A proposal of grinding media standardization for ball mill abrasion test

Una propuesta de estandarización del medio de molienda para el test de abrasión con molino de bolas

Carlos Daniel García Mendoza[1] https://orcid.org/0000-0002-6580-2560
Luis Santiago Quiroz Fernández[2] https://orcid.org/0000-0002-2962-0583
Neyfe Sablón Cossío[3]* https://orcid.org/0000-0002-6691-0037

Recibido 07 de septiembre de 2022, aceptado 11 de noviembre de 2023
Received: September 07, 2022 Accepted: November 11, 2023

ABSTRACT

The Ball Mill Abrasion Test (BMAT) is a laboratory experiment used to measure the resistance of materials under high-stress abrasion conditions. This test, however, has yet to be standardized. In this work, statistical theory determines the optimal number of spheres per material to be included in BMAT. This theory and the optimization method presented in this paper show that the optimal number of spheres for the usual experimental conditions is six. Finally, it is shown that if the optimization process is extended over a broader range of experimental conditions, the optimum number of spheres per material is also six.

Keywords: Ball Mill Abrasion Test, sample size, standardization, optimization.

RESUMEN

El Test de Abrasión con Molino de Bolas es un experimento de laboratorio usado para medir la resistencia de materiales bajo condiciones de abrasión de alta presión. Este test, sin embargo, no ha sido estandarizado. En este trabajo, fundamentos estadísticos son considerados para determinar el número óptimo de esferas por tipo de material a ser incluido en el experimento. Usando esta teoría, junto con un método de optimización presentado en este trabajo, se muestra que el número óptimo de esferas para condiciones experimentales usuales es seis. Finalmente se muestra que, si el proceso de optimización es extendido a condiciones experimentales generales, el número óptimo de esferas por material es también seis.

Palabras clave: Ball Mill Abrasion Test, tamaño muestral, estandarización, optimización.

INTRODUCTION

The Ball Mill Abrasion Test aims to measure the resistance of various materials under abrasion conditions similar to those experienced in ball mills in the mining industry. The experiment consists of a rotating drum containing spheres of the materials to be studied, together with an abrasive medium, usually adding a containment medium such as water or alcohol to avoid the production and spread of

[1] Universidad Técnica de Manabí. Facultad de Ciencias Básicas. Facultad de Posgrado. Grupo de Producción y Servicios. Portoviejo, Ecuador. E-mail: daniel.garcia@utm.edu.ec
[2] Universidad Técnica de Manabí. Facultad de Posgrado. Portoviejo, Ecuador. E-mail: santiago.quiroz@utm.edu.ec
[3] Universidad Técnica de Manabí. Facultad de Posgrado. Grupo de Producción y Servicios. Portoviejo, Ecuador. E-mail: neyfe.sablon@utm.edu.ec
* Autor de correspondencia: neyfe.sablon@utm.edu.ec

dust. By rotating the drum below its critical speed (the speed at which centrifugation of the contents occurs), the spheres (also known as grinding media) interact between themselves and the abrasive material, gradually leading to material wear.

In this test, numerous spheres of different materials can be included depending on the mill size to study their absolute and relative performance. Given the industrial relevance of this process, some scientific communities began to opt for this method to determine the resistance of materials under high-stress abrasion conditions. For this reason, extensive studies based on this test can be found in the literature, analyzing, for example, the effect of the mill dimensions and general experimental conditions [1]-[5], the contribution of the different wear mechanisms in the total wear [6], the effect of the microstructure and general characteristics of the grinding material [7]-[9], the influence of the abrasive mineral [10], and others. These results are intended to determine the most appropriate materials and configurations for optimizing these processes in the industry.

However, this experiment needs a standardized base of methodologies. These standardizations are necessary to ensure the credibility and reproducibility of the information obtained. This work will focus on analyzing the possible standardization of the number of spheres per material to be included in Ball Mill Abrasion Tests (BMAT). Therefore, this work aims to determine the optimal number of grinding spheres per type of material in BMAT.

BMAT IN CONTEXT

A search for the term "BMAT" in the Scopus database identified 89 documents. These have been developed over the last 96 years (Figure 1) and in different areas of knowledge (Figure 2). The first article registered with this technique dates to 1925, analyzing the abrasion resistance of rubber. Despite this, in 2020, research on this topic continues, given the high relevance of its results to the industry.

The most representative areas of knowledge of the published texts focus on 36.4% engineering, followed by 22.4% materials sciences, 13% physics, 10% chemistry, 9.1% earth and the planet, and 6.1% chemical engineering. These represent 5 and 8 texts

Source: Scopus database until 2021.

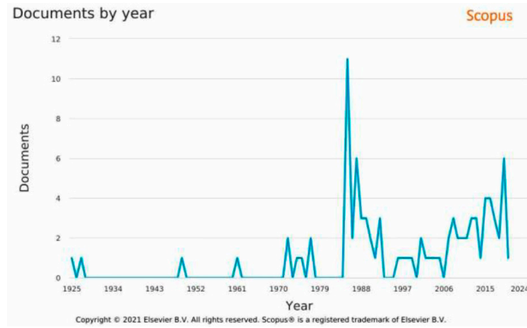

Figure 1. Documents published per year.

Source: Scopus database until 2021.

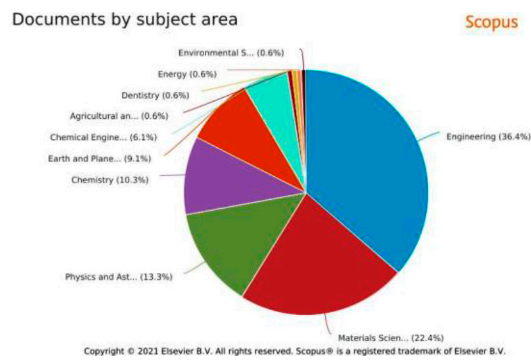

Figure 2. Documents by area of knowledge.

from the University of Minnesota Twin Cities, Pennsylvania State University, and The University of Queensland (Figure 3).

The author who published the most of this technique is Professor Iwasaki (Figure 4).

Source: Scopus database until 2021

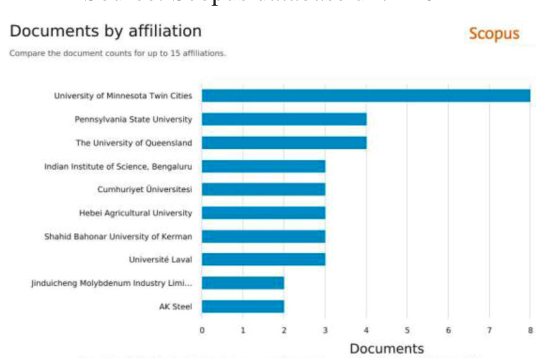

Figure 3. Documents by institutions.

Source: Scopus database until 2021.

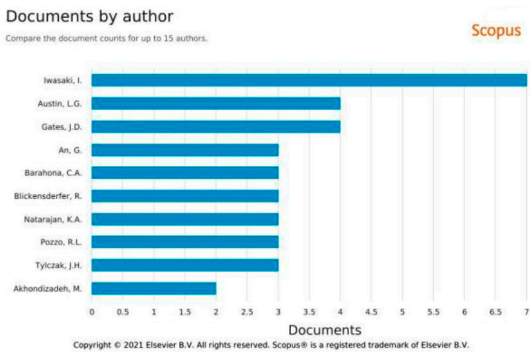

Figure 4. Documents by author.

It is for this reason that the following studies are part of the theoretical basis of this work:

- 1988: In this study, the results of marked ball wear tests are used to discuss the relative importance of corrosive and abrasive wear in wet milling [11].
- 1987: The interaction of nanomagnetic sulphide mineral, pyrite, and debris of worn metal and its effects on the corrosion wear mechanism is studied [12].
- 1989: Good agreement was found when the corrosion currents measured by electrochemical methods were compared with those estimated in the marked ball-wear tests [13].
- 1992: This study uses white cast iron specimens with varying percentages of chromium. The study showed that the electrochemical results agree with the flotation results and with data of corrosive wear obtained employing marked ball tests [14].
- 1992: The effect of oxygen and nitrogen atmospheres on the abrasive wear of the grinding medium is analyzed using a quartz mineral abrasion medium, contrasting with the corrosive, abrasive wear behavior and passivation behavior of cast iron with chromium [15].

In regards to the types of documents produced on this topic, the following were found: articles (78.8%), conference papers (19.1%), reviews, and reports (1.1%), as seen in Figure 5.

STATISTICAL CONSIDERATIONS

Given that the sample size is relatively small in BMAT experiments, the t-student distribution is used since it allows us to approximate the errors better. The parameter of interest in this study is the 95% confidence interval, given by the following expression.

$$I = \overline{X} \pm \frac{t_{(1-a,\, n-1)}\sigma}{\sqrt{n}} \tag{1}$$

Where $t_{(1-a,\, n-1)}$ corresponds to the t-value of the t-student distribution for a given confidence range, σ represents the standard deviation, and n is the sample size. If the mean is shifted to the origin, then the first term of this expression vanishes. Furthermore, if $t_{(1-a,\, n-1)}$ is replaced by the t value for a 95% confidence interval, equation (1) can be used to calculate the confidence interval as multiples of the standard deviation σ for different sample sizes, obtaining the result shown in Figure 6.

Source: Scopus database until 2021.

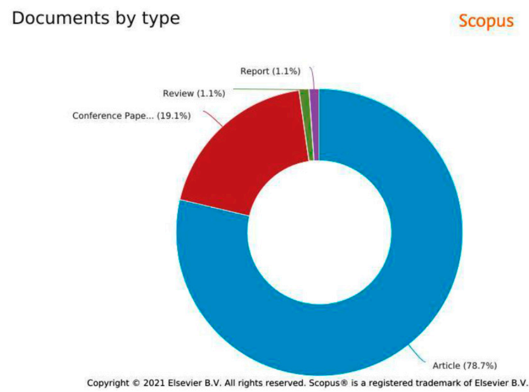

Figure 5. Type of published documents.

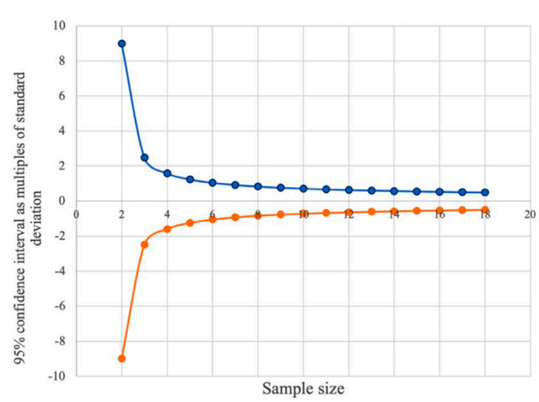

Figure 6. 95% Confidence limits as multiples of standard deviation based on sample size.

It is observed in Figure 6 that the limits of the confidence interval rapidly contract when the sample size is initially increased. In particular, this significant reduction in the interval occurs when the sample size is increased to approximately n = 4. Of particular interest is the fact that when the sample size is 6, the confidence interval can be given as a multiple of approximately one standard deviation. From this point on, the confidence interval reduces at a lower rate. Taking 11 extra determinations to reduce the interval to half of that at n = 6. For this reason, n = 6 is usually taken as the candidate to be the optimum sample size for estimating a parameter of interest. This hypothesis will be evaluated in the context of the BMAT experiments, verifying that it is fulfilled for all or most of the experimental conditions that can be given in this test.

ASTM standard on sample size

Within the standards established by ASTM, the designation E1 22-17 can be found, whose topic is "Standard practice for calculating simple size to estimate, with specified precision, the average for a characteristic of a lot or process" [16], in which different methods are explored to calculate an appropriate sample size to obtain results with a certain precision. This standard has been approved for use by the US Department of Defense agencies. It is generally taken as a reference for conducting experiments involving the estimation of a characteristic of a batch or process, as is the case of BMAT. Although this standard does not explicitly state that by using 6 specimens per material, the mean will be within one standard deviation of the population, this result can be derived from one of the equations presented in it.

$$m = \left(\frac{3\sigma_0}{E} \right)^2 \quad (2)$$

Where *n* represents the sample size taken from a batch or process, σ_0 represents an advanced estimate of σ, E the maximum acceptable difference between the actual mean and the estimated mean (equation (2)). The desired variable of this expression is precisely E, expressed in terms of σ_0, with which we obtain:

$$E = \frac{3\sigma_0}{\sqrt{n}} \quad (3)$$

It is important to note that, as specified in the standard, the multiplicative factor 3 corresponds to a low probability that the difference between the result of measuring all the units in the lot and the sample estimate is more significant than E. This factor is included in the equation (3) arbitrarily and is simply recommended for general use. Suppose the approximate probability of exceeding E is set to be 0.010. In that case, the multiplicative factor is replaced by 2.56, and if n = 6 is chosen (since it is the candidate for the optimal sample size number), the following is obtained:

$$E = 1.04\sigma_0 \quad (4)$$

This result is precisely the outcome obtained in the previous section. The equation (4) expresses that the maximum difference between the actual and sample mean is approximately one standard deviation, provided that the approximate probability of exceeding E is 0.01 and the sample size is n = 6. It is important to note that the equation shown in this standard can be obtained in normal distribution theory, where E is generally represented as $\bar{X}$. It is known, and taken as standard practice, that if the sample size is less than 30, the distribution to be used is the t-student distribution, as it best approximates the errors in small sample sizes, as indicated above. Using this distribution, the *t* value for the 95% confidence interval with *n-1* degrees of freedom yields a multiplicative factor of 2.57, producing essentially the same result shown above.

MATERIALS AND METHODS

Existing results from Ball Mill Abrasion Tests (BMAT) were used. These results correspond to experiments in which the effect of the rotational speed of the mill on the absolute and relative wear of the materials is evaluated. The rotational speeds were varied from 15% to 85%. In these experiments, a neutral grinding medium (whose performance is not measured) was added to achieve the desired mill fill percentages. Finally, water was added to reduce the risks associated with inhaling dust from the grinding of the abrasive medium. The parameter considered after each experiment is the mass loss per sphere, which is then processed so that the yield units are mg/(dm^2*h), thus considering the variations in surface area and duration of the experiment. Unless stated otherwise, the amounts mentioned in this work will correspond to these units. Table 1 shows the material's chemical specifications, whose performance was considered and analyzed in this work.

Table 1. Chemical composition of the material to be analyzed in BMAT.

Chemical composition of the material (wt%)						
C	Cr	Mo	Cu	Mn	Si	Ni
3.13	10.62	0.01	0.10	0.50	0.36	0.12

A Python script was designed to extract and process the experimental results from a datasheet. From a list of 'm' data points corresponding to the material performance, and for a given rotational speed, the code generates a collection of lists of all possible unique combinations of 'n' values, that is $\frac{m!}{n!(m-n)!}$ combinations. Then, the average and standard deviation of each list of combinations is calculated, and this information is stored in two variables: 'Avg (comb)' and 'Stv (comb).' From the information stored in these variables, it is possible to generate histograms that show the recurrence of the different ranges of means and standard deviations for a chosen value of 'n.' This process can be repeated for all n≤m to observe the impact of the number of determinations on the histograms of means and standard deviation.

Likewise, the mean of the values contained in 'Stv (comb)' can be calculated, and this information can, in turn, be used to construct the 95% confidence intervals for the different values of n ≤ m. Since it has been shown by ASTM-International [16] and in previous sections that a potential candidate for the optimal number of spheres per material in BMAT is six, the optimization process is carried out on this sample size value. The optimization process involves choosing a combination of six data points whose mean is within the range with the highest recurrence for the variable 'Avg (comb)'. From this point on, the combinations that produce this mean are probed, and the one with the lowest standard deviation is chosen. This step makes it possible to calculate the optimized 95% confidence interval for this 'n' number of spheres. In turn, this can be compared with the confidence interval produced with the 'm' values available.

RESULTS

Results from 15% of critical speed

This section shows the histograms of means and standard deviation undergo an evolution as the number of determinations is increased, partly due to the increase in the number of possible combinations of spheres given by $\frac{m!}{n!(m-n)!}$. Given the available number of spheres for these experiments, it is found that the maximum number of unique combinations occurs when the value of n is approximately 6. When the combinations are made with two values only, Figure 7 is obtained.

The combination of two values shows a strong weakness in predicting the actual value of the mean since the mean values of combinations are spread almost evenly over a significantly extensive range. With this, it is not possible to determine an acceptable range of the mean, so the optimization process cannot be carried out successfully. However, as the number of combinations grows due to the increase in n, the histograms resemble a normal distribution, as shown in Figure 8.

Given this distribution, it is possible, with greater confidence, to claim that the actual mean of the population is located around the central zone, given that it resembles the behavior of a normal distribution. Through filtering the results, a combination can be found that has a mean within the central range and also has a relatively low standard deviation. This argument will be used to optimize the confidence interval for this sample size, which will be specified in the following sections. Furthermore, when considering the combination of all available data points (n = 10), the mean is approximately 96.4, and the standard deviation is approximately 11.4. It is evident that for this number of spheres, it is not possible to carry out the optimization process as it coincides with the maximum number of spheres available, preventing the algorithm from finding a combination with a lower standard deviation. Figure 9 is obtained by calculating and plotting the mean of the standard deviations for each sample size.

It is observed that the mean standard deviation increases as the sample size increases; this is mainly due to the pre-existing physical differences in the spheres (size or shape). The effect of these differences can be eliminated by normalizing the results. However, the normalization process only partially allows to vanish the influence of these differences, as has been shown by [17]. It should be emphasized that the values analyzed in this

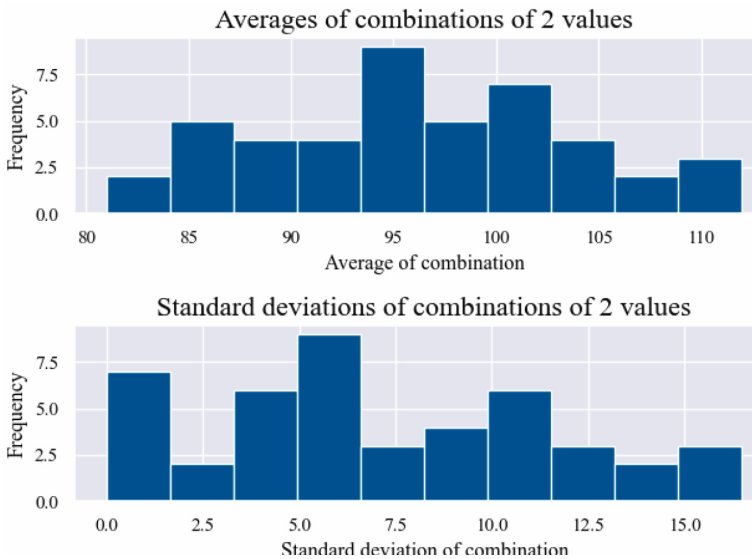

Figure 7. Histogram of means and standard deviations for combination of 2 values.

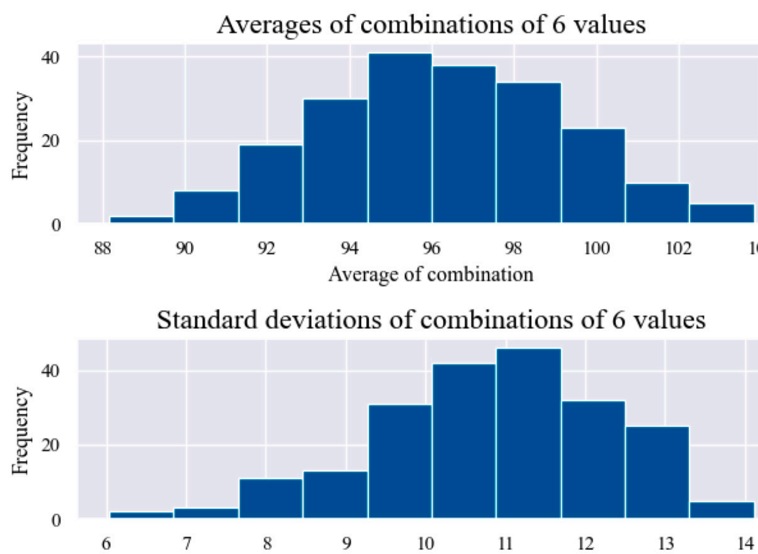

Figure 8. Histogram of means and standard deviations for a combination of 6 values.

work have been normalized prior to processing so that the increase observed in the average of the standard deviations results only from the collection of combinations that have relatively distant data. Based on this, the 95% confidence intervals can then be calculated, substituting σ for the mean standard deviation values for each n value, thus obtaining the results shown in Figure 10.

Figure 10 was constructed with the values seen in Table 2. This table contains the standard deviation calculated for each n value. Consequently, the upper and lower limits for the 95% confidence interval can be calculated, as also shown in Table 2 below.

Through the optimization process described in earlier sections, the standard deviation value can

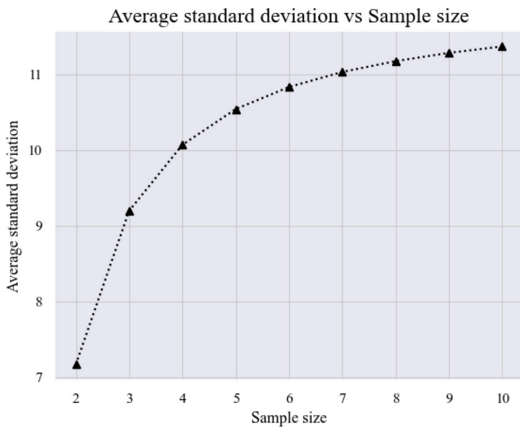

Figure 9. Average standard deviation vs sample size.

Figure 10. 95% confidence intervals vs sample size.

be reduced for n = 6, thus reducing the confidence interval, as shown in Table 3.

These results show that the 95% confidence interval reduction for n = 6 is significant, being only 0.7% higher than that obtained with n = 10. There is no merit in increasing the sample size to eleven (without considering significant pre-existing differences) since results with essentially the same experimental relevance can be obtained with six systematically chosen elements. The reduction of the confidence interval at n = 6 can be visualized using Figure 11.

Figure 11 shows how the upper and lower limits of the confidence interval for n = 6 contract, reaching levels very close to those reached for n = 10.

Extension of the optimization process

As shown in the previous section, the optimization procedure followed for the 15% rotational speed can be carried out for the rest of the speeds for which the experiment was performed. The following table summarizes the results for all the speeds analyzed in this work, concentrating on the dimension of the

Table 2. Upper and lower limits of the 95% confidence intervals for sample size n.

n	Standard deviation	95% confidence interval	
		Upper limit	Lower limit
2	7.167	64.3929402	–64.39294
3	9.195	22.8436336	–22.843634
4	10.068	16.0204347	–16.020435
5	10.539	11.060422	–11.060422
6	10.831	10.0177534	–10.017753
7	11.030	9.22143617	–9.2214362
8	11.173	8.5887124	–8.5887124
9	11.281	8.07064946	–8.0706495
10	11.367	7.63652169	–7.6365217

Table 3. Optimization of the upper and lower limits of the confidence interval for n = 6.

n	Standard deviation	95% confidence interval	
		Upper limit	Lower limit
2	7.167	64.3929402	–64.39294
3	9.195	22.8436336	–22.843634
4	10.068	16.0204347	–16.020435
5	10.539	11.060422	–11.060422
6	7.3352	7.69782031	–7.6978203
7	11.030	9.22143617	–9.2214362
8	11.173	8.5887124	–8.5887124
9	11.281	8.07064946	–8.0706495
10	11.367	7.63652169	–7.6365217

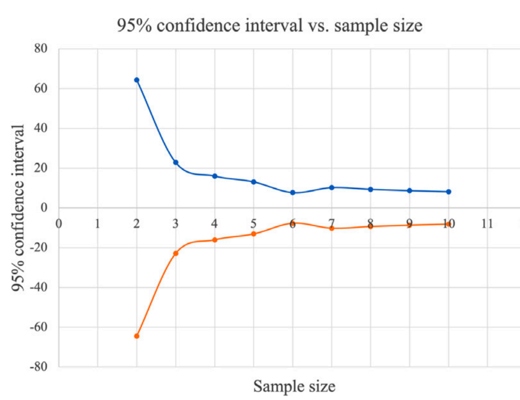

Figure 11. 95% confidence intervals and with optimization for n = 6.

confidence interval for n = 6 before and after the optimization process and comparing the optimized value with that obtained for n = 10.

It can be seen in Table 4 that through the optimization process followed, the dimension of the 95% confidence interval for n = 6 can be significantly reduced. On average, a reduction of 26.1% of the confidence interval is achieved, a significant and necessary change to improve the credibility of the information obtained in these experiments. Furthermore, the dimensions of the confidence intervals for optimized n = 6 are close to those for n = 10, with an average difference of 4.8%. These results form important evidence to affirm that there is no merit in increasing the sample size of the materials in BMAT if this increase introduces elements whose characteristics differ significantly from the existing sample. It is enough to include six elements in the sample whose characteristics are uniform to obtain relevant results on the performance of the materials. Figure 12 illustrates the optimization of the confidence intervals.

It can be seen in Figure 12 that the optimization process is capable of reducing the dimension of the confidence interval for all the speeds analyzed in this work, which include those speeds usually applied in the industry (~ 65%). Additionally, as mentioned above, the optimized intervals are significantly close to those obtained with 10 elements, thus confirming the hypothesis that it is sufficient to include six elements per material in the BMAT experiments to obtain reproducible and relevant results for the scientific community, ensuring that these elements have uniform characteristics before being included in the experiments.

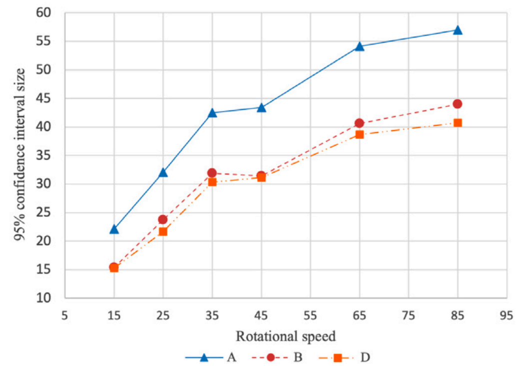

Figure 12. 95% confidence intervals before and after the optimization process.

DISCUSSION

Similar studies are found in the literature regarding the attainment of the minimum number of specimens required for a given experiment [18], [19], ensuring that this minimum number still produces relevant results for the scientific community. For example, Jie Cui *et al.* [18] evaluate the possibility of estimating the number of specimens required in a mechanical experiment. Although [18] do not reach an explicit determination of the optimal number of specimens (due to the numerous varieties of the properties of the materials analyzed in this study), it is concluded that methods such as the one followed in this work are suggested, given the availability of specimens for the accumulation of experience and understanding of their behavior under different conditions. In this case, the BMAT experiments show high replicability of their results [20], thereby ensuring this last point.

It should be remarked that in the study of [18], the approaches for determining the number of specimens

Table 4. Comparison of the optimized confidence interval for n = 6 with the confidence interval for n = 10.

Speed (% of critical speed)	A	B	C	D	E
	Non-optimised interval	Optimised interval	% difference of A and B	Interval for n = 10	% difference of B and D
15	22.12	15.39	30.4	15.26	0.8
25	32.08	23.74	26.0	21.68	9.5
35	42.52	31.89	25.0	30.36	5.0
45	43.44	31.44	27.6	31.12	1.0
65	54.14	40.59	25.0	38.70	4.9
85	57.01	43.99	22.8	40.71	7.5
Average % difference of B - D					4.8

Source: [18].

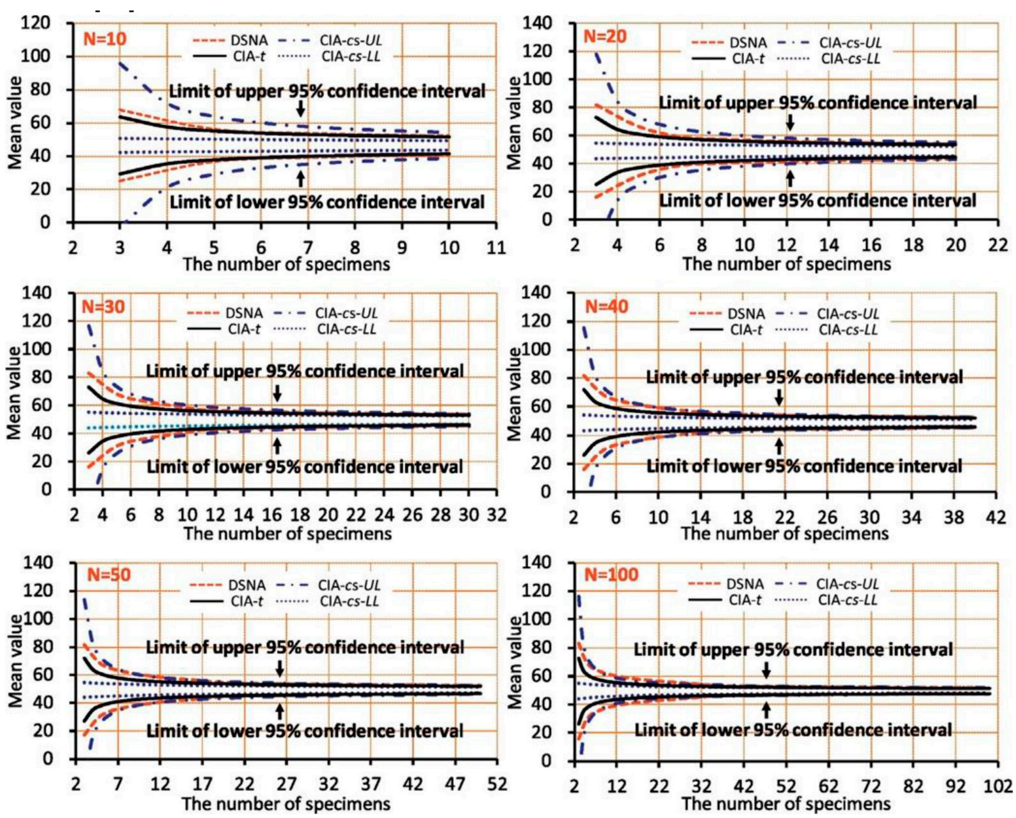

Figure 13.Contrast of the deviation limit curves of parameter mean calculated with DSNA and CIA.

are also classified into two groups, called 'Decision of the simple number approach (DSNA)' and 'Confidence Interval approach (CIA)'. It is within the latter category where the methodology followed in this work focuses. Similar mechanisms can be found in works such as those of Smith, Denis, and Borradaile [21]-[23] within the CIA.

Given that the considered BMAT experiments did not have more than 10 specimens, the upper left part of Figure 13 can be considered, where the 95% confidence intervals through CIA and DSNA are compared. The difference between the limits generated by CIA-t (the approach used in this work) and those generated by DSNA are negligible from approximately 5 specimens. Thus, considering that in this work, it is proposed that the optimal number of specimens is 6, it is concluded that the confidence intervals, especially those optimized, are the minimum possible among the possible intervals that can generate different statistical approaches.

Unlike other works shown in the literature, this analysis has demonstrated the possibility of optimizing the confidence intervals given an arbitrary set of samples for BMAT. It is clear that, due to the nature of the BMAT experiment and the high reproducibility of the results given by it, the confidence intervals behave as those predicted by the theory; however, it has also been possible to find an optimization method that significantly reduces these intervals, if the sample has been chosen arbitrarily. The optimized sample comprises those grinding components whose initial mass (and therefore initial surface area) are the least distant from each other. This finding was corroborated by the optimization method presented, which, apart from choosing a set of spheres with low standard deviation, can also find a set that simulates the entire population's behavior.

CONCLUSIONS

The BMAT experiment has been very beneficial for the scientific community to determine the material's performance in machinery in the mining industry. However, difficulty was found in determining the appropriate or necessary amount of the grinding medium (metallic spheres) that ensures the correct determination of the material's performance without the need to resort to an excessive amount of starting material. In this study, statistical methods have been used to theoretically determine the ideal number of spheres per material, concluding that using six spheres makes it possible to obtain necessary and relevant results for the scientific community. An extensive analysis of pre-existing results from BMAT experiments confirmed this result. Additionally, it was possible to build an optimization method that could significantly reduce the confidence intervals of the material's performance for a given sample size. This process was carried out for various experimental conditions (different rotational speeds), concluding that the optimal value of spheres per material is six. On average, the optimization method achieved a 26.1% reduction in the confidence interval, differing only by 4.8% from the results of the sample composed of eleven arbitrarily selected spheres. It is concluded that it is optimal for future BMAT experiments to include only six spheres per material, using these results to promote this laboratory equipment's standardization process.

REFERENCES

[1] A.K. Gangopadhyay and J.J. Moore, "The role of abrasion and corrosion in grinding media wear," *Wear*, vol. 104, no. 1, pp. 49-64, 1985, doi: 10.1016/0043-1648(85)90245-5.

[2] V. Rajagopal and I. Iwasaki, "The properties and performance of cast iron grinding medi," *Mineral Processing and Extractive Metallurgy Review*, vol. 11, no. 1-2, pp. 75-106. 2007, doi: 10.1080/08827509208914215.

[3] J. Sepúlveda, "Methodologies for the evaluation of grinding media consumption rates at full plant scale," *Minerals Engineering*, vol. 17, no. 11-12, pp. 1269-1279, 2004, doi: 10.1016/j.mineng.2004.08.007S.

[4] I. Iwasaki, J.J. Moore, and L.A. Lindeke, "Effect of ball mill size on media wear," *Mining Metallurgy & Exploration*, vol. 4, pp. 160-166, 1987, doi: 10.1007/BF03402685.

[5] P. Radziszewski, R. Varadi, T. Chenje, L. Santella, and A. Sciannamblo, "Tumbling mill steel media abrasion wear test development," *Minerals Engineering*, vol. 18, no. 3, pp. 333-341, 2005, doi: 10.1016/j.mineng.2004.06.006.

[6] P. Radziszewski, "Exploring total media wear," *Minerals Engineering*, vol. 15, no. 12, pp. 1073-1087, 2002, doi: 10.1016/S0892-6875(02)00228-5.

[7] T. Chandrasekaran, K.A. Natarajan, and Kishore, "Influence of microstructure on the wear of grinding media," *Wear*, vol. 147, no. 2, pp. 267-274, 1991, doi: 10.1016/0043-1648(91)90184-V.

[8] T.W. Chenje, D.J. Simbi, and E. Navara, "Relationship between microstructure, hardness, impact toughness and wear performance of selected grinding media for mineral ore milling operations," *Materials & Design*, vol. 25, no. 1, pp. 11-18, 2004, doi: 10.1016/S0261-3069(03)00168-7.

[9] E. Albertin and A. Sinatora, "Effect of carbide fraction and matrix microstructure on the wear of cast iron balls tested in a laboratory ball mil," *Wear*, vol. 250, no. 1-12, pp. 492-501, 2001, doi: 10.1016/S0043-1648(01)00664-0.

[10] J.D. Gates, *et al.*, "Effect of abrasive mineral on alloy performance in the ball mill abrasion test," *Wear,* vol. 256, no. 5-6, pp. 865-870, 2008, doi: 10.1016/j.wear.2008.01.008.

[11] I. Iwasaki, R.L. Pozzo, K.A. Natarajan, K. Adam, and J.N. Orlich, "Nature of corrosive and abrasive wear in ball mill grinding," *International Journal of Mineral Processing*, vol. 22, no. 1-4, pp. 345-360, 1988, doi: 10.1016/0301-7516(88)90072-5.

[12] R.L. Pozzo and I. Iwasaki, "Effect of pyrite and pyrrhotite on the corrosive wear of grinding media," *Minerals and Metallurgical Processing*, vol. 4, pp. 166-171, 1987, doi: 10.1007/BF03402686.

[13] J.W. Jang, I. Iwasaki, and J.J. Moore, "Effect of galvanic interaction between martensite and ferrite grinding media wear," *Corrosion*, vol. 45, no. 5, pp. 402-407, 1989, doi: 10.5006/1.3582036.

[14] V. Rajagopa, A.S. Malicsi, and I. Iwasaki, "Effect of chromium on the cast-iron media properties and performance in wet grinding," *Mining Metallurgy & Exploration*, vol. 9, pp. 34-40, 1992, doi: 10.1007/BF03402966.

[15] V. Rajagopal and I. Iwasaki, "Nature of corrosive and abrasive wear of chromium-bearing cast iron grinding media," *Corrosion*, vol. 48, no. 2, pp. 132-139, 1992, doi: 10.5006/1.3299819.

[16] Standard practice for calculating sample size to estimate, with specified precision, the average for a characteristic of a lot or process, ASTM, E122-17, 2017. [Online]. Available: https://www.astm.org/e0122-17r22.html

[17] J.D. Gates, G.J. Gore, M.J. Hermand, M.J. Guerineau, P.B. Martin, and J. Saad, "The meaning of high stress abrasion and its application in white cast Irons," *Wear*, vol. 263, no. 1-6, pp. 6-35, 2007, doi: 10.1016/j.wear.2006.12.033.

[18] J. Cui *et al.*, "Estimation of the number of specimens required for acquiring reliable rock mechanical parameters in laboratory uniaxial compression tests," *Engineering Geology*, vol. 222, pp. 186-200, 2017, doi: 10.1016/j.enggeo.2017.03.023.

[19] D.E. Gill, R. Corthésy and M.H. Leite, "Determining the minimal number of specimens for laboratory testing of rock properties," *Engineering Geology*, vol. 78, no. 1-2, pp. 29-51, 2005, doi: 10.1016/j.enggeo.2004.10.005.

[20] J.D. Gates, P.J. Bennet, L.J. McInnes, and B.R. Tunstall, "The challenge of accurate prediction of industrial wear performance from laboratory tests," in *International Symposium on Wear Resistant Alloys for the Mining and Processing Industryl*, São Paulo, Brazil, 2005.

[21] G.N. Smith, *Probability and statistics in civil engineering: an introduction*. London, UK: Nichols Publishing Company, 1986.

[22] D.E. Gill, R. Corthésy, and M.H. Leite, "A statistical approach for determining practical rock strength and deformability values from laboratory tests," *Engineering Geology*, vol. 78, no. 1-2, pp. 53-67, 2005, doi: 10.1016/j.enggeo.2004.10.006.

[23] G. Borradaile, *Statistics of Earth Science Data: Their Distribution in Time, Space and Orientation*, Berlin, Germany: Springer, 2003.