FACTOR ANALYSIS APPROACH-TAGUCHI-PARETO METHOD TO CASTING A356 ALLOY COMPOSITE FOR LIGHTWEIGHT WHEEL RIM COVER OF VEHICLES

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ABSTRAK

Memperkuat paduan A356 yang dapat digunakan kembali dengan bahan organik adalah prinsip, keberhasilan namun meluas dalam lingkup pengembangan produk baru. Meskipun demikian, penggunaan metode Taguchi-Pareto memiliki potensi untuk ditingkatkan. Tujuan artikel ini adalah untuk mengkaji metode analisis faktor-Taguchi-Pareto di mana identifikasi faktor-faktor kunci dapat dicapai sekaligus mengoptimalkan faktor-faktor tersebut. Titik integrasinya adalah pada penentuan varians dari pembebanan faktor dan komunalitas yang tidak diputar. Sinergi antara analisis faktor dan metode Taguchi-Pareto memberikan bantuan praktis kepada para insinyur pengecoran logam untuk secara bersamaan memilih faktor-faktor kunci sekaligus mengoptimalkannya. Faktor-faktor tersebut tercatat efektif dan responsif terhadap metode yang diusulkan. Nilai delta masing-masing adalah 0, 0,84 dan 0 untuk LC1, WC1 dan HC1, sedangkan peringkatnya adalah WC1 sebagai yang pertama sedangkan posisi kedua dibagi antara LC1 dan HC1. Pengaturan parametrik yang optimal adalah $LC1_1WC1_1HC1_1$, $LC1_1WC1_1HC1_2$, $LC1_2WC1_1HC1_1$ atau $LC1_2WC1_1HC1_2$¬. Salah satu pengaturan parametrik yang optimal adalah 0,280m LC1 dengan 1,788kg WC1 dan 0,036m HC1. Temuan ini memberikan langkah-langkah baru untuk identifikasi faktor bersamaan dan optimasi dalam pilihan pengaturan parametrik yang optimal untuk proses tersebut. Ini adalah langkah pertama menuju praktik pengecoran yang berkelanjutan.

Kata kunci: *Pengelompokan, algoritma, coran, coran, paduan A356, bala bantuan*.

ABSTRACT

Reinforcing re-usable A356 alloys with organic matters is a principal, success yet expanding in scope regarding new products development. Despite this, the use of the Taguchi-Pareto method has potential for improvement. The purpose of this article is to examine the factor analysis-Taguchi-Pareto method at which identification of the key factors could be achieved while concurrently optimizing the factors. The point of integration is at the variance determination of the unrotated factor loadings and communality. The synergy between factor analysis and the Taguchi-Pareto method provides practical assistance to foundry engineers to concurrently select key factors while optimising them. The factors were noted to be effective and responsive to the proposed method. The delta values are 0, 0.84 and 0 for LC1, WC1 and HC1, respectively while the ranks are WC1 as first while the second position is shared between LC1 and HC1. The optimal parametric settings are $LC1_1WC1_1HC1_1$, $LC1_1WC1_1HC1_2$, $LC1_2WC1_1HC1_1$ or $LC1_2WC1_1HC1_2$. One of the optimal parametric settings is 0.280m of LC1 with 1.788kg of WC1 and 0.036m of HC1. The finding provides novel steps to the concurrent factor identification and optimisation in the choice of optimal parametric setting for the process. It is the first step towards sustainable foundry practice.

Keywords*: Clustering, algorithms, castings, castings, A356 alloy, reinforcements*.

INTRODUCTION

Producing automobile-rim covers with a focus on sand casting geometry is a concept that entails the measurement of sizes and shapes of rim covers and this process generates substantial data [1],[2],[3],[4],[5],[6],[7],[8],[9]. However, defect-free auto wheel cover is the goal of the foundry engineer, who compares results of casting with standards in weight appearance and shape [10],[11]. At present, there is clear evidence from the literature that reports on sand casting geometry with the A356 alloy composite has downplayed efforts on selective data processing to yield novel information on the selection of key factors and their concurrent optimization in the sand casting process [7],[8],[9]. This situation is striking and disturbing considering the lost potential opportunities for commercial enhancement of the composite in the foundry industry.

Amazingly, the potential of A356 alloy composite in applications and its robust design opportunities that factor analysis and optimisation bring about is lost due to poor understanding of their application to foundry practice. Apart from the auto cover that is the focus of this work, the organic-based A356 alloy composite can be used for other products such as blowers, frame parts, chassis parts, flywheel casting, oil pans, pump bodies, impellers, auto transmission cases, and machine parts [7],[8],[9]. It is disturbing that huge data is presented during the sand casting of these products and wastefully allowed to expire without due process for robust enhancement of the foundry shop.

Interestingly, the factor analysis and Taguchi-Pareto method seem to be the best fits to bridge the research gap [12],[13],[14],[15]. Alongside, K-means is introduced to enhance the clustering characteristics of the data. K-means clustering is a straightforward unsupervised learning technique that works on literature procedures and creates compartments for datasets into determined clusters [14],[16]. The concept is to establish "K" centres and map a centre to each cluster. The several advantages of K-means include the fact that it assures convergence. It has the potential to commence the positioning of centroids, adapt with ease to problems and the ability to simplify data to clusters, which possess various sizes and shapes [14],[16]. The second technique used, factor analysis is a statistical approach, which explains the variability of the observed and correlated parameters regarding the probable reduction of the number of factors [12],[13],[15],[17]. As a unique attribute, factor analysis offers a straightforward approach to lowering variables to important ones [17]. The strong benefit of this approach is that it assists the foundry engineer to focus attention on the significant factors that control the process. It also explains the obtained results. Taguchi-Pareto is an optimization method with an increasing reputation for concurrent optimization and prioritization [18],[19]. Consequently, clustering and analysis of casting data for the desired geometry of products from organic reinforced A356 alloy composite are compelling to bring the product to high quality and acceptable level and bring efficiency and quality decision into the production process. Furthermore, the optimisation of the parameters at the point of applying factor analysis is of significant advantage to the foundry engineer.

Concurrently, during the production of A356 alloy composite, the foundry worker engages in the mixing of the reinforcements, namely abori wood, pineapple stalk and *Delonix regia*. In this endeavour, the quantity by volume and weight, colour, appearance, small and other attributes are generated and noted. The foundry worker and the researchers would cautiously trail these measurements but the data is lost as the mixing of these reinforcements are done. In this circumstance, there is no clear understanding of the immense power in the data on identifying data clusters from the reinforcement materials. There is also poor knowledge of what factors are essential and those to direct attention at identifying and concentrating on the important factors for casting efficiency. These factors may also be optimised. Unfortunately, the dimensions of this research problem keep expanding given the radical explosion of product demands of engineered products. The increase in the demand for A356 alloy composites to convert into useful products is envisaged in the nearest future and this brings urgency into solving this important gap. Based on these concerns, the present authors conceived the idea to analyse the cast data concerning the A356 alloy reinforced with abori wood, pineapple stalk and *Delonix regia* using the factor analysis-Taguchi-Pareto method and the K-means clustering algorithm is also used to analyse the results. These methods were reported in previous studies to have success in extracting useful clustering and selection information from practical data in other areas of engineering endeavour.

Consequently, this paper aims to build up a factor analysis-Taguchi-Pareto method and K-means clustering algorithmic framework to analyse the casting data developed as it is optimised when A356 alloy and organic matters are mixed in a sand casting environment for the extraction of the most important elements from the data. It is essential to complement the earlier research that uses the Taguchi methods (Taguchi architecture, Taguchi-ABC and Taguchi-Pareto), the response surface methodology (comprising of the Box-Behnken design) [7],[8],[9]. It is known that lean manufacturing is the order of the day. However, this philosophy also argues for the effective use of manufacturing data for enhanced performance. Hence, this paper that focuses on information extraction from the abundant data on A356 alloy composite casting is a timely intervention to the research gap previously discussed. This paper reacts to the call by Nwafor et al. [7],[8],[9] to conduct more investigations in this area. In the work, two stages of casting are involved. The first concerns the casting of canoe-shaped casts and the second is the production of cuboid-shaped casts. In addition, the K-means clustering algorithm and factor analysis have not been previously applied in the research domain reported in the present work. The obtained data used for this paper were extracted from the literature. These are from Nwafor et al. [7],[8],[9]. The value of the tools used in the literature is the ability to analyse the interactions of the factors involved in the casting process and understand the process better. From the foregoing, this study is a unique interaction to the way data is gathered and managed in the foundry when producing organic-based A356 alloy composites for automobile rim covers. Previously, the challenging yet essential data management practice in a foundry during the casting of organic-reinforced A356 alloy composites was downplayed. This function has not been fully understood by the foundry technician and engineer. Fortunately, this report demonstrates an innovative way that introduces two key tools, K-means clustering algorithm and factor analysis to the act of effective information extraction through clustering and factor analysis. This is meant to revolutionalise the thinking pattern concerning the generation of data and its use for A356 alloy composite product enhancement. The outcome of this study will be valuable to foundry involvers, to enrich their understanding of how to improve product features through the data generated. This will certainly improve foundry activity planning and improve the economics of the process of casting.

Based on the above discussion, it was thought that the k-means clustering approach might help to understand the A356 alloy organic reinforced composite better. The combination of the organic reinforcements, such as powdered abori wood, *Delonix regia* and pineapple stalk may be done better as one looks for meaningful groups and collections considering all the important issues associated with these organic matters, these are the total weight of organic materials, the volume of cast 1, weight of 1, the weight of cast 2, the width of cast 1, and weight loss during preparation of the organic materials according to weights while another perspective is to organize it by volume. How one chooses to group the organic materials assists one to understand more concerning the item as separate pieces of reinforcement materials. The composite designer may have a deep affinity for weight, which could be further broken down. This could be weighed when the powdered reinforcements have tapped the container holding the fine-grained reinforcement (bulk weight). The composite designer may also be interested in the true weight (when the porosity of the gains occurs).

On the other hand, the composite designer might look at the reinforcements from the volumetric perspective. Here, the composite designer might be able to understand how the reinforcements are understood how the reinforcement may be measured geometrically (measuring lengths), by water displacement or by pysnometry. In the two instances, the composite designer wishes to learn some interesting things about the reinforcement even though different approaches have been taken. So, grouping the data on reinforcements is conceived as a first step to understanding the best way to fabricate the organic-based A356 alloy composites. Consequently, christening the reinforcement data is essential for the process undertaken in this paper. Therefore, this study aims to implement the k-means clustering algorithm on the data collected on reinforcements for the A356 alloy. This is taken as the first objective of this paper.

In the above description, many variables have been identified and described. It is also conceived that a way to condense these data occurring in several variables to a few variables may be essential to understand the best way to produce the organic-reinforced A356 alloy composite. Thus, the second aim of this study is to implement the factor analysis principle in the data collected on reinforcements for the A356 alloy.

LITERATURE REVIEW

Inclusion Criteria, Exclusion Criteria and Research Strategy

The current research was initiated as part of targets to build up and confirm the conversion of disposed waste engine products, A356 alloy with organic matters, to reduce environmental impacts in the use of such materials. The organic materials, namely, abori wood, pineapple stalk and *Delonix regia* had been used in a field experiment, part of which is reputed here. However, readers are referred to the three earlier papers on the subject, including Nwafor et al. [7],[8],[9]. Only skeletal reports are given on the experiments here. However, the focus of this paper is to examine the factor analysis method as a classification scheme to improve choice to parameters and consequently enhance the sand casting experience to produce automobile wheel covers using waste.

A review exercise was conducted but on guidance by some criteria to produce a robust review. First, the research reported in peer-reviewed journals and conferences, which included papers with A356 alloy, were potentially eligible for the review carried out in this paper. However, restrictions were made to exclude papers that are more than twenty years (i.e. published before 2000). The language was restricted to English while works of literature published in other languages were ignored. The target situation was an instance where A356 alloy has been mixed with organic materials. Furthermore, the work targets the A356 alloy literature that has considered factor analysis in its content! Besides, the study is open to various methods of processing (production), including stir casting, vortex, the use of graphite crucible only and various other methods that are variants of the mentioned methods. They include double stir casting and stir plasma sintering as well as sand casting methods [9]. This work also included theoretical studies, beyond experimental-oriented research. Studies were excluded if the publication fails to follow the standard format of a research paper. Examples are commentaries and letters to editors. The search method focused on the following databases: Scopus and Directory of Open Access Journals (DOAJ). A search strategy was conducted in August 2019 and revised in July 2020.

Organic-Assisted A356 Alloy

The main focus of this work is the works of literature that have discussed organic matters to reinforce A356 alloy but with interest in the factor analysis and K-means clusters as an analysis tool. In a review endeavour, several categories of organic matters were observed to have been used as reinforcements in A356 alloy. These works of literature are reviewed in this section.

Cow Horn-Assisted A356 Alloy

Cow horn has been used as reinforcement and studies on cow horn-based A356 alloy composites have been intensive. Research in this aspect was due to Ochieze et al. [20]. The attention of the author was to wear experiments. This was attained using Taguchi architecture to optimise the wear parameters. However, despite the substantial data generated that may have been enhanced by the K-means clustering techniques, the enhancement power of this tool was not exploited. Moreover, factor analysis that exhibits the potential to distinguish factors according to their importance with the goal of wear measurements was uncovered.

The report of Ochieze et al. [21] linked the control parameters of the sintering process that include the holding time, heating rate, temperature and pressure. While the report declared a decayed density rate of the reinforcement, the interesting aspect of clustering the data for value-added information, using the K-means clustering technique was downplayed. Besides, the factor analysis and its resident potential to enhance data interpretation and understanding into the cow horn-based A356 alloy composite were not exploited. The cow horn-based A356 composite research was enhanced by Nwobi-Okoye and Ochieze models were tested by the authors. These include the response surface method, an architecture based on simulated annealing; and neural networks structures. While the models were approved with data under the age-hardening method, there is no guide on how to utilise the robust structure of the K-clustering approach to enhance the interpretation of the data. Besides, the exploit of the factorial analysis classification scheme was omitted in the work. The correlation coefficient that the ANN predictions yielded were resulted in more convincing than the repose surface approach. The authors also reported almost equal results of the experimental outcomes with the neural network system.

The pioneering modelling approach of the optimisation scheme for A356/cow horn composite in Nwobi-Okoye and Ochieze's [22] paper was succeeded by Nwobi-Okoye et al. [23]. This new work compared the ANFIS model with the artificial neural network scheme. Surprisingly, the abundant data produced was utilised properly. But more intense usage would have been demonstrated in clustering and factor analysis, which was absent in the research. To summarise observations on the use of cow-horn reinforcements in the A356 alloy for composites, it was noted that sufficient data was generated during the fabrication processes of the A356 alloy. However, the utmost utilisation of such data in clustering activities is not reported in the literature. Furthermore, the powerful advantage of using factor analysis to identify the most important factors during the casting process was ignored in all the reports reviewed. This prompts the current researchers to seek in correcting this important research and practice gap.

Research on Rice Husk Based Composites

The commercial appeal to use rice husk ash to fabricate A356 alloy composite was reported by several authors. Subrahmanyam et al. [24] focused on adding rice husk ash to A356 alloy by examining the mechanical properties of the product regarding hardness, tensile, impact and percentage elongation. A uniform distribution of the reinforcement was noticed within the A356.2 matrix. Despite the massive data generated in the report, the advantage of the clustering method and factor analysis to identify the important factors and characteristics of the casting data was not exploited.

Melon Shell Powder Based A356 Alloy Composite

Abdulwahab et al. [25] pioneered reinforcing A356 alloy with melon shall powder. While focusing on the wear features of the new product, it was noticed that wear confrontation of the A356 composite enhanced substantially. With the growth in percentage reinforcements, another key result is the presence of plastic deformation of the matrix stage as revealed in the report on a microstructural examination of the A356 composites. Although a huge amount of data was generated through analysis, the work has not reported having taken advantage of the clustering opportunity and factor analysis in processing the data

Palm Kernel Based A356 Composite

The contribution of Aigbodion and Ezema [26] is pronounced in this domain with an effort to evaluate some mechanical properties of the composite. The A356 alloy was fuzed with palm kernel powder and promising results were obtained. Notwithstanding, despite the substantial data generated, the advantages brought about by the clustering algorithm and the factor analysis were not explained in the work.

Bagasse Powder-Based Alloy Composite

Satishkumar et al. [27] analyzed the use of bagasse powder to reinforce A356 alloy. The wide range of reinforcement weight percentage addition to the matrix was extended from 8 wt% to 10 wt%. The density mechanical characteristics and microstructural features of the A356/bagasse composite were analyzed. Despite the substantial characteristic data available to the authors, the advantage in using the clustering algorithm and the factor analysis has not been fully exploited.

Locust Bean Powder-Based A356 Composite

Usman et al. [28] used locust bean powder to reinforce A356 alloy. The method of production applied in the study is the traditional stir casting procedure. A comprehensive analysis integrating wear property evaluation with mechanical properties was successfully pursued. A significant decline in the wear rate was also reported as the weight ratio of the powder locust bean A356 alloy composite increased. While the information for advancement in the field is provided, the authors have not exploited the clustering opportunity for the data. Also, factor analysis has not been exploited.

Summary and Literature Gaps

In the literature review, the related studies on K-means clustering algorithm and factor analysis were broadly examined. Within the limits of the search conducted in this paper, powders of organic matter used to fortify A356 alloy has ranged to contain melon shell, palm kernel shell, bagasse and locust bean. It was argued that substantial data is generated in the domains of focus by the papers. Authors have studied the wear properties and mechanical properties of organic-based A356 alloy composites. However, these data have not been fully exploited in their clustering ability and the potential for factor analysis that they have. Observing trends in clustering and understanding the most influential factors in an A356 alloy composite development endeavour would strengthen robust design choices and the creation of products with unique and outstanding features since the best attributes of the composites developed are exploited. Previous research on organic-based A356 composite development has shown less attention to clustering at activities in data management during the A356 alloy composite fabrication. It has also shown substantially less interest in the choice of influential factors for processing. Thus the use of K-means clustering algorithm and factors analysis has not been made in the production of organic-based A356 alloy composites.

METHODS

Factor Analysis-Taguchi Pareto Method

The following steps were followed to implement the proposed method:

Step 1: Choose and evaluate the group of reinforcement variables as input into the A356 composite development
Step 2: Screen the evaluated data and prepare the correlation matrix
Step 3: Extract the factors
Step 4: Initiate the factor rotation to enhance interpretability
Step 5: From the various percentage values, obtain the cumulative frequency variance and establish a cut off of about 80% according to the Pareto rule of 80-20 for analysis
Step 6: Extract the levels from the original data to permit factor level analysis
Step 7: Establish the orthogonal array fit for the design
Step 8: Compute the signal-to-noise ratios for the established experiments
Step 9: Evaluate the S/N ratio response table through the average of the ratios mapped to levels
Step 10: Determine the optimal parametric settings for the parameters

The following details may be helpful for the steps mentioned above

Collection of data and correlation matrix creation

Practical data previously published in Nwafor et al. [7],[8],[9] were used to illustrate the working of the model. It discusses the casting of 9 samples of reinforcements to the A356 alloy for A356 composite development. Data were gathered from every casting and measurements of the parameters made, including length of cast 1 (LC1), Weight of cast 1 (WC1), Height of cast 1 (HC1), Width of cast 1 (WiC1), Weight of cast 2 (WC2), Length of cast 2 (LC2), Breadth of cast 2 (BC2), Total weight of organic materials (TWOM). The data was applied based on the principles declared by Archana [13], Equation (1):

$$A_{vxv} = B_{vxn}\alpha_{nxn}B'_{nxv} + \beta_{vxv} \quad (1)$$

where v is the total number of variables involved in the analysis, n represents the total number of common factors, A_{vxv} reveals the correlation matrix of the v observable variables that reckons with the evaluation which will be used in the A356 alloy casting process. Furthermore, α_{nxn} is defined as the identity matrix, which B_{vxn} is the correlation matrix of the n unobservable common factors while β_{vxv} represents the covariance matrix of the v unobservable specific factors.

Furthermore, Archana [13] analysed the variance of the exposed model by employing a particular variable a_d as in Equation (2):

$$a_d = \sum_{e=1}^{n} l_{de}h_e + t_{ddjd} = h_d + v_d \quad (2)$$

where a_d is a specific variable, h_e is the common factors, h_d is the common part of the variable, which is the part of a function for the common factors, and v_d is the particular part of the observed variable.

As the variance operator is used on both sides of the equation, Equation (3) is given by Archana [13]:

$$1 = \sum_{e=1}^{n} l_{de}^2 + t_{dd}^2 = Var(h_d) + Var(v_d) \quad (3)$$

The common variance of an observed variable can be written as the sum of squares of the components of the equivalent row *d* of the factor pattern matrix [13].
This value is noted as s_d^2 and is known as communality [13]:

$$s_d^2 = Var(h_d) = \sum_{e=1}^{n} l_{de}^2 \quad (4)$$

Cluster k-means

Cluster analysis refers to various groups of variables for the same and separate groups [29]. Two classes are distinguished: Hierarchical clustering and non–hierarchical clustering. Euclidean distance is used to measure the distance between each variable m and k as shown in Equation (5) [30]:

$$c_{mk} = \sqrt{(\sum_{j=m}^{n} z_{mj} - z_{kj})^2} \quad (5)$$

where *n* is the number of variables, c_{mk} represents the euclidean distance between objects *m* and *k*, while z_{mj} is the value of the variable *m* and z_{kj} is the value of the variable *k*.

For the Taguchi method, the smaller the better criterion is used [18],[19]:

$$\text{S/N} = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (6)$$

where y_i represents the performance attribute of interest for the i^{th} observed value
n represents the experimental trial number

RESULTS AND DISCUSSION

The data that forms the foundation for the analysis carried out in this work is shown in Table 1. The data in Table 1 was copied from an MS Excel sheet to the worksheet of a Minitab-16. Minitab-16 was used to generate the correlation matrix, factor loadings for equimax, xarimax and qaurtimax.

Table 1. Measurements of A356 alloy (canoe-shaped and cuboid shaped) [7],[8],[9]

S/N	Length of cast 1 (m)	Weight of cast 1 (kg)	height of cast 1 (m)	width of cast 1 (m)	Weight of cast 2 (kg)	length of cast 2 (m)	breadth of cast 2 (m)	total weight of organic materials (kg)
1	0.281	1.808	0.036	0.096	1.72	0.265	0.24	0.2712
2	0.291	1.975	0.039	0.103	1.84	0.264	0.24	0.2965
3	0.285	1.91	0.038	0.103	1.74	0.264	0.241	0.2865
4	0.285	1.828	0.036	0.098	1.74	0.264	0.241	0.23476
5	0.28	1.788	0.036	0.095	1.58	0.265	0.241	0.22351
6	0.282	1.863	0.037	0.099	1.72	0.262	0.24	0.23288
7	0.287	2.215	0.04	0.106	2.04	0.264	0.24	0.22131
8	0.285	1.915	0.038	0.098	1.7	0.264	0.24	0.191
9	0.285	1.865	0.038	0.096	1.74	0.264	0.24	0.1865

Factor Analysis-Taguchi-Pareto Method

The first objective of this study is to address the question; "How do we integrate factor analysis with the Taguchi-Pareto method? This involves first obtaining the correlation matrix (Table 2) from Table 1 and then computing the unrotated factor loading and communality (Table 3).

Table 2. Correlation Matrix for A356 alloy cast

	LC1	WC1	HC1	WiC1	WC2	LC2	BC2	TWOM
LC1	1.000	0.626	0.772	0.705	0.665	-0.130	-0.276	0.263
WC1	0.626	1.000	0.900	0.866	0.934	-0.145	-0.380	-0.008
HC1	0.772	0.900	1.000	0.815	0.808	-0.203	-0.468	0.001
WiC1	0.705	0.866	0.815	1.000	0.836	-0.265	-0.131	0.397
WC2	0.665	0.934	0.808	0.836	1.000	-0.162	-0.426	0.113
LC2	-0.130	-0.145	-0.203	-0.265	-0.162	1.000	0.289	0.107
BC2	-0.276	-0.380	-0.468	-0.131	-0.426	0.289	1.000	0.192
TWOM	0.263	-0.008	0.001	0.397	0.113	0.107	0.192	1.000

Table 3. Unrotated Factor loadings and Communality

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Communality
LC1	0.810	-0.194	-0.011	-0.137	-0.521	0.125	0.028	0.003	1.000
WC1	0.939	0.053	0.201	0.184	0.184	-0.026	0.070	0.038	1.000
HC1	0.942	0.101	0.129	0.037	-0.131	-0.247	-0.079	0.006	1.000
WiC1	0.911	-0.302	-0.153	0.183	0.114	-0.077	0.046	-0.044	1.000
WC2	0.931	0.002	0.124	0.035	0.216	0.256	-0.068	-0.004	1.000
LC2	-0.274	-0.460	0.824	-0.184	0.021	-0.024	0.008	-0.010	1.000
BC2	-0.462	-0.632	-0.015	0.612	-0.109	0.026	-0.026	0.010	1.000
TWOM	0.162	-0.816	-0.364	-0.389	0.150	-0.040	-0.013	0.017	1.000
Variance	4.4356	1.4183	0.9070	0.6476	0.4162	0.1519	0.0194	0.0040	8.0000
% Var	0.55445	0.177288	0.113375	0.08095	0.052025	0.018988	0.002425	0.0005	1.000
Cumm % Var	0.55445	0.731838	0.845213	0.926163	0.978188	0.997176	0.999601	1.000000	-

The output of Table 3 regarding the percentage variance offers the point of integration of the factor analysis and the Taguchi-Pareto method. This leads to the emergence of Taguchi-Pareto's orthogonal array table, factors and the computation of the signal-to-noise ratio. The factors and levels are first established (Table 4) and the S/N ratios are computed (Table 5).

Table 4. Factors and levels

Factor	Level 1	Level 2
LC1	0.280	0.291
WC1	1.788	1.975
HC1	0.036	0.040

Table 5 Taguchi-Pareto's orthogonal arrays, factors and signal to noise ratios

Expt. No.	Orthogonal array LC1	WC1	HC1	Factors LC1	WC1	HC1	S/N ratios
1	1	1	1	0.280	1.788	0.036	–0.38
2	1	2	2	0.280	1.975	0.040	–1.23
3	2	1	2	0.291	1.788	0.040	–0.39
4	2	2	1	0.291	1.975	0.036	–1.23

Furthermore, the response Table is established (Table 6). New, explaining the process in detail, Table 2 is first computed. Using the Minitab computational feature, data from Table 1 was placed on the spreadsheet and the correlation matrix was obtained (Table 2). A high correlation that ranged from 0.626 to 0.722 is obtained between LC1 and WC1, LC1 and WC2. This suggests a high volume and density of most samples. Since it is desirable to lower these physical quantities the Taguchi-Pareto method is applied to optimise to reduce the quantities. It is further noted that WC1 and HC1 as well as WC1 and WiC1 have a high correlation, which manifests in the density and volume of cast 1 of most samples.

Table 6. Taguchi SN ratio response table

Level	LC1	WC1	HC1
1	–0.81*	–0.39*	–0.81*
2	–0.81*	–1.23	–0.81*
Delta	0	0.84	0
Rank	2	1	2

Besides, HCI and WICI have a correlation that shows a high volume of cast 1 among the samples. By examining HC1 and WC2, a high value is also noticed, which reflects the increase in density among some samples. It was noted that all the correlation coefficients are not positive which shows that there is a rise in some of the measured variables linked with a particular ascend in other variables [31]. Next, factor extraction is conducted. This was conducted as it is understood that every observed value may be expressed in linear integration of the factors. The choice of the central factors is guided by the fact that the fundamental vector is an aspect that is largely accountable for the arising variances. Consequently, Table 3 was generated using the principal component factor analysis of the correlation matrix. By applying the Guttman-Kaiser rule, factors whose eigenvalues are greater than 1 should be retained. However, factors that interpret 70-80% of the variance should be retained. Besides, it is necessary to retain all factors before the breaking point or elbow. Thus, after generating the Scree plot, 2 to 3 factors can be extracted.

Having established the Taguchi-Pareto method, the remaining aspect of the factor analysis is hereby discussed. By using three factors, Table 7 is established. This shows the unrotated factor loadings and communality for three factors. It contains variants of rotated factor loadings with equamax rotation, varimax rotation and quartimax rotation. The variants show that the factors are consistent in all rotations. The elements LC1, WC1, HC1, WiC1 are common in factor 1 in all rotations. However, LC2 is common in factor 3 in all rotations while factor 3 has BC2 and TWOM as common variables under it in all rotations.

In the deployment of factor analysis to the A356 composite development, it is understood that the different reinforcements to be added to A356 melt can be treated as factors with several features. It is known that the mixture of these wastes affects the final quality of the automotive cover to be produced from such a fabrication endeavour. The composite engineer is interested in knowing how the quality of the product is affected to develop an action plan for future production processes. To establish these dimensions, factor analysis is deployed to establish the underlying dimensions. The mechanism of treatment in factor analysis is that the particular issues that highly correlate are classified to be in a specific dimension. These groups are the composites of the particular variables, which permits the interpretation and description of the dimensions.

Cluster k-means Analysis

Minitab clusters data of eight variables of A356 alloy cast into three clusters established on the initial partition that was selected. Table 8 shows the final partition where cluster1 has 5 observations which speak for the most important measurements of the A356 alloy cast, cluster 2 has 1 observation which represents the least important measurement and cluster 3 has 3 observations which represent the more important. The higher value of the within–cluster sum of squares of cluster 1 shows the observations have great variability within the cluster. The average distance from centroid and maximum distance from the centroid of cluster 1 also shows that the observation has greater variability within it.

Table 7. Unrotated factor loadings, rotated factor loadings (equamax rotation), rotated factor loadings (varimax rotation), rotated factor loadings (quartimax rotation) and communality for 3 factors

	Unrotated factor loadings			**Rotated factor loadings (equamax rotation)**			**Rotated factor loadings (varimax rotation)**			**Rotated factor loadings (quartimax rotation)**			
Variable	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 1**	**Factor 2**	**Factor 3**	**Communality**
LC1	0.810	-0.194	-0.011	**0.804**	-0.166	-0.142	**0.812**	-0.163	-0.087	**0.815**	-0.170	-0.029	0.694
WC1	0.939	0.053	0.201	**0.946**	0.150	-0.093	**0.949**	0.153	-0.025	**0.950**	0.143	0.051	0.925
HC1	0.942	0.101	0.129	**0.926**	0.162	-0.176	**0.935**	0.165	-0.109	**0.942**	0.157	-0.034	0.914
WiC1	0.911	-0.302	-0.153	**0.882**	-0.324	-0.248	**0.898**	-0.319	-0.190	**0.907**	-0.325	-0.127	0.944
WC2	0.931	0.002	0.124	**0.927**	0.070	-0.136	**0.934**	0.073	-0.070	**0.937**	0.065	0.002	0.882
LC2	-0.274	-0.46	0.824	-0.017	-0.066	**0.980**	-0.085	-0.077	**0.976**	-0.159	-0.094	**0.965**	0.965
BC2	-0.462	-0.632	-0.015	-0.369	**-0.584**	0.367	-0.392	**-0.589**	0.334	-0.422	**-0.591**	0.292	0.612
TWOM	0.162	-0.816	-0.364	0.176	**-0.890**	-0.025	0.180	**-0.890**	-0.022	0.173	**-0.891**	-0.026	0.824
Variance	4.4356	1.4183	0.907	4.2004	1.3245	1.236	4.3065	1.3292	1.1252	4.3873	1.3364	1.0372	6.7609
%Var	0.554	0.177	0.113	0.525	0.166	0.154	0.538	0.166	0.141	0.548	0.167	0.130	0.845

Table 8. Final partition table

	No of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	5	0.027	0.065	0.127
Cluster2	1	0.000	0.000	0.000
Cluster3	3	0.020	0.077	0.098

Table 9 is the cluster centroid which denotes the average observation within the cluster across all the variables in the analysis

Table 9. Cluster centroid

Variable	Cluster1	Cluster2	Cluster3	Grand centroid
LC1	0.2826	0.2870	0.2870	0.2846
WC1	1.8304	2.2150	1.9333	1.9074
HC1	0.0366	0.0400	0.0383	0.0376
WiC1	0.0968	0.1060	0.1013	0.0993
WC2	1.7000	2.0400	1.7600	1.7578
LC2	0.2640	0.2640	0.2640	0.2640
BC2	0.2404	0.2400	0.2403	0.2403
TWOM	0.2298	0.2213	0.2580	0.2382

The distance between cluster centroids is shown in Table 10.

Table 10. Distance between Cluster centroids

	Cluster1	Cluster2	Cluster3
Cluster1	0.0000	0.5135	0.1226
Cluster2	0.5135	0.0000	0.3989
Cluster3	0.1226	0.3989	0.0000

On the foundation of percentage variance described through the diverse factors, the following reveals the pecking order of the A356 alloy composite casting factors:

- Length of cast 1 (canoe–shaped), 55.4%
- Weight of cast 1 (canoe–shaped), 17.7%
- Height of cast 1 (canoe–shaped), 11.3%
- Width of cast 1 (canoe-shaped), 8.1%
- Weight of cost 2 (cuboid-shaped), 5.2%

Conversely, the k–means clustering method used in the analysis revealed that five observations/variables are more important than the others, which confirm the results from factor analysis. The length of cast 1 (canoe–shaped) is the most important factor group when weighed against others. The inference from this outcome is that the length at the initial casting before the introduction of the green matter should be contemplated as the main concern for the conversion of the A356 alloy into a composite. For instance, in the cooling slope casting process (Kumar et al., 2015), the length parameter of the casting process is principally declared to influence the morphology as well as the size of the X–Al stage. Without a superior choice of length of the cast product, it will be challenging to properly structure the elements of the A356 alloy and offer the desired structure to the customers of casting products [32]. The weight of cast 1 is subsequent in the hierarchy of comparative significance. It involves association with the important product properties of tensile strength, yield strength, fluidity ductility, pressure, and hardness. Impending customers while unaware will appraise the related aforementioned properties of the cast product ahead of substituting the purchase of a composite product for the other. To offer an outstanding and acceptable weight of the A356 alloy cast, the foundry engineer should compare the anticipated and the real density of the cast and also relate it with the previously mentioned properties to reach a balance on cost as to what the customer can afford as a product and willing to pay for. The height of cast 1 (canoe–shaped) should be tackled while casting the A356 alloy into new products. Changes in the product stature are motivated by variations in height as casting. With height limitations for most structural applications of composites, the use of height is crucial to control other product features such as size and weight if we assume a uniform density of the A356 alloy product. The width of the cast product is essential to make the customer delighted and to enhance the universal stance of the customer just before the order for custom made A356 alloy products. According to the analysis, a condensed weight of cast 2 ought to enhance the satisfaction of the customer noticeably.

Limitations and Recommendation

The newly proposed method adopts the Taguchi-Pareto method as one of its components. However, despite the utility of this component method to provide a streamlining scheme where the decision-maker would concentrate decision making on important parameters, it has some limitations. A key limitation of the method is the inability of the optimal parametric setting to state which of the factors has more importance when the results in different units are compared. Thus, future studies may overcome this limitation by introducing a global index that converges all values to a point and weighs one against the other.

Contributions

By drawing on the theories of factor analysis, Taguchi-Pareto and k–means clustering, this research seeks to make two contributions. Although there is an expanding body of scholarship on reinforcing A356 alloy with organic matter, such as cow horn, to the best of the authors' knowledge, there is no study that has reinforced the A356 alloy with a combination of particulate abori wood, pineapple stub and *Delonix regia* while using the sand casting production route. Our exploration of A356 alloy composite research, therefore, extends studies on organic–reinforced composite fabrication by introducing particulate abori wood, pineapple stubs and *Delonix regia* and demonstrating the feasibility of producing novel composites from the synergic influence of these reinforcements. Second, at variance with prior scholarship, the theoretical and practical strengths of factors analysis and k–means cluster analysis were synergically exploited to appraise and optimize the dimensional variables of A356 alloy composites for the first time. Consequently, our research may be employed to check whether the A356 alloy composite cast data exhibit unidimensional attributes or not and prove the melting and solidification data. In this manner, our research is different from that often found in the A356 alloy composite literature.

The Novelty of the Article

In the past few years, reinforcing A356 alloy has attracted the increasing interest of investigators in the composite field. Reinforcements could be optimised and efforts have been made to use tools such as artificial rural networks and Taguchi methods. Research to identify the parameters in a wide range of factors tends to analyse using the Taguchi-Pareto and Taguchi-ABC methods. However, there is no work exploring how the multiple factors may be selected in search of the key factors controlling the casting process. At the same time, no research is available to concurrently select and optimise the desired factors. In this work, for the first time, a new method, the factor Analysis-Taguchi-Pareto method has been proposed and validated with experimental data from the A356 composite casting process. The novel elements of the method are the unique dependence on the percentage variance generated from the correlation matrix that analyses the association of the factors among themselves.

Furthermore, foundries focus on material mixtures and additives that yield the utmost properties of the work material from mechanical wear, fracture and commotion perspectives, among others. Novel methods are often desired in foundry technology. Therefore, this paper studies the performance of reinforcements used in an organic context by integrating the factor analysis and Taguchi-Pareto through the various generation procedure point of introduction of the Taguchi-Pareto scheme. The integrated factor analysis-Taguchi-Pareto method is introduced as a new type of procedure in the optimisation of the reinforcement content in A356 alloying with organic reinforcements. Overall, based on the results of the study, the integrated method as an important classification and optimisation procedure has a strong potential to serve as a novel performance enhancement method.

CONCLUSION

In this paper, a new approach is proposed into which factor analysis is coupled with the Taguchi-Pareto method for the first time in the A356 composite literature. The point of coupling is at the generation of the percentage variance when the correlation matrix is suggested. It is different from a previous study by Nwafor et al. [7] where no factor analysis is considered but the Taguchi-Pareto method is employed directly on the data. By examining the results of this study, the following conclusions are valid.

1. The factor analysis-Taguchi-Pareto method can be used as a valid evaluation tool to understand the principal factors that are important when combining organic matters as reinforcements to A356 composite and concurrently optimise them.
2. The principal factors established by the factor analysis as the controlling factors for the experiment are three: Length of cast 1, the weight of cast 1 and height of cast 1. Those were attained at a cut-off of roughly 84% as directed by the relevant rules.
3. The smaller-the-better criterion in the choice signal-to-noise ratio is the most appropriate criterion for the problem as the goal is to reduce the physical properties of the reinforcements regarding density, volume and height toward producing competitive A356 composites
4. The optimal parametric settings are established in four options. The optimal parametric settings are $LC1_1WC1_1HC1_1$ or $LC1_1WC1_1HC1_2$ or $LC1_2WC1_1HC1_1$ or $LC1_2WC1_1HC1_2$. For the first optimal setting, the interpretation is 0.280m of LC1 with 1.788kg of WC1 and 0.036m of HC1. The second optimal setting is interpreted as 0.280m of LC1 with 1.788kg of WC1 and 0.036m of HC1. The third and fourth optimal parametric settings are still the same as the first one.

In the future, research may be proposed to fuse the Taguchi ABC method with the factor analysis for improved optimisation results. Secondly, an understanding of the sensitivity of the parameters of the method could be launched in future studies.

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