 & 4.4 \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} \quad (28)$$

$$a = (X^TX)^{-1}X^T, y \quad 29a)$$

$$a = \begin{bmatrix} 20 & 85.37 & 62.58 & 42.07 \\ 85.37 & 365.04 & 266.90 & 180.71 \\ 62.58 & 266.90 & 196.36 & 130.93 \\ 42.07 & 180.71 & 130.93 & 92.55 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 1 & 1 \\ 4.1 & \vdots & 4.4 \\ 3.1 & \vdots & 2.9 \\ 1.6 & \dots & 2.6 \end{bmatrix} \begin{bmatrix} 0.9 \\ \vdots \\ 2.1 \end{bmatrix} \quad 29b)$$

$$= \begin{bmatrix} 87.95 & -12.54 & -11.47 & 0.75 \\ -12.54 & 3.00 & 0.42 & -0.74 \\ -11.47 & 0.41 & 2.83 & 0.41 \\ 0.74 & -0.74 & 0.41 & 0.53 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 4.1 & \vdots & 4.4 \\ 3.1 & \vdots & 2.9 \\ 1.6 & \dots & 2.6 \end{bmatrix} \begin{bmatrix} 0.9 \\ \vdots \\ 2.1 \end{bmatrix} \quad 29c)$$

$$= \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} exp(-7.16) \\ 1.42 \\ 0.63 \\ 0.37 \end{pmatrix} = \begin{pmatrix} 0.000774 \\ 4.123078 \\ 1.873672 \\ 1.449908 \end{pmatrix} \quad (29)$$

Then, Eq. (29) is derived to assess the degree of damage product (%) results (Eq.30).

$$y = 0.000774{x_1}^{4.12}{x_2}^{1.87}{x_3}^{1.45} + \epsilon \quad (30)$$

Once the values of a_0, a_1, and $a_2 . a_3$ have been determined, Eq. (30) can be utilized for prediction calculations to assess the degree of damage product (%), as shown in Table 5.

3.4. Model Validation

Based on the model equation that has successfully optimized product quality when shipping in percent, an evaluation is carried out using the correlation coefficient method shown in Eq (22). The results of the calculation of the two-equation models formed are shown in Table 5, along with the correlation coefficient value.

Table 5. Result Model and Validation (R^2)

Deegre of damage (%) Actual	Deegre of damage (%) Prediction (Linear model)	Deegre of damage (%) Prediction (Nonlinear model)
2.5	3.20	3.33
4	4.42	4.43
6.5	6.06	5.92
8	8.72	9.13
3.5	2.56	2.51
5	4.06	3.94
7	6.48	6.14
6	7.13	7.67
3	2.84	2.97
2.5	4.89	4.34
3	3.62	3.65
7.5	6.97	6.53
8	8.06	7.66
9	8.58	8.38
5	4.30	4.31
4	4.46	4.54
4.5	4.72	4.81
6	5.32	5.45
7	6.14	5.44
8	7.42	6.85
(R^2)	0.8334	0.7319

3.5. Analyzing Results from the RSM Model

The R² method assesses the performance of both RSM (Response Surface Methodology) models in optimizing the shipping process by considering three factors: humidity, temperature, and shipping duration, which influence the product damage rate. The linear RSM model outperforms the nonlinear model in optimizing product quality during shipment, as it has a higher R^2 value of 0.83 (83%) compared to the nonlinear model's R^2 of 0.73 (73%) in explaining data variance. It indicates that the linear model is more effective in assessing product quality, particularly damage caused by environmental factors like humidity, temperature, and shipping duration. The analysis also reveals that these three variables linearly affect product quality during shipment. The remaining 17% of the variance is due to factors not considered in this study, and the limitations of the linear model in achieving a correlation above 90% highlight the need for further research to enhance optimization (Putra & Mohamad, 2022; Samura et al., 2024; Seikh et al., 2019). Fig. 3 presents the data distribution of the established model.

3.6. Sensitivity Model

In this study, the best model for optimizing the quality of textile products during delivery was subjected to sensitivity analysis to ensure that the model does not suffer from overfitting or excessive adherence to the data distribution. The sensitivity process involves altering values for important parameters or variables (Bala et al., 2017). Therefore, this study tests sensitivity by modifying the variable X_3, delivery duration. The results of the sensitivity analysis are shown in Fig. 4.

Based on Fig. 4, it is evident that the visual distribution changes between the best RSM model and the RSM model modified with changes to the value of X_3. The coefficient of determination for this sensitivity analysis is 0.307. This coefficient of determination indicates that data variability can explain the model's sensitivity to changes. The model's sensitivity is important because it identifies variables that most impact the model's results, assists in making more accurate adjustments and validations, and provides insights into the model's robustness against data variations. By understanding the model's sensitivity, necessary improvements can be made to enhance the model's reliability and interpretability in practical applications.

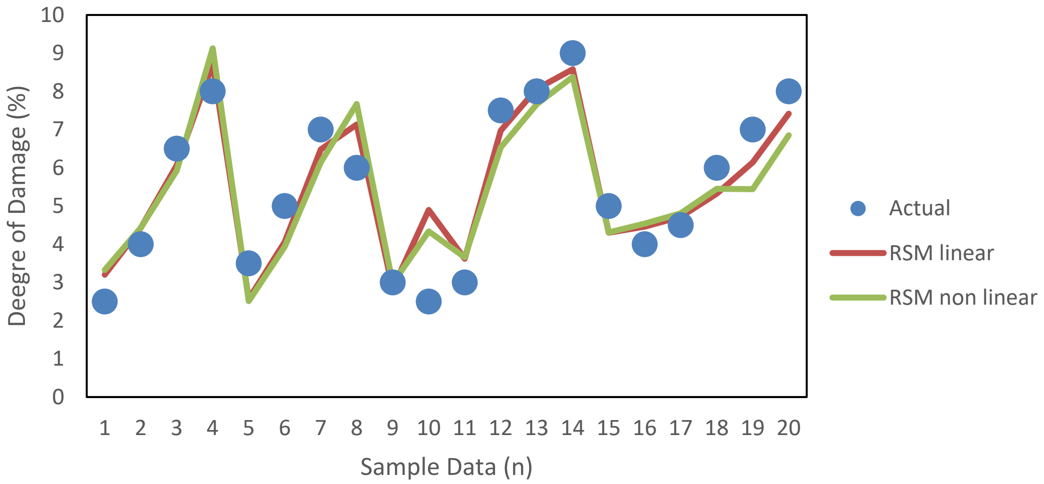

Fig. 3. Data Distribution (Actual and Model)

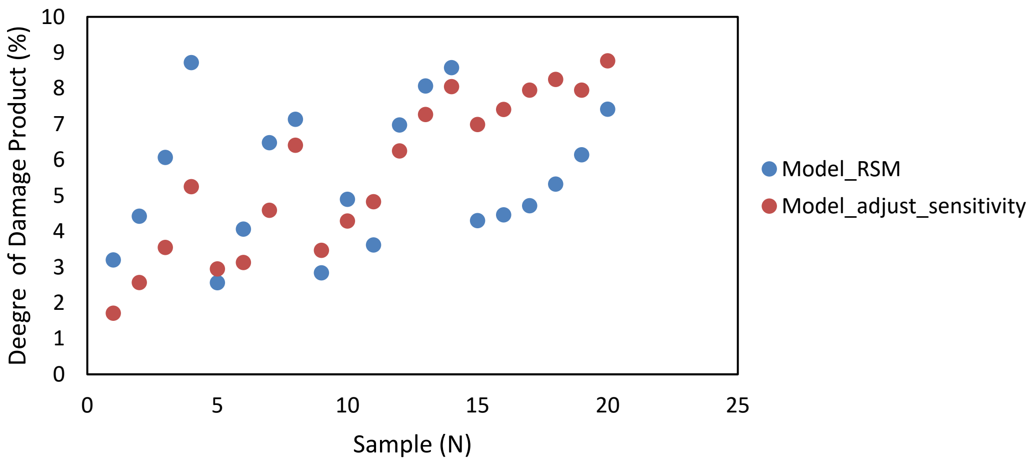

Fig. 4. Result Sensitivity Analysis

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3.7. Findings Enrich Existing Understanding

This research successfully developed a significant mathematical model to optimize process parameters to prevent damage to textile products during shipping. Parameters such as humidity, temperature, and shipping duration have high uncertainty yet significantly affect the quality of the final product. Two statistical-based response models were used to find the most relevant model with the percentage of product damage as the analyzed variable.

The results showed that the linear-based Response Surface Methodology (RSM) model was highly relevant in optimizing product damage as a function of humidity, temperature, and delivery duration. The model achieved a relevance rate of 83%, indicating a good fit with the actual data set. This finding is essential for the field of textile science, particularly textile logistics, as it confirms that the quality of the final product is affected not only by production process factors but also by factors in the shipping process.

The modeling also reveals that simple RSM techniques can produce optimization models with solid correlations, in contrast to previous studies that used AI-based models for modeling the yarn-spinning process with very high correlation coefficients (Putra et al., 2017; Putra & Mohamad, 2023). A high correlation coefficient can indicate the model's effectiveness but also risks overfitting, making the model less sensitive to different datasets (Kumar & Chong, 2018).

Although this study has limitations, such as not considering packaging methods and material types in determining product quality from the shipping process, its strength lies in applying mathematical methods in textile logistics to analyze the impact of environmental uncertainties on final product quality. It is the first study to model the delivery process with a focus on the final quality of textile products, and it was successfully proven with a model correlation coefficient of 0.83.

4. CONCLUSION

This study addresses a significant gap in textile logistics and quality control by developing a Linear Response Surface Methodology (RSM) model to evaluate the impact of environmental uncertainties, such as humidity, temperature, and shipping duration, on textile product quality. The model achieves an 83% correlation coefficient, highlighting its utility in optimizing shipping conditions to enhance product integrity. This contribution underscores the importance of considering shipping conditions as a crucial factor influencing product quality beyond the production stage.

However, the model's focus on shipping parameters limits its scope, as it does not account for other factors that might affect product quality, such as material type and packaging methods. Future research should expand this model by including additional relevant variables and exploring more complex modeling approaches. Longitudinal studies across shipping scenarios and geographic locations could also enhance the model's robustness and generalizability.

REFERENCES

Abdullah, F., Rahmawati, N., & Putra, V. (2023). Penerapan Algorithma Genetika Pada Masalah Penugasan Maklon di Industri Garmen dan Apparel. *Jurnal Sains Dan Informatika*, *9*(1), 15–23. https://doi.org/10.22216/jsi.v9i1.1522

Bala, K. B., Arshad, M. F., & Noh, M. K. (2017). System dynamics simulation and modelling. In *Springer Texts in Business and Economics* (1st ed., Issue 1). springer. https://doi.org/10.4324/9780203112694-14

Chan, E. M. H., Cheung, J., Leslie, C. A., Lau, Y. Y., Suen, D. W. S., & Tsang, C. W. (2024). Revolutionizing the Textile and Clothing Industry: Pioneering Sustainability and Resilience in a Post-COVID Era. *Sustainability (Switzerland)*, *16*(6), 1–17. https://doi.org/10.3390/su16062474

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, *7*, 1–24. https://doi.org/10.7717/PEERJ-CS.623

Harsanto, B., Primiana, I., Sarasi, V., & Satyakti, Y. (2023). Sustainability Innovation in the Textile Industry: A Systematic Review. *Sustainability (Switzerland)*, *15*(2). https://doi.org/10.3390/su15021549

Heldayani, & Yuamita, F. (2022). Perbaikan Work Station Dan Pengukuran Waktu Kerja Dalam Menentukan Waktu Standar Guna Meningkatkan Produktivitas Pada Lini Kerja Spot Assembly (Studi Kasus Pt Indonesia Thai) Summit Auto. *Jurnal Ilmiah Multidisiplin*, *Vol.1*, *No.*(2810–0581), 2954–2956. https://journal-nusantara.com/index.php/JIM/article/view/688

Jadhav, S. B., Chougule, A. S., Shah, D. P., Pereira, C. S., & Jadhav, J. P. (2015). Application of response surface methodology for optimizing textile effluent biodecolorization and its toxicity perspectives using plant toxicity, plasmid nicking assays. *Clean Technologies and Environmental Policy*, *17*(3), 709–720. https://doi.org/10.1007/s10098-014-0827-3

Jerath, K., Kim, S. H., & Swinney, R. (2017). Product quality in a distribution channel with inventory risk. *Marketing Science*, *36*(5), 747–761. https://doi.org/10.1287/mksc.2017.1041

Köksal, D., Strähle, J., Müller, M., & Freise, M. (2017). Social sustainable supply chain management in the textile and apparel industry-a literature review. *Sustainability (Switzerland)*, *9*(1), 1–32. https://doi.org/10.3390/su9010100

Kumar, S., & Chong, I. (2018). Correlation analysis to identify the effective data in machine learning: Prediction of depressive disorder and emotion states. *International Journal of Environmental Research and Public Health*, *15*(12). https://doi.org/10.3390/ijerph15122907

Marolleau, A., Salaun, F., Dupont, D., Gidik, H., & Ducept, S. (2017). Influence of textile properties on thermal comfort. *IOP Conference Series: Materials Science and Engineering*, *254*(18). https://doi.org/10.1088/1757-899X/254/18/182007

Masruroh, N. A., & Prasetyorini, A. V. (2015). Model Penjadwalan Pengiriman Pasokan pada Strategi Multi-Supplier dengan Variasi Harga dan Lead Time untuk Permintaan Stokastik. *Jurnal Teknik Industri*, *17*(1), 35–46. https://doi.org/10.9744/jti.17.1.35-46

Moazzem, S., Crossin, E., Daver, F., & Wang, L. (2022). Environmental impact of apparel supply chain and textile products. *Environment, Development and Sustainability*, *24*(8), 9757–9775. https://doi.org/10.1007/s10668-021-01873-4

Mohd Rozalli, N., Chin, N., & Yusof, Y. (2014). Simultaneous multiple responses modelling, optimization and correlation of Asian type peanuts (Arachis hypogaea L.) roasting using response surface methodology. *Acta Alimentaria*, *43*(1), 142–157. https://doi.org/10.1556/AAlim.43.2014.1.15

Mourya, V., Bhore, S. P., & Wandale, P. G. (2024). Multiobjective optimization of tribological characteristics of 3D printed texture surfaces for ABS and PLA Polymers. *Journal of Thermoplastic Composite Materials*, *37*(2), 772–799. https://doi.org/10.1177/08927057231185710

Patwary, S. (2020). Clothing and textile sustainability: Current state of environmental challenges and the ways forward. *Textile and Leather Review*, *3*(3), 158–173. https://doi.org/10.31881/TLR.2020.16

Putra, V. G. V., & Mohamad, J. N. (2022). Response surface methodology and artificial neural network modeling of work of adhesion on plasma-treated polyester–cotton-woven fabrics. *Journal of Adhesion Science and Technology*, *37*(6). https://doi.org/10.1080/01694243.2022.2053349

Putra, V. G. V., & Mohamad, J. N. (2023). A novel model for predicting tenacity and unevenness of ring-spun yarn: a special case in textile engineering. *Mathematical Models in Engineering*, *9*(3), 102–112. https://doi.org/10.21595/mme.2023.23406

Putra, V. G. V., Rosyid, M. F., & Maruto, G. (2017). New theoretical modeling for predicting yarn angle on OE yarn influenced by fibre movement on torus coordinate based on classical mechanics approach. *Indian Journal of Fibre and Textile Research*, *42*(3), 359–363. https://nopr.niscpr.res.in/handle/123456789/42726

Sakhi, D., Elmchaouri, A., Rakhila, Y., Abouri, M., Souabi, S., Hamdani, M., & Jada, A. (2020). Optimization of the treatment of a real textile wastewater by coagulation–flocculation processes using central composite design. *Desalination and Water Treatment*, *196*, 33–40. https://doi.org/10.5004/dwt.2020.25929

Samura, L., Pratama, M. D., Galih, V., Putra, V., Achmad, F., Yusuf, Y., & Abdullah, F. (2024). A new mathematical model for optimizing laser cutting parameters to improve fabric quality. *Mathematical Models In Engineering*, *10*(4), 1–15. https://doi.org/10.21595/mme.2024.24204

Seikh, A. H., Mandal, B. B., Sarkar, A., Baig, M., Alharthi, N., & Alzahrani, B. (2019). Application of response surface methodology for prediction and modeling of surface roughness in ball end milling of OFHC copper. *International Journal of Mechanical and Materials Engineering*, *14*(1). https://doi.org/10.1186/s40712-019-0099-0

Setiawati, A. E., & Kusnadi, J. (2021). Optimization of fermentation time and grain concentration for water kefir production from butterfly pea flower (Clitoria ternatea). *IOP Conference Series: Earth and Environmental Science*, *924*(1). https://doi.org/10.1088/1755-1315/924/1/012081

Suprayogi, S., & Paillin, D. B. (2018). Algoritma Genetika untuk Pemecahan Masalah Rute Kendaraan dengan Ukuran dan Campuran Armada, Trip Majemuk, Pengiriman Terbagi, Produk Majemuk, dan Kendaraan dengan Kompartemen Majemuk. *Jurnal Teknik Industri*, *19*(2), 115–124. https://doi.org/10.9744/jti.19.2.115-124

Suprayogi, S., & Ramdhani, H. (2015). Model Optimisasi untuk Penjadwalan Ulang Perjalanan Kereta Api. *Jurnal Teknik Industri*, *17*(2). https://doi.org/10.9744/jti.17.2.97-104

Warasthe, R., Brandenburg, M., & Seuring, S. (2022). Sustainability, risk and performance in textile and apparel supply chains. *Cleaner Logistics and Supply Chain*, *5*(July), 100069. https://doi.org/10.1016/j.clscn.2022.100069

Yue, W. (2023). Export duration and export product quality of firms: evidence from China. *Journal of Applied Economics*, *26*(1). https://doi.org/10.1080/15140326.2023.2285129

 http://dx.doi.org/10.30656/intech.v9i2.8695