Research Article / Review Article FUPRE JOURNAL 7(2):110-117 (2023)

FUPRE Journal

of

Scientific and Industrial Research

ISSN: 2579-1184(Print) ISSN: 2578-1129 (Online)

http://fupre.edu.ng/journal

A Factorial Study of Variables affecting the Formulation and Production of Polyurethane Foam

OYEJIDE, O. J.[1,*], *ACHEBO, J. I.*[2] *OZIGAGUN, A.*[3]

[1]*Department of Mechanical Engineering, Federal University of Petroleum Resources, Effunrun, Delta State, Nigeria*

[2, 3]*Department of Production Engineering, University of Benin, Benin City, Edo State, Nigeria.*

ARTICLE INFO

Received: 12/12/2022
Accepted: 29/03/2023

Keywords

Factor loadings, Foam, Scree plot, Polyol

ABSTRACT

Polyurethanes are the most demanding type of polymers in the present era because of the versatility in properties and in the synthesis. There are several reasons why the variables affecting the formulation and production of foams made from petroleum bye products should be identified and planned for. This study uses statistical analytics to provide enlightenment and deep insight about the insidiousness of these factors, their wider implications, and justification to manufacturers and industrialists for their importance. A survey approach involving the use of Principal Component Analysis (PCA) facilitated by StatistiXL software package was employed. Thirty-two variables identified were used to craft questionnaires that were scaled with Rensis Likerts 5-point attitudinal scale and which were subsequently administered to respondents. Prior to this step, Kendall Coefficient of Concordance was applied as to establish merit order sequentiality among the identified factors. Our results showed an index of agreement among the judges in ranking the variables is W= 0.54, and that a null hypothesis of discordance among the judges was rejected at a p-value of 0.01. Again, the study was successful in distilling the gamut of variables into 10 manageable dimensions that trumps polymer type as the most significant factor. The authors affirm the basic variables needed to synthesize flexible polyurethane foam, that their desired end properties of the foam is based on the choice of the specific variables along with their required quantities.

1. INTRODUCTION

The global polyurethane market is estimated to undergo a growth phase, in which its size will increase considerably from around 15 million tonnes in 2020 to 20 million tonnes by 2025, growing at a rate of 7.5% per year during that period (Kiss, G. et al., 2021, Mitrevska, M.J. et. al., 2022). Due to their wide range of properties, adaptability, and capacity to cling to various materials, polyurethane foams are widely used in a variety of industrial sectors, including automotive, aviation, construction, furnishings, among others. Particularly in the creation of multifunctional hybrid composites, this popularity is apparent. (Kiss, G. et al., 2021) (Kaushik et al., 2015) (Seyed E. S., et. al., 2023). Rigid polyurethane foams are commonly employed as insulators in cold storage equipment, such as freezers, as well as insulation packaging and lagging to prevent heat loss. Meanwhile, there is a significant demand for flexible polyurethane foam in Sub-Saharan Africa, primarily for furniture such as beds, pillows, and cushions. The increasing urbanization and industrialization associated with the growth of the global economy has raised concerns

*Corresponding author, e-mail:author@fupre.edu.ng
DIO
©Scientific Information, Documentation and Publishing Office at FUPRE Journal

about ergonomics and orthopedics related to completing tasks, relaxation, and sleeping. (Seyed E. S., et. al., 2023).

In developing countries, Foam manufacturing along with producing affordable (cost) foams, faces more specific ergonomic and orthopedic requirements. Some of these requirements includes reduced percentage elongation, increased density, increased compression resistance to load and affordability, hardness (Nuno et al., 2018). Initially, polyurethane foam was not utilized with most of or all these requirements in mind. Instead, only one was focused on as it was employed as a substitute for rubber and as a protective coating for other prevalent materials of the time, such as wood and metals. (Suleman et al., 2014). In recent years, numerous techniques have been evaluated and implemented, demonstrating the economic and ecological advantages of processing Polyurethane foam. However, the heightened focus on environmental issues has led to significant scientific endeavors to address all aspects of polyurethane recycling and reuse. As a result, the majority of polyurethane waste is currently disposed of in landfills. (Kemona, A and Piotrowska, M.; 2020), hence, the need for manufacturers of polyurethane foam constituents to produce biodegradable and cost friendly foams. Previous research such as Ahmad et. al (2022), have discussed the impact of TDI index on the morphology and physical properties of flexible slab stock polyurethane foams. Audrey, et. al., 2020 showed that new advancements in analytical techniques for optimizing Polyurethane foam production and biodegradation have emerged. Hence, the current study aims at utilizing statistical analytics to rank and cluster accordingly a broad range of factors that affects foam formulation and production. The variables will be ranked according to their significance and merit order of sequentiality by the Kendall Coefficient of Concordance, and factor loadings will make it easier to summarize the data for the variables and group them into clusters. Stemming from this gap, this study seeks to identify the number of variables relating to the formulation and production of a developed polyurethane foam (Oyejide et. al., 2020a, Oyejide et. al., 2020b) and the associated constituents variables. The database for this study were pair reviewed articles obtained from google scholar and scopus.com.

Foam formulation and production are influenced by a multitude of factors, and the primary challenge is often how to reduce these complex factors to their simplest form to achieve parsimony. The next step is to cluster these factors based on their factor loadings to create policy variables for professionals in the foam industry. These factors may be technical or human-related, making it crucial to identify and scale their influence to determine their correlation. By perceived intercorrelations, the factors can be clustered, and production policies can be developed. Factor Analysis identifies sets of inter-correlated items by using a process called Factor Extraction. In factor extraction, hypothetical variables are placed in the best position to capture the pattern of inter-correlations in the correlation matrix (Widaman, 1993). Technical or human elements both may be present. Therefore, in order to assess their correlation, these influence elements must be recognized and scaled. The components can be grouped based on perceived intercorrelations, and production strategies can be created as a result. Factor Analysis is a statistical technique used to identify a relatively small number of factors that explain observed correlations among variables, and it is primarily used for data reduction or structure detection. In Factor Extraction, hypothetical variables are strategically placed to capture the intercorrelation patterns in the correlation matrix (Widaman, 1993). Marija (2003) is one of the early researchers who used factor analysis to isolate a relatively small number of factors to account for observed relationships between variables. This technique involves identifying and scaling the influence factors to assess their correlation and grouping the components based on perceived intercorrelations to create production strategies.

2. METHODS

The mathematical principles or theories used should be included as appropriate.

(i) Kendall Coefficient of Concordance (KCC)

The Kendall Coefficient of Concordance (W), which measures the degree of agreement between the judges is obtained from the equation (2.1)

$$W = \frac{12S}{K^2(N^3 - N)} \quad \text{or} \quad W = \frac{S}{\frac{1}{12}K^2(N^3 - N)} \qquad (1)$$

where $s = \sum\left(R_j - \frac{\sum R_j}{N}\right)^2 =$ Rank variance (2)

The KCC is useful in establishing merit order sequence of the variables.

R_j = Column sum of ranks

N = Total number of Variables being ranked

S = Sum of Variance

K = Number of judges

(ii) The Principal Component Analysis (PCA)

In this dimension, the correlation coefficient r_{ij} is first computed like so:

$$r_{ij} = \frac{\sum xy}{\sqrt{(\sum x^2)(\sum y^2)}} \qquad (3)$$

Where, $x = X_{ij} - \bar{X}_{.j}$ (4)

$$y = Y_{ij} - \bar{Y}_{.j} \qquad (5)$$

The matrix of correlation coefficient is used to conduct principal component analysis, PCA and factor extraction is done.

3. RESULTS AND DISCUSSION

3.1 Results

An exploratory survey of the variables relating to formulation and production of foam was conducted using well-crafted questionnaires. Key variables (scale items) that have potential to be considered by Foam manufacturers and producers were identified through a wide range of methods namely: Delphi technique, literature review, interviews, and group discussions. The merit order of these variables was statistically determined using Kendall Coefficient of Concordance (W) that required 13 Judges to provide an ordinal scale ranking of the items as shown Figure 1. The Judges were drawn from a homogenous set of professionals and practicing managers in industry and academia.

3.1.1. Kendall Coefficient of Concordance

Kendall coefficient of concordance W is given by:

i.e. $W = \frac{S}{\frac{1}{12}K^2(N^3 - N)}$

i. $S = \sum\left(R_j - \frac{\sum R_j}{N}\right)^2$

Also, $\chi^2_{cal} = K(N_{SI} - 1)W$

where, K = 13, N_{SI} = 32, W = 0.54

χ^2cal. = 217.682

3.1.1.1 Test of Hypothesis for Scale Items

(i) H_0: the ranking of the thirteen (13) judges are not coherent.

(ii) H_1: the ranking of the thirteen (13) judges are in agreement.

Since $\chi^2_{cal} = 217.682 > \chi^2_{tab} = 99.588$, We reject the null hypothesis (H_0) and concluded that the judges invariably ranked the 32 scale items. The computed coefficient of concordance was W = 0.54, which is middling. At 0.01 significant levels, the chi square test identifies the key value as 99.6, thus resulting in the rejection of the null hypothesis, as there is incoherence in the judges' rankings. Therefore, inferring the conclusion that the judges adequately ranked each scale item according to the same set of criteria. Furthermore, our study's results offered scant support for the null hypothesis that there was no ranking discrepancy among the designated judges. In other words, a p-value of 0.01 indicated that the null hypothesis was not accepted. Thus, as shown in Figure 1, the statistical analytical tool carried out by the Kendall Coefficient of concordance tool was able to order to represent the scale items to their corresponding merit order of sequentiality.

3.1.2 Principal Component Analysis

The scale items were structured into a questionnaire in correspondence with the 5-point likert's attitudinal scale and then distributed accordingly to 90 survey respondents. Altogether, 32 scale items, were administered to respondents. Based on the analytical outputs of the respondents' scores, a data matrix measuring 32 by 90 was developed accordingly.

3.1.3 Factor Interpretation

The factor matrix pinpoints factor loadings with their corresponding values, thus, in creating a data matrix, the respondents' responses are compiled. Thus, ensuring the matrix is being served as the input for factor analysis. While StatistiXL was used to obtain the outputs of the Eigen Values, OriginPro 2023 was used to obtain the Unrotated and Rotated Factor Loadings distributions as shown in Figure 2, Scree Plot as shown in Figure 3 and Cluster Plot in Figure 4. On plotting the scree plots, it was observed that having the eigenvalue being equal to 1, the highest factor computed is 10. Moreso, upon visual perusal of the correlation coefficients, it was observed that they had distinct values, thus, implying the potentiality of the factor analytical model. Additionally, the communalities produced, for the most part, meritorious values indicating that the variables have a common variance.

3.1.4 Interpretation from Cluster Plot

A Factor analysis using Principal Component Analysis method has been able to reduce the thirty-two (32) variables to five. The principal component method is used in the study to extract factors from the correlation matrix. All factors that have eigenvalues greater than or equal to 1 are selected and creatively named and categorized, as shown in Table 1 to 5 from the cluster plots in which five factors extracted were given meaningful interpretation. The Table below depicts the variables loaded under various clusters.

Cluster 1 represented in Table 1 is creatively labelled *Quality Expectations*. The scale items reflect the view of respondents that the attributes that make a good foam like noise absorber, tensile strength, weight per unit of volume, resistance to tear, thermal conductivity and fire resistance should be given due consideration to make foam safe for usage. Polymer type is scale item 1 with factor loading in this cluster (0.698) also shows that the use of the right polymer is key in the production of foam. Higher performing polymers will often result in quality foams. These are followed by comfort with a factor loading of 0.698, half-life consideration 0.651. Comfort level of foam users is important in terms of surface firmness, hysteresis loss and resistance to bottoming out. Respondents believe that foam design should be carried out in a way that will bring high comfort level to users and for the assessment of their lifetime.

Cluster 2 represented in Table 2 is creatively labelled *Manufacturing Considerations*. Most significant in this cluster are Ambient Conditions, Mixing, and Mould shape with a factor loading of 0.826, 0.793, and 0.789 respectively. Respondents believe these factors are important when manufacturing of foam is being considered. Next to this is production procedure. The procedure deployed in foam manufacture is vital. It could be a unit process (batch) for manufacturing different shapes using a mould or by a continuous process for making slabstock.

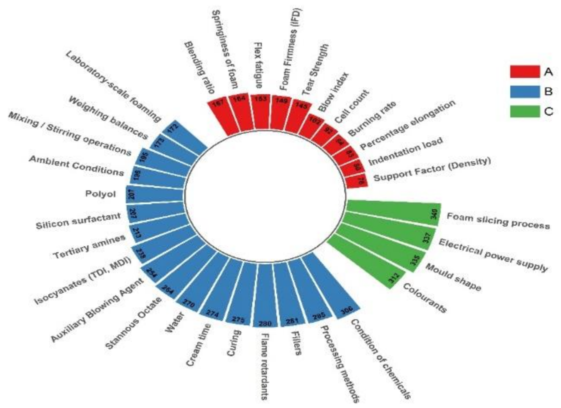

Fig. 1: Ordinal scale ranking of the items

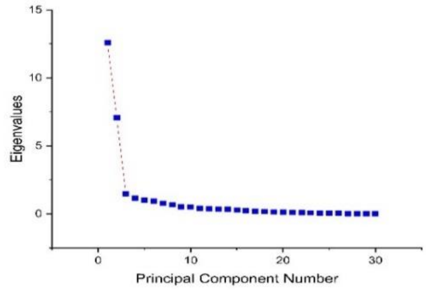

Figure 2: Scree Plot

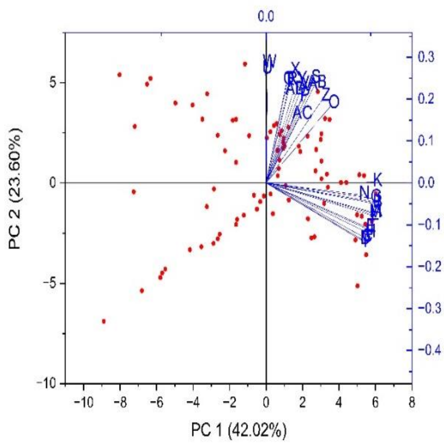

Figure 3: Factor Loadings distribution

Cluster 3 represented in Table 3 is creatively labeled *Measurement Efficacy***.** This cluster consists of a trio of weighing balances, cream time and processing methods. These factors have middling loadings, iterating the fact that their influence in foam formulation and production is moderate.

Cluster 4 represented in Table 4 is creatively labeled *Density or the support factor*. It is a lone output that characterizes all foam produced and is substantial for all foam type.

Cluster 5 represented in Table 5 is creatively labeled *Polyol Effect.* Polyol is a key constituent in foam formulations. The polyol is the main key item in this clustering with a variable loading of 0.819. This implies that it is a very relevant factor to be considered in the foam manufacture process. Curing, Silicon surfactant has factor loadings of 0.526 and 0.568 each as respondents believe that a foam manufacture must have these essential elements.

3.1. Discussion

Arising from the mathematical analysis carried out in this study, it is inferred that many factors have influence on the quality of foam manufactured and applied. The factor analysis model adopted has provided an objective weighting tool for categorizing and ranking the factors and for reviewing the actual effects as well as the interplay that exists amongst the cluster of variables. In this case study, Support Factor (Density), Indentation load, Burning rate and Cell count are principal factors that should be considered for foam production effectiveness. Therefore, we can generalize that these factors should be considered by any foam industry in planning the production process.

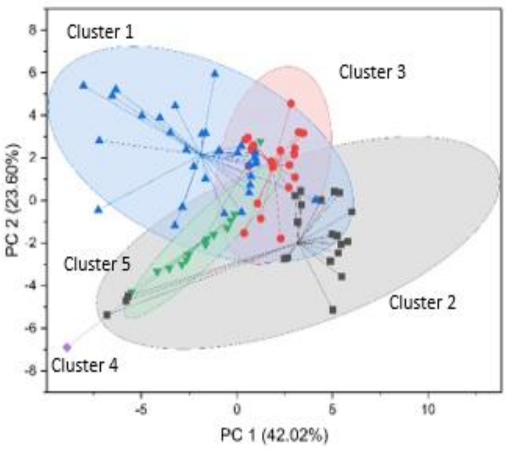

Figure 4: Cluster Plot

Table 1: Factor 1 (F_1) Quality Expectations

S/N	Variable description	Factor loading
2	Indentation load	0.815
4	Burning rate	0.594
7	Tear Strength	0.811
9	Foam durability (Flex fatigue)	0.739
10	Resilience / Springiness of foam	0.527
11	Blending ratio	0.830
12	Laboratory-scale cup-foaming	0.723
17	Silicon surfactant	0.624
19	Isocyanates (TDI, MDI)	0.787
20	Auxiliary Blowing Agent	0.790
21	Stannous Octate	0.771
26	Fillers	0.783
29	Colourants	0.667

Table 2: Factor 2 (F_2) Manufacturing Considerations

S/N	Variable description	Factor loading
3	Hysteresis/Percentage elongation	0.776
5	Cell count	0.742
6	Blow index	0.724
8.	Foam Firmness (IFD)	0.737
10	Resilience / Springiness of foam	0.555
13	Weighing balances	0.597
14	Mixing / Stirring operations	0.793
15	Ambient Conditions (Temp., Humidity)	0.826
17	Silicon surfactant	0.500
18	Tertiary amines	0.667
22	Water	0.776
23	Cream time	0.584
25	Flame retardants	0.786
28	Storage and conditions of chemicals	0.721
30	Mould shape	0.710
31	Electrical power supply	0.789
32	Foam slicing process	0.567

Table 3: Factor 3(F_3) Measurement Efficacy

S/N	Variable description	Factor loading
13	Weighing balances	0.619
23	Cream time	0.561
27	Processing methods	0.594

Table 4: Factor 4(F_4) Density

S/N	Variable description	Factor loading
1	Support Factor (Density)	0.794

Table 5: Factor 5 (F_5) Polyol Effect

S/N	Variable description	Factor loading
16	Foam Type (Petroleum/Plant) oil Polyol	0.819
17	Silicon surfactant	0.526
24	Curing	0.568

4. CONCLUSION

The study has been successful in achieving significant data reduction on 32 foam variables studied. The degree of parsimony realized seems substantial and helpful in adapting the key factors for policy instruments which can guide production managers to action.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The ideology of this study is birthed by Late Prof. Anthony Clement Igboanugo, a Professor of Design and Manufacturing. His legacies live on. Also, to the Management, production managers and staff of Happinex Happinex Foam Industries Nigeria Limited, located at 147, Upper Mission Extension, Uteh Quarters, Benin City, Edo State and Bethel foam Industries Ltd. NNPC Road, Opp. Hotel Baladi, Aviele, Auchi, Edo State.

References

Ahmad, Z. R., and Mahanwar, P. A., (2022). Synthesis and properties of foams from a blend of vegetable oil based polyhydroxyur ethane and epoxy resin. *Cellular Polymers*, 02624893221101170.

Audrey M., Eric Pollet, Vincent Phalip, Luc Avérous, (2020). Evaluation of biological degradation of polyurethanes, Biotechnology Advances, Volume 39, 107457, ISSN 0734-9750, https://doi.org/10.1016/j.biotechadv.2019.107457.

Kaushik, C., Prakash, K., and Achutha, M. (2015). Design and Development of Automation System for Polyurethane Foaming Machine. International Journal of Research Studies in Science, Engineering and Technology, 2, 33-41.

Kemona, A.; Piotrowska, M.. (2020). Polyurethane Recycling and Disposal: Methods and Prospects. Polymers, 12, 1752.

Kiss, G.; Rusu, G.; Bandur, G.; Hulka, I.; Romecki, D. (2021). Advances in Low-Density Flexible Polyurethane Foams by Optimized Incorporation of High Amount of Recycled Polyol. Polymers, 13, 1736.

Marija, J. N. (2003). SPSS 12.0 Statistical Procedures Comparison, Prentice Hall, Upper Saddle River, New Jersey.

Mitrevska, M.J.; Mickovski, V.; Samardzioska, T.; Iannace, G. (2022). Experimental and Numerical Investigation of Sound Absorption Characteristics of Rebounded Polyurethane Foam. Appl. Sci., 12, 12936. https://doi.org/10.3390/app122412936

Nuno V, G., Artur, F., and Barros-Timmons, A. (2018). Polyurethane Foams: Past, Present, and Future. Material

Oyejide O.J., Achebo I.J., Okwu M.O, Tartibu L.K., (2020): 'Computational Fluid Dynamics and Simulation of a Mixing Mould Unit of a Mini Foam Batch Production Plant'. Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management (IEOM Society International) Harare, Zimbabwe, December 7-10, 2020.

Oyejide O.J., Achebo I.J., Okwu M.O, Tartibu L.K., (2020). 'Development of a Mixing and Moulding Unit for Mini Foam Batch Production Plant. Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management (IEOM Society International) Harare, Zimbabwe, December 7-10, 2020.

Seyed E. S., Umberto B., Hasan A. M., Parham S. and Ebrahim T., (2023). Optimization and modeling of the sound absorption behavior of polyurethane composite foams reinforced with kenaf fiber, Applied Acoustics, 202,109176, doi.org/10.1016/j.apacoust.2022.109176.

Suleman, S., Khan, S. M., Gul, N., Aleem, W., Shafiq, M., and Jamil, T. (2014). A Comprehensive Short Review on Polyurethane Foam. International Journal of Innovation and Scientific Research, 4(12): 165-169.

Widaman, K. F. (1993). Common factor analysis versus principal component analysis: Differential bias in representing model parameters? Multivariate Behavioral Research, Vol. 28, pp 263-311.