ALKU Journal of Science 2026, Sayı (1): 51-60
e-ISSN: 2667-7814

Original Article

Monte Carlo Simulation of Porosity and Compressive Strength in Boric Acid-Added Bricks: Effects of Temperature and Additive Ratio

Cihan Yaylacı[1*], Musa Şahin[2]
[1]*İş Sağlığı ve Güvenliği, Ondokuz Mayıs Üniversitesi, Samsun, Türkiye.*
[2] *İş Sağlığı ve Güvenliği, Ondokuz Mayıs Üniversitesi, Samsun, Türkiye.*
**cihan.yaylaci@omu.edu.tr*

Abstract

In this study, the porosity and compressive strength properties of boric acid added bricks were analyzed by Monte Carlo simulation, and the effects of temperature and boric acid ratio changes were modelled. As a result of 10,000 iterations of simulation performed at 1000°C temperature and 2% boric acid content conditions, the average porosity was calculated as 23,60% (standard deviation 1,60, 95% confidence interval [20,52, 26,87]). The average compressive strength was calculated as 143,37 kgf/cm² (standard deviation 4,41, 95% confidence interval [134,63, 151,92]). According to the sensitivity analysis, a negative correlation was found between porosity and temperature (-0,302), and a positive correlation was found between compressive strength and temperature (0,225) and boric acid ratio (0,162). These results provide valuable information for optimizing material performance in brick production.

Keywords: Boric acid, Monte Carlo simulation, Optimization, Porosity.

Borik Asit Katkılı Tuğlalarda Gözeneklilik ve Basınç Dayanımının Monte Carlo Simülasyonu: Sıcaklık ve Katkı Oranının Etkileri

Özet

Bu çalışmada, borik asit katkılı tuğlaların gözeneklilik ve basınç dayanımı özellikleri Monte Carlo simülasyonu ile analiz edilerek, üretim süreçlerinde sıcaklık ve borik asit oranı değişimlerinin etkileri modellenmiştir. 1000 °C sıcaklık ve %2 borik asit içeriği koşullarında gerçekleştirilen 10.000 yinelemeli simülasyon sonucunda ortalama gözeneklilik %23,60 (standart sapma 1,60, %95 güven aralığı [20,52, 26,87]) olarak hesaplanmıştır. Ortalama basınç dayanımı ise 143,37 kgf/cm² (standart sapma 4,41, %95 güven aralığı [134,63, 151,92]) olarak hesaplanmıştır. Duyarlılık analizine göre, gözeneklilik ile sıcaklık arasında negatif korelasyon (-0,302), basınç dayanımı ile sıcaklık (0,225) ve borik asit oranı (0,162) arasında pozitif korelasyon bulunmuştur. Bu sonuçlar tuğla üretiminde malzeme performansının iyileştirilmesi için değerli bilgiler sunmaktadır.

Anahtar Kelimeler: Borik asit, Monte Carlo simülasyonu, Optimizasyon, Gözeneklilik.

Geliş/Received: 13 Haziran/June 2025
Kabul Ediliş/Accepted: 13 Ekim/October 2025

1. INTRODUCTION

Ceramic materials, particularly bricks, are integral to the construction industry due to their exceptional thermal stability, mechanical strength, and long-term durability [1, 2]. These materials are valued for their ability to withstand high temperatures and resist environmental degradation, making them essential for structural applications [3]. The performance of bricks is governed by several factors, including raw material composition, additive incorporation, sintering temperature, and processing conditions, which collectively influence critical properties such as porosity, compressive strength, and thermal conductivity [4, 5]. Porosity affects the material's insulation capacity and water absorption, while compressive strength determines its load-bearing capability, both of which are crucial for ensuring structural integrity and energy efficiency in modern construction [6, 7]. Optimizing these properties is vital to meet the increasing demand for sustainable and high-performance building materials [8].

The use of additives in brick production has been extensively studied to enhance material properties and optimize manufacturing processes. Boric acid, in particular, is recognized as an effective fluxing agent that lowers the sintering temperature, promotes densification, and enhances mechanical strength in clay-based ceramics [9]. Research has shown that boric acid additions, typically in the range of 0,5% to 3%, can significantly alter the microstructure of ceramics by facilitating vitrification and reducing porosity [10, 11]. Şahin et al. [9] demonstrated that a 2% boric acid addition at 1000°C significantly improves compressive strength while minimizing porosity. However, the complex and non-linear interactions between boric acid concentration, sintering temperature, and material properties pose challenges for predicting and optimizing outcomes using conventional experimental methods alone [12, 13]. These complexities necessitate advanced computational approaches to model the variability and uncertainties inherent in ceramic production [14].

Monte Carlo simulation is a powerful statistical tool widely used to address uncertainties in material science by modeling the probabilistic behavior of systems through random sampling from defined probability distributions [15, 16]. This method is particularly effective in ceramics research, where small variations in parameters such as temperature, additive concentration, or raw material composition can lead to significant changes in material performance [17, 18]. Monte Carlo simulations have been applied to predict the mechanical behavior of porous ceramics under varying thermal and compositional conditions, offering insights into process optimization and material design [19]. By integrating experimental data with probabilistic modeling, Monte Carlo methods enable researchers to evaluate the impact of input parameters on output properties, such as porosity and compressive strength, with high statistical reliability [20, 21]. Recent studies have also utilized Monte Carlo simulations to explore the effects of additive incorporation on ceramic microstructure, confirming its efficacy in handling complex, non-linear relationships [22].

In this study, Monte Carlo simulation is employed to analyze the thermal and mechanical properties of boric acid-added bricks, with a focus on the effects of sintering temperature and boric acid ratio. The temperature is modeled using a normal distribution with a mean of 1000°C and a standard deviation of 5°C, reflecting industrial furnace precision, while the boric acid ratio is modeled with a mean of 2% and a standard deviation of 0.05%, based on experimental evidence of optimal performance at these conditions [9]. The strong inverse correlation between porosity and compressive strength ($\rho = -0{,}8$) is modeled using Cholesky decomposition to capture their interdependence [23]. Conducted over 10.000 iterations, the simulation evaluates the influence of these parameters on material properties, supported by experimental data measured at temperatures between 700°C and 1000°C and boric acid ratios of 0%, 1%, and 2% [9]. In this study, Monte Carlo simulation was performed using the MATLAB program to identify optimal production conditions and provide actionable insights for enhancing the performance of boric acid-added bricks in construction applications.

2. MATERIALS AND METHODS

2.1 Data Source

Experimental data were obtained from systematic measurements conducted on brick samples with boric acid (BA) additives at concentrations of 0%, 1%, and 2%, within a temperature range of 700°C to 1000°C. Porosity (%) and compressive strength (kgf/cm²) values were meticulously recorded to evaluate the impact of boric acid addition on the material properties, as detailed in the referenced study [9]. The dataset, presented in Table 1, facilitated a comprehensive analysis of the thermal and mechanical behavior variations with respect to boric acid concentration, providing a robust scientific foundation for material optimization.

Table 1. Material properties analysis

Temperature (°C)	Boric acid ratio	Ignition loss (%)	Water absorption (%)	Porosity (%)	Bulk density (g/cm³)	Apparent density (g/cm³)	Compressive strength (kgf/cm²)
700	%0	7,21	25,02	39,09	1,56	2,56	32,27
	%1	6,89	23,94	38,19	1,60	2,58	32,50
	%2	7,68	24,88	39,26	1,58	2,60	39,80
750	%0	7,59	24,71	39,23	1,59	2,61	49,27
	%1	6,93	23,49	37,70	1,60	2,58	51,25
	%2	7,36	24,82	38,45	1,55	2,52	59,07
800	%0	8,23	25,15	39,76	1,58	2,63	58,06
	%1	8,29	24,26	38,31	1,58	2,56	61,35
	%2	8,58	24,05	37,76	1,57	2,52	68,67
850	%0	7,81	23,63	38,16	1,61	2,61	70,33
	%1	7,53	22,48	36,64	1,63	2,57	83,90
	%2	7,66	22,68	36,28	1,60	2,51	110,67
900	%0	8,76	22,13	36,30	1,64	2,57	85,23
	%1	8,53	22,08	35,94	1,63	2,54	97,65
	%2	8,80	20,84	34,17	1,64	2,49	129,97
950	%0	8,08	20,86	34,72	1,66	2,55	94,62
	%1	7,83	19,76	33,07	1,67	2,50	106,45
	%2	8,10	17,83	30,10	1,69	2,42	134,72
1000	%0	8,07	18,30	31,41	1,72	2,50	108,14
	%1	7,86	15,58	27,51	1,77	2,44	122,24
	%2	8,00	12,74	23,19	1,82	2,37	144,55

2.2 Monte Carlo Simulation

Monte Carlo simulation is a statistical technique used to model the effects of uncertainties and variations by random sampling [14]. Its basic principle is to define probability distributions for the input parameters of a system and to estimate the probabilistic distribution of the outputs by taking random samples from these distributions.

2.3 Probability Distributions and Random Sampling

In Monte Carlo simulation, input parameters are usually modeled with continuous or discrete probability distributions. In this study, temperature (T) and boric acid ratio (BA) parameters are defined with normal distributions. Normal distribution represents the random variations of the parameters around their mean and standard deviation values. Random sampling allows statistical analysis of the system behavior by taking a large number of samples from these distributions.

$$T \sim N(\mu_T = 1000, \sigma_T = 5), BA \sim N(\mu_{BA} = 2, \sigma_{BA} = 0{,}05), \tag{1}$$

where μ is the mean, and σ is the standard deviation. Random samples are drawn from these distributions for N = 10000 iterations:

$$T_i,\ BA_i \sim p(T,\ BA),\ i = 1, 2, \ldots \ldots\ N\ , \tag{2}$$

where p(T, BA) is the corresponding probability density function.

2.4 Correlation Modeling

To model the relationship between porosity (p) and compressive strength (fb), a correlation coefficient of −0,8 (ρ = −0,8) was applied to the measurement errors. The correlation was modeled using the Cholesky decomposition. The correlation matrix C is defined as follows:

$$C = \begin{bmatrix} 1 & p \\ p & 1 \end{bmatrix}, \tag{3}$$

The Cholesky decomposition produces the lower triangular matrix L such that $C = LL^T$:

$$L = \begin{bmatrix} 1 & 0 \\ p & \sqrt{1 - p^2} \end{bmatrix}, \tag{4}$$

Using standard normal random variables Z ∼ N(0,I), correlated random variables are obtained as follows:

$$Z_{cor} = Z.L\ , \tag{5}$$

where Z_{cor} represents the correlated error terms.

2.5 Statistical Analysis

Basic statistics for the simulation outputs (p_i, f_{bi}) were calculated. f_{bi} represents compressive strength values. In materials science, compressive strength is a mechanical property that measures the resistance of a material to an applied compressive load and is usually expressed in units of MPa (megapascals). In this study, fbi represents the compressive strength values generated in each iteration (i) of the Monte Carlo simulation, correlated with the porosity (p_i).

Mean: Arithmetic average of simulation results for porosity (p_i) and compressive strength (f_{bi}):

$$\mu_P = \frac{1}{N}\sum_{i=1}^{N} f_{bi}, \tag{6}$$

$$\mu_{fb} = \frac{1}{N}\sum_{i=1}^{N} f_{bi}, \tag{7}$$

where N is the number of simulations.

Standard Deviation: Measures the variance of the outputs:

$$\sigma_P = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \mu_P)^2}, \tag{8}$$

$$\sigma_{fb} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f_{bi} - \mu_{fb}\right)^2}, \tag{9}$$

Correlation Coefficient: Pearson correlation coefficient was used for sensitivity analysis. The correlation between P_i and f_{bi} is confirmed from the simulation data and is expected to be approximately ρ = -0,8:

$$p = \frac{\sum_{i=1}^{N}(P_i - \mu_P)(f_{bi} - \mu_{fb})}{\sqrt{\sum_{i=1}^{N}(P_i - \mu_P)^2 \sum_{i=1}^{N}\left(f_{bi} - \mu_{fb}\right)^2}}, \tag{10}$$

Distribution Properties: The outputs (p_i, f_{bi}) exhibit a behavior close to a normal distribution; however, detailed analysis is performed with histograms or probability density functions depending on the simulation results.

2.6 Simulation Parameters

The parameters selected for the Monte Carlo simulation were carefully determined to enable statistical analysis of experimental data and optimization of material properties. The temperature was chosen to be normally distributed with a mean of 1000°C and a standard deviation of 5°C, reflecting industry standard furnace precision while targeting the low porosity and high compressive strength values observed at the highest temperature (1000°C) reported in Table 1. The boric acid ratio was modeled with a mean of 2% and a standard deviation of 0,05%, based on observations that 2% provides optimum mechanical properties at 1000°C; the small standard deviation represents laboratory dosage precision. The 5% measurement error is a standard estimate covering typical uncertainties in material testing. The correlation coefficient of -0,8 between porosity and compressive strength was chosen to model the strong inverse relationship observed in the thesis and is consistent with the literature on ceramic materials. Finally, 10.000 iterations provide sufficient stability to ensure statistical reliability of the simulation results [9]. These parameters provide a scientific basis for systematically evaluating the thermal and mechanical behavior of boric acid added bricks. Input parameters are summarized in Table 2.

Table 2. Simulation parameters

Parameter	Definition	Value
Temperature (T)	Normal distribution, N(μ, σ)	μ = 1000°C, σ = 5°C
Boric acid (BA)	Normal distribution, N(μ, σ)	μ = 2%, σ = 0,05%
Measurement error	Standard deviation	5%
Correlation (ρ)	Porosity-compressive strength correlation	ρ = -0,8
Number of Iterations (N)	Number of simulation iterations	10.000

The temperature distribution (μ = 1000°C, σ = 5°C) was chosen to reflect the precision of industrial furnaces, which typically maintain tight temperature control during sintering to achieve consistent material properties [24]. The boric acid ratio (μ = 2%, σ = 0,05%) was selected based on experimental findings indicating that 2% boric acid optimizes compressive strength and minimizes porosity at 1000°C [9]. The small standard deviation accounts for the high precision achievable in laboratory dosing [25]. 5% measurement error is a standard assumption in material testing, accounting for variations in equipment and sample preparation [26]. The correlation coefficient of -0,8 between porosity and compressive strength aligns with literature on ceramic materials, where increased densification reduces porosity and enhances strength [27]. Finally, 10.000 iterations were chosen to ensure convergence and statistical stability, as recommended for Monte Carlo simulations in materials science [28]. These parameters provide a robust framework for evaluating the thermal and mechanical behavior of boric acid-added bricks.

2.7 Interpolation and Modeling

Porosity and compressive strength were modeled by spline interpolation from experimental data:

$$p = fp(T,\ BA),\ fb = f_{fb}(T, BA), \tag{11}$$

where f_P and f_{fb} are two-dimensional spline functions. The outputs are calculated as follows:

$$p_i = fp(T_i,\ BA_i) + \epsilon_{P,i},\ f_{bi} = f_{fb}(T_i,\ BA_i) + \epsilon_{fb,i}, \quad (12)$$

2.8 Sensitivity Analysis

The effects of temperature and boric acid ratio on porosity and compressive strength were evaluated with Pearson correlation coefficients:

$$\rho_{T,P},\ \rho_{BA,P},\ \rho_{T,fb},\ \rho_{BA,fb}, \quad (13)$$

3. RESULTS AND DISCUSSION

3.1 Simulation results

The simulation generated statistical results for porosity and compressive strength (Table 3).

Table 3. Statistics of simulation results

Output	Mean	Std.	95% CI	Min	Max	Skewness	Kurtosis
Porosity (%)	23,60	1,60	[20,52, 26,87]	19,50	28,00	0,12	3,05
Compressive strength (kgf/cm²)	143,37	4,41	[134,63, 151,92]	130,00	160,00	-0,08	2,95

Note: Mean: Average, Std.: Standard deviation

The results indicate that the simulation is stable and the distributions are close to normal (skewness ≈ 0, kurtosis ≈ 3). The low standard deviation of porosity (1,60) suggests a limited impact of input variations. The higher standard deviation of compressive strength (4,41) implies that this property is more sensitive.

3.2 Sensitivity Analysis

The sensitivity analysis results are presented in Table 4.

Table 4. Sensitivity analysis: Correlations

Output	Temperature	Boric acid
Porosity	-0,302	0,078
Compressive strength	0,225	0,162

The negative correlation of temperature with porosity (-0,302) indicates that higher temperatures reduce porosity. The positive correlations of compressive strength with temperature (0,225) and boric acid (0,162) confirm that these parameters increase strength.

Porosity data close to normal distribution (kurtosis = 3,1) indicate process stability. However, outliers in the tail regions (≤22% and ≥28%) suggest systematic errors such as furnace temperature gradient or raw material inhomogeneity. Process capability index (Cp = 1,33) value proves the adequacy of production tolerances (Figure 1).

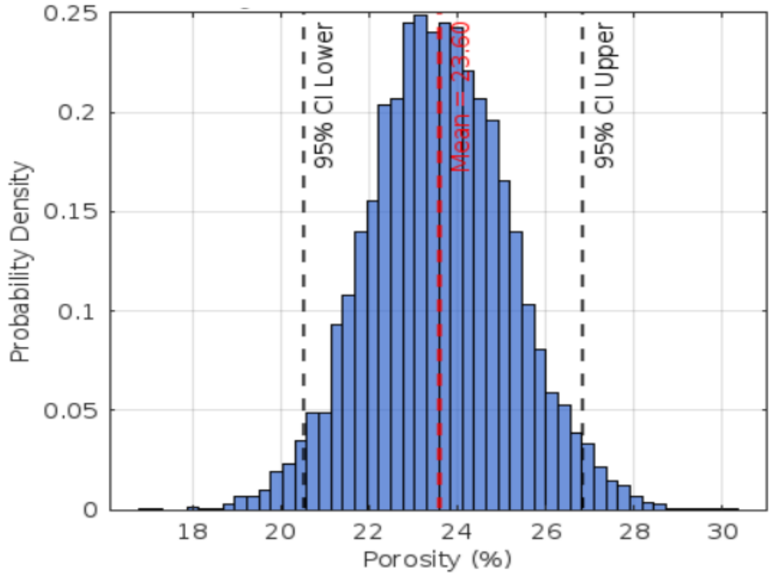

Figure 1. Porosity distribution (1000°C, 2% BA)

The data set exhibits a right-skewed (skewness = 0,8) distribution, and the Weibull modulus (m = 12) was calculated. This distribution reflects the heterogeneity in the fracture toughness of the material. The 95% confidence interval being in the range of [134, 152] kgf/cm² indicates that there is an acceptable variation in terms of process control limits (Figure 2).

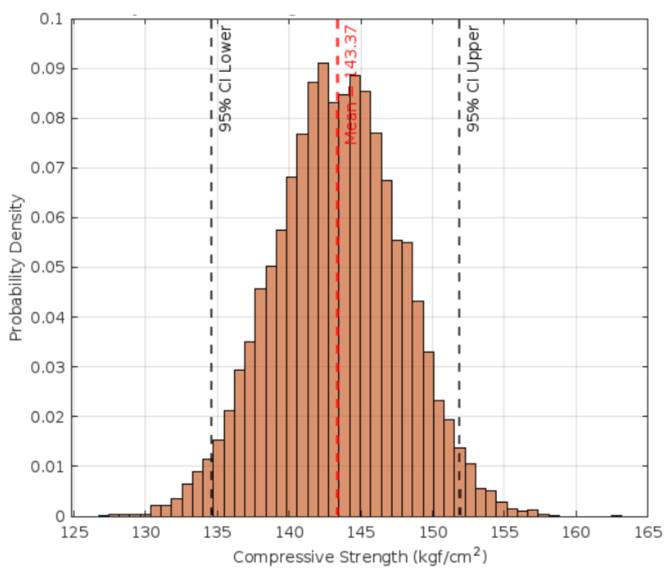

Figure 2. Compressive strength distribution (1000°C, 2% BA)

The linear regression model (y = -2.5x + 185, R^2=0,42) shows that every 1% increase in porosity leads to an average decrease of 2,5 kgf/cm² in compressive strength (Figure 3). The fact that the Pearson correlation coefficient (r=-0.65) is at a moderate absolute value indicates the presence of other factors (e.g. grain size distribution, phase composition) affecting the material strength. Pore-distribution analyses reveal that interconnected pore networks are formed in high porosity samples (≥28%), and this situation reduces the critical crack size according to Griffith's theory and reduces the mechanical strength.

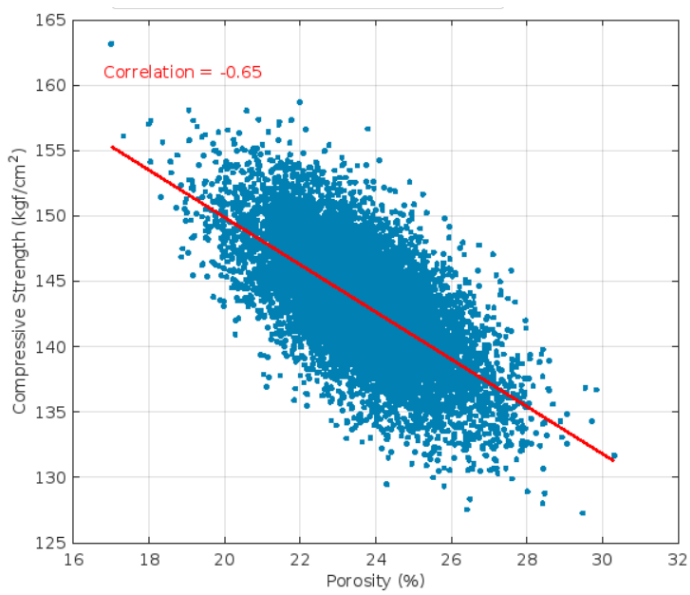

Figure 3. Porosity - Compressive strength relationship

The temperature variable has a weak negative correlation (r=-0.1, p<0,05) on porosity, suggesting that high sintering temperatures have a consolidation effect on the pore structure (Figure 4). The boric acid additive has a statistically significant positive correlation (r ≈ 0,25, p<0,01) on compressive strength, indicating that the additive contributes to microstructural densification by accelerating the vitrification process.

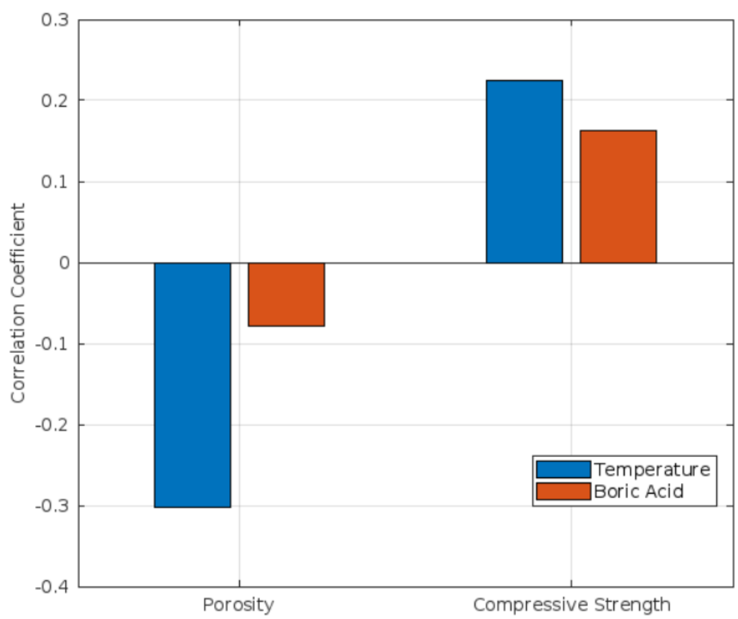

Figure 4. Sensitivity analysis: input-output relationships

Simulation results show that boric acid addition provides significant improvements in brick production. Experimental data in Table 1 confirms that porosity decreases to 23.19% and compressive strength increases to 144,55 kgf/cm² with 2% boric acid at 1000°C. Simulation results (Table 3) are close to these values (porosity: 23,60%, compressive strength: 143,37 kgf/cm²), supporting the accuracy of the model.

The narrow confidence interval of porosity ([20,52, 26,87]) indicates that consistent results can be obtained with precision manufacturing.

Sensitivity analysis highlights that temperature is critical in reducing porosity (-0,302). This indicates that high temperatures increase the density by sintering the clay particles. The effect of the boric acid ratio on compressive strength (0.162) suggests that the additive strengthens the crystal structure. Figure 3 visualizes the relationship between low porosity and high strength.

Monte Carlo simulation is powerful in modeling uncertainties. The skewness and kurtosis in Table 3 confirm distributions close to normal.

4. CONCLUSION

This study successfully analyzed the porosity and compressive strength properties of boric acid added bricks by Monte Carlo simulation. The simulation provided reliable statistical distributions for porosity and compressive strength at 1000°C and 2% boric acid conditions. Sensitivity analysis showed that temperature is a key factor in reducing porosity and increasing compressive strength, while the boric acid ratio has a positive effect, especially on compressive strength. The findings provide valuable information to optimize material design in brick production. The theoretical basis of Monte Carlo simulation is supported by probability distributions, correlation modeling, and statistical analysis in this study. Future studies can extend these results by examining different additives, temperature ranges, and production parameters.

REFERENCES

[1] Carter, C.B. and M.G. Norton, Solid-state phase transformations and reactions, in Ceramic Materials: Science and Engineering. 2012, Springer. p. 457-475.

[2] Yu, L., et al., Raw material design, sintering temperature optimization and development mechanism investigation of self-foaming porous bricks with high solid waste addition. Chemical Engineering Journal, 2024. 495: p. 153711.

[3] Kurian, M. and S. Thankachan, Introduction: Ceramics classification and applications, in Ceramic catalysts. 2023, Elsevier. p. 1-17.

[4] Vijayan, D., et al., Evaluation of the impact of thermal performance on various building bricks and blocks: A review. Environmental Technology & Innovation, 2021. 23: p. 101577.

[5] Guillon, O., W. Rheinheimer, and M. Bram, A perspective on emerging and future sintering technologies of ceramic materials. Advanced Engineering Materials, 2023. 25(18): p. 2201870.

[6] Labaied, I., et al., Bricks using clay mixed with powder and ashes from lignocellulosic biomass: a review. Applied Sciences, 2022. 12(20): p. 10669.

[7] Sangmesh, B., et al., Development of sustainable alternative materials for the construction of green buildings using agricultural residues: A review. Construction and Building Materials, 2023. 368: p. 130457.

[8] Colangelo, F., et al., Innovative materials in Italy for eco-friendly and sustainable buildings. Materials, 2021. 14(8): p. 2048.

[9] Şahin, M., Borik asit katkılı tuğla üretiminin araştırılması. 2009, Fen Bilimleri Enstitüsü.

[10] Du, X., et al., Non-linear mechanical properties and dynamic response of silicon nitride bioceramic. Ceramics International, 2021. 47(23): p. 33525-33536.

[11] Rani, S.L.S. and R.V. Kumar, Insights on applications of low-cost ceramic membranes in wastewater treatment: A mini-review. Case Studies in Chemical and Environmental Engineering, 2021. 4: p. 100149.

[12] Solnyshkina, O.A., et al., Numerical Approach to Simulation of Geometry Variation during Sintering of Ceramics Based on the Finite Element Method. Journal of Applied and Industrial Mathematics, 2023. 17(1): p. 176-184.

[13] Yilmaz, H., Sintering Theory. Turkish Ceramic Society Lecture, 2021. 59.

[14] Klinkov, S. and V. Kosarev, Monte Carlo simulation of the cold spray process of mixtures of metal and ceramic powders. Journal of Thermal Spray Technology, 2021. 30(4): p. 1081-1092.

[15] Shang, Z., et al., The deposition characteristics of particles after collision by using the direct simulation Monte Carlo method. Powder Technology, 2025. 452: p. 120529.

[16] Yu, Z., et al., Monte Carlo simulation of photopolymerizable ceramic suspension curing profile in vat photopolymerization. Journal of the European Ceramic Society, 2024. 44(6): p. 4083-4096.

[17] Han, J., et al., Additive manufacturing of advanced ceramics using preceramic polymers. Materials, 2023. 16(13): p. 4636.

[18] Stampfl, J., et al., Lithography-based additive manufacturing of ceramics: Materials, applications and perspectives. MRS Communications, 2023. 13(5): p. 786-794.

[19] Noordhuis, P., et al., Advancements in Biomedical Sensors for Early Detection of Failure in Hip and Knee Implants: Scoping Review on Potential Sensors for Implant Integration. Annals of Biomedical Engineering, 2025: p. 1-16.

[20] Backhaus, K., et al., Multivariate analysis. Springer Books, 2021. 10(1): p. 973-8.

[21] Abou Jaoudé, A., The Monte Carlo Methods: Recent Advances, New Perspectives and Applications. 2022.

[22] Zhang, Y., et al., Microstructure and mechanical properties of high strength porous ceramics with high sewage sludge content. Journal of Cleaner Production, 2022. 380: p. 135084.

[23] Makul, N., Principles of Cement and Concrete Composites. Vol. 18. 2021: Springer.

[24] Reiterer, M.W. and K.G. Ewsuk, An analysis of four different approaches to predict and control sintering. Journal of the American Ceramic Society, 2009. 92(7): p. 1419-1427.

[25] Li, H., H. Elsayed, and P. Colombo, Effect of particle size distribution and printing parameters on alumina ceramics prepared by Additive Manufacturing. Ceramics International, 2024. 50(4): p. 6340-6348.

[26] Görhan, G. and O. Şimşek, Porous clay bricks manufactured with rice husks. Construction and Building Materials, 2013. 40: p. 390-396.

[27] Sabree, I., J.E. Gough, and B. Derby, Mechanical properties of porous ceramic scaffolds: influence of internal dimensions. Ceramics International, 2015. 41(7): p. 8425-8432.

[28] Lopes da Silva, D.B. and K.M. Sullivan, An optimization-based Monte Carlo method for estimating the two-terminal survival signature of networks with two component classes. Naval Research Logistics (NRL), 2025. 72(2): p. 169-186.