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Reliable Estimation of Compressive Strength of Sandcrete Blocks in the Context of Limited Test Samples

Stephen Adeyemi ALABI[1], Tolulope Abidemi ALABI[2]

[1]*Department of Civil Engineering, The Federal University of Technology. Akure, Nigeria*
saalabi@futa.edu.ng

[2]*Department of Computer Science, The Federal University of Technology. Akure, Nigeria*
ayodeltolulope@gmail.com

Corresponding Author: saalabi@futa.edu.ng

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Abstract: *Sandcrete blocks are the primary material used in Nigeria as partition walls and sometimes as load-bearing walls. The quality of the constituent materials, the curing methods, and the mixing methods influence quality. However, the quality of blocks is usually evaluated using the compressive strength, f_B. However, different studies have shown no unique f_B value for block due to high inherent variability. The uncertainty associated with f_B is reportedly evaluated using a traditional statistical method that requires a significant amount of test results. Extensive data are usually not available due to the practical challenges in preparing the compression test sample. Therefore, this study utilizes the Markov chain Monte Carlo (MCMC) Bayesian probabilistic approach to solve local testing data challenges and the uncertainty inherent in the test results to ensure the block's quality. The framework begins with developing a general probability model called the likelihood function to evaluate the marginal posterior probability based on a limited number of f_B data. The mean and coefficient of variation (COV) values of the MCMC generated sample and the f_B's direct measurement were 0.94 N/mm^2 and 13.10%, and 1.03 N/mm^2 and 19.20%, respectively. The difference between the samples' average values from the MCMC approach and the direct measurement is 0.09 N/mm^2, representing a relative difference of 8.77%. On the other hand, the COV difference is 6.10%, showing a considerable variation of 31.80%. The slight difference between the average values indicates that the mean values agree well, inferring that the probabilistic MCMC-based method performs excellently. It can be concluded that integrating prior knowledge, limited compression test data, and Bayesian inference methods into the design process can contribute to a more reliable structure even with higher allowable stress. Finally, engineers can logically integrate factors such as the degree of uncertainty in the design of walls or structures.*

Keywords: *Sandcrete block, compressive strength, MCMC sample approach, quality control, compliance level.*

1. INTRODUCTION

The code of practice, also known as standards, provides a useful guide for the engineers and designers to ensure that the structures' integrity and stability are achieved. These standards' intended purpose also includes protecting the public from building collapse and encouraging innovative, low-cost, and sustainable materials.

Many standards are currently available for use in concrete, bricks, and sandcrete blocks related structural applications. Most of these standards were developed majorly, considering only their indigenous materials and local weather conditions, which may not suit any other countries adopting it. One such measure is the Nigerian Industrial Standard: Standard for Sandcrete Blocks (NIS 87 [1]), which provides a guide for producing sandcrete blocks of acceptable quality. This standard describes different types and classes of sandcrete in terms of shapes, sizes, and compressive strength. The lowest strength class requirements are 2.5 N/mm^2 and 3.45 N/mm^2 for individuals and a minimum of five blocks, respectively.

However, more than 90% of Nigeria's physical infrastructures were constructed using sandcrete blocks and, this has been estimated to cover about 22% of the total cost of buildings [2]-[4]. Hence, there has been some concern of non-compliance to this standard. The indications that the compressive strength results are below the minimum strength requirement have resulted in the continued collapse of buildings in major economic cities such as Lagos, Ibadan, Port Harcourt, and Abuja. However, this could result from government workers' inaptitude to enforce the standard, or the standard requirements are not economical for the manufacturers. In other words, more strength requirements will incur more materials, which will, in turn, increase the price of the sandcrete blocks in the market.

Based on the literature, [2][5], all the randomly tested samples in all parts of Nigeria does not conform to the recommendation of NIS 87 [1]. The quality of blocks in terms of texture and strength were usually determined by visual inspection combined with the touching and kicking. Visual inspection is good at assessing the surface properties, but it may not be suitable for evaluating its strength. Achieving higher compressive strength is often accompanied by improving constituents' quality, production methods, curing methods, delaying sales, and possibly more expensive [6]. These observations suggested that there could be a need for stricter regulation for the manufacturers or that the standard would also have to be amended if the existing strength requirements are not appropriate for all parts of the country. The situation could also be that both problems exist simultaneously, in which some manufacturers are producing expensive blocks that are not fit for intended purposes.

Because of heavy reliance on the test results of sandcrete blocks, there is a need to provide a greater assurance that the results are a reliable indication of the strength of blocks the sample represents. One of this paper's objectives is to propose modifications in the acceptance criteria for sandcrete blocks and guide the producer in complying with these criteria with a uniform degree of assurance [7]. Therefore, it is expected that the block manufacturers will meet the requirement of this lowest strength class.

However, when there is no possibility of a direct compression test to obtain f_B to design load-carrying masonry walls, the engineers may utilize the minimum strength recommended in various NIS 87 [1]. Multiple studies have shown that there is no threshold identifier of f_B due to high variability. The Identified sources of uncertainties in the f_B are summarized in Figure 1. The chance is expressed in this study as the variability due to environmental influence, which is usually unnoticed while the assignable results from man, machine, and raw material used for making blocks. Hence, this leads to how much uncertainties are responsible for the low compressive strength compared to the standard's minimum requirements since f_B is inherently variable.

This paper developed a probabilistic method to characterize f_B. In other words, to obtain its mean, standard deviation, and full probabilistic distribution by integrating the prior information about f_B using available limited data. Also, to assess how well the blocks standard NIS 87 [1] works to guide sandcrete blocks' production and discuss the possible change. The framework begins with modeling the variability in f_B following normal distribution and then following the likelihood model's formulation to determine the occurrence probability based on the limited data from the Northcentral, Nigeria. This method is different from the previous one that needs many f_B to draw the comparison.

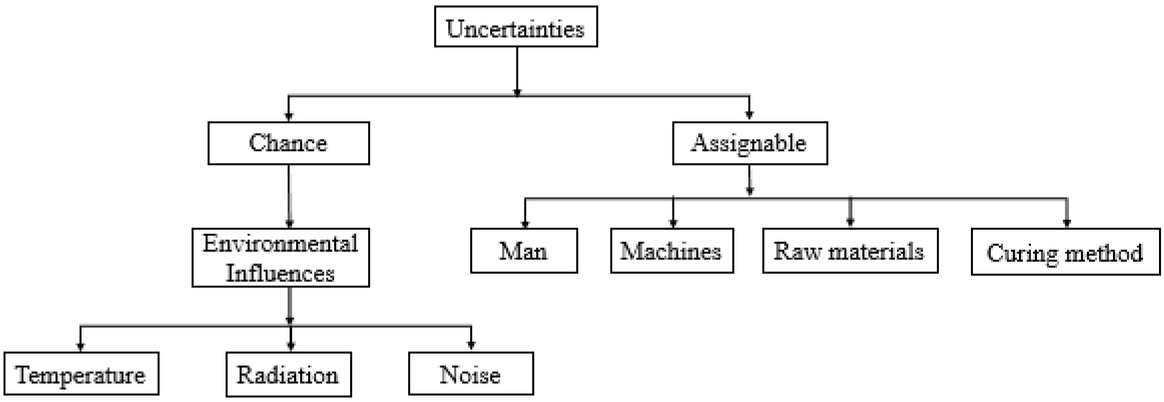

Figure 1: Sources of uncertainties associated with the quality of sandcrete blocks.

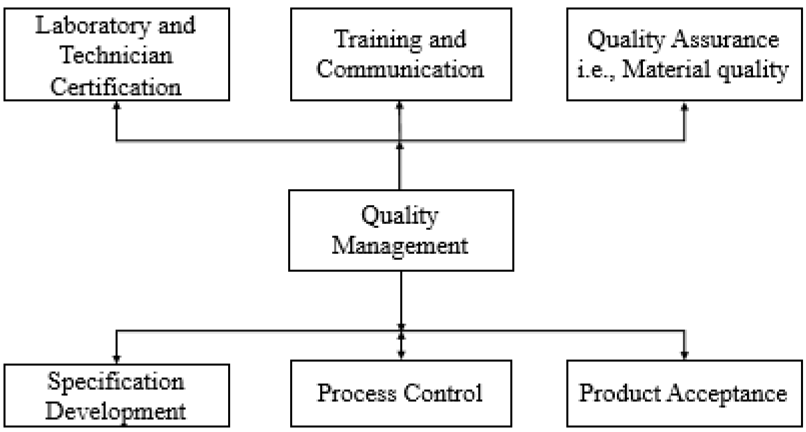

Figure 2: Quality control framework for sandcrete blocks.

2. PROBABILISTIC QUALITY CONTROL METHOD FOR SANDCRETE BLOCKS

In this paper, blocks quality is expressed as the blocks' target mean strength with low uncertainty (i.e., low variability). However, quality is a significant factor that cannot be undermined in building construction. It is a function of the method used in the production process and constituent materials [8]-[13]. The blocks' quality has been observed to be affected by the quality of materials used, batching of aggregates, mixing constituent materials, molding, curing, transportation and storage, mix ratio, and water content [14]. Figure 2 summarizes the proposed aspects of the quality standard required in block production.

In the production of sandcrete blocks, there are inherent variabilities in the properties of the materials used and the production methods. For instance, the quality of cement supplied, the grading, and particle shape of the aggregates vary. These variations may be observed within the batching process, production, curing, and testing of specimens, even if they are conducted following standard recommendations. These uncertainties result in variation of strength from manufacturer to manufacturer and within a batch of each manufacturer. Hence, this makes the block strength challenging to assess, influencing the structures' quality and integrity. Therefore, all these uncertainties can be modeled into the $\boldsymbol{f_B}$ as:

$$f_B = f_B\left(\mu, \sigma\right) + \varepsilon \tag{1}$$

where $f_B(\mu,\sigma)$ is the predicted strength; ε is the prediction error, which is modeled as a zero-mean Gaussian random variable with variance σ^2 [15][16]. It is assumed that the prediction errors follow independent and identically distributed (i.i.d.) distributions [17].

Sandcrete blocks comprise different constituent materials (i.e., heterogeneous) such as cement, sand, and water. Therefore, its properties vary spatially and show inherent variability within the population of block samples. This variability of the block properties can be modeled as a random variable that follows the normal distribution:

$$F_B \sim N\left(f_B \left| \mu_B, \sigma_B^2\right.\right) \tag{2}$$

where F_B is the probability density function (PDF). Hyper-parameters determine the distribution: mean, μ_B, and standard deviation, σ_B of f_B.

$$\mu = \mu_B \text{ and } \sigma = \sigma_B \tag{3}$$

The normal distribution is used in this study to model the f_B because of its successful applications in the literature and its mathematical convenience [15][18][19].

In engineering practice, the f_B of sandcrete blocks are usually performed discretely. Therefore, the N data points can be considered weakly correlated or even independent [15]. However, $\boldsymbol{D}$ = [$f_B^{(i)}$, I = 1,2,3,…,N_s] can be treated as N_s independent realization of Gaussian random variable f_B with a mean μ_B and a standard deviation σ_B. Then the likelihood function is expressed as

$$\left(f_B^{(i)} \left| \mu_B, \sigma_B^2\right.\right) \sim p\left(f_B^{(i)} \left| \mu_B, \sigma_B^2\right.\right) \tag{4}$$

The Bayesian approach incorporates an engineer's judgment or experience about the f_B before the measurement can be considered. However, since the compressive strength model in Eq. (1) is not entirely known, one can represent the modeling error (i.e., prediction error) as the prior random variable (μ_B, σ_B) ~ $p(\mu_B, \sigma_B)$. Then mutually independent prior random variables can be considered as $\mu_B \sim p(\mu_B)$ and $\sigma_B \sim p(\sigma_B)$.

The prior joint information can be expressed as:

$$p\left(\mu_B, \sigma_B\right) = p\left(\mu_B\right) p\left(\sigma_B\right) \tag{5}$$

The-prior joint uncertainty Eq. (5) can be improved by Bayesian data analysis using experimental measurements. When there is no general prior knowledge on μ_B and σ_B, $p(\mu_B, \sigma_B)$ can be represented by a non-informative uniform distribution and explicitly expressed as:

$$p\left(\mu_B, \sigma_B\right) = \begin{cases} \dfrac{1}{\mu_{\max} - \mu_{\min}} \times \dfrac{1}{\sigma_{\max} - \sigma_{\min}} & \text{for} \quad \mu_B \in \left[\mu_{\min}, \mu_{\max}\right], \sigma_B \in \left[\sigma_{\min}, \sigma_{\max}\right] \\ 0 & \text{for} \quad \text{others} \end{cases} \tag{6}$$

where $\mu_{\min}$ and $\mu_{\max}$ are the minimum and maximum values of μ_B, respectively; $\sigma_{\min}$ and $\sigma_{\max}$ are the minimum and maximum values of σ_B, respectively. They can be estimated following their physical meaning and typical ranges reported in the literature.

Therefore, the Bayesian identification approach mainly aims to calculate the posterior probability density function (PDF) $p(\boldsymbol{\theta} = [\sigma, \mu]|\boldsymbol{D})$, as in Eq. (7), of the uncertain model parameter vector $\boldsymbol{\theta}$ conditional on a given set of experimental data $\boldsymbol{D}$.

$$p(\mu, \sigma \mid \boldsymbol{D}) = cp(\boldsymbol{D} \mid \mu, \sigma) p(\mu, \sigma) \tag{7}$$

where c is a normalizing constant such that the integration of the PDF over the parameter space is equal to unity; $p(\sigma, \mu)$ is a prior PDF of model parameters defined Eq. (4), which allows the engineer's knowledge and experience to contribute to the model updating process. $p(\boldsymbol{D}|\mu,\sigma)$ is the likelihood of obtaining the set of experimental data, $\boldsymbol{D}$, conditional on the uncertain model parameters σ, and μ.

Bayesian identification is accomplished by conditioning the prior distribution $p(\mu_B, \sigma_B) = p(\mu_B)\, p(\sigma_B)$ on the measured data

$f_B^{(i)}$. Substitute Eqs. (4) and (5) into Eq. (7), gives the posterior predictive model distribution as in Eq. (8)

$$p\left(\mu_B, \sigma_B \middle| f_B^{(i)}\right) \propto p\left(\sigma_B, \mu_B\right) \prod_{i=1}^{N_s} p\left(f_B^{(i)} \middle| \mu_B, \sigma_B\right) \tag{8}$$

The posterior predictive PDF for the f_B as defined in Eq. (8), usually cannot be obtained explicitly, not only because the posterior PDF may have a complex format, but also because it requires the evaluation of integrals over the space of the model parameters, which is not analytically available and cannot be computed straightforwardly by numerical integration. Thus, it is proposed in this paper to evaluate and represent the posterior PDF of f_B defined in Eq. (8) by statistical samples drawn from the posterior PDF via Markov chain Monte Carlo (MCMC) simulation [17]. One commonly implemented Monte Carlo simulation method for drawing samples from the target PDF is the Metropolis-Hastings (MH) algorithm ([20][21]. The MCMC simulation generates a sequence of f_B such that the complete chain converges to the target PDF. The transition from one state to the next occurs by random perturbation of the current state, determined by the proposal distribution. The MCMC algorithm creates a chain of samples whose statistical distribution can approximate the target PDF by either accepting or rejecting the proposed samples from the parameter space. When the proposed sample is rejected, the previous sample is used in the current state. The procedures of the MCMC-based Bayesian estimation algorithm are briefly summarized in the flowchart in Figure 3.

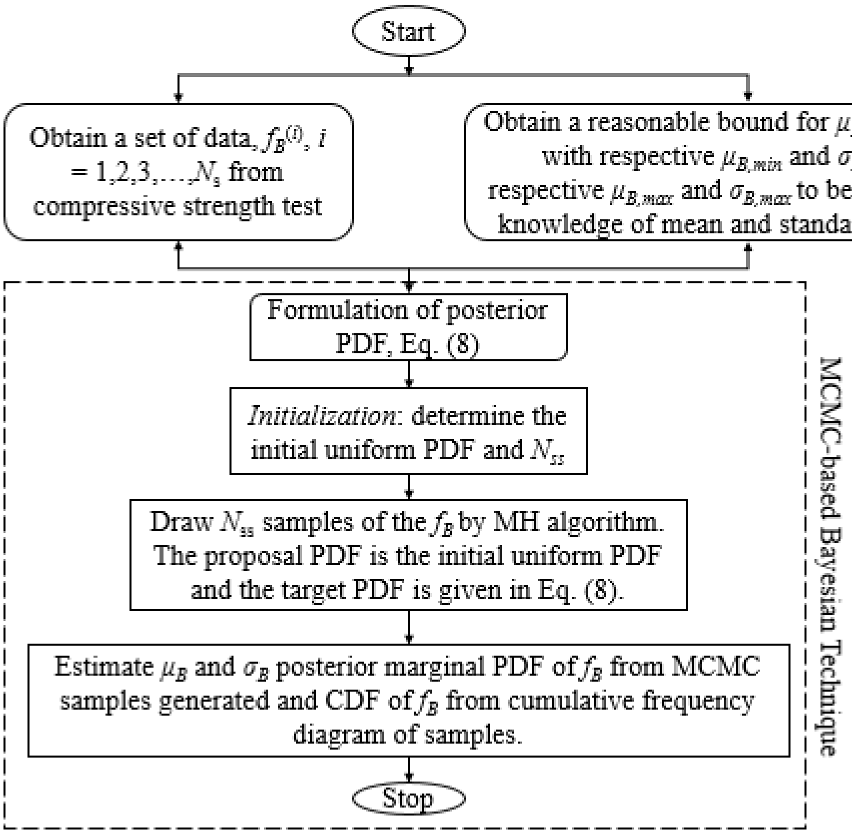

Figure. 3: Flowchart for the implementation of the proposed MCMC-based Bayesian technique.

3. REAL DATA – ILLUSTRATIVE EXAMPLE

The approach developed in this study is applied for the characterization of f_B using limited test samples (24 compressive strength values collected from blocks production sites in Idah, Kogi State, Northcentral part of Nigeria, ref. [10]. The validation was done by comparing the distribution and statistics of the samples generated by MCMC simulation with the 24 f_B data from the test data reported by ref. [10], as shown in Table 1. In real-life engineering practice, test data of f_B of blocks is generally limited due to limited resources, time, and degree of machining process required to prepare samples for compression test.

Also, Table 2 summarizes the prior information on the f_B used in this study. The prior knowledge is adopted from the previous engineering experience reported in the literature. This prior knowledge is relatively uninformative, and it can be taken as a joint uniform distribution of μ_B and σ_B with respective minimum values of $\mu_{B,min}$ and $\sigma_{B,min}$ and individual maximum values of $\mu_{B,max}$, and $\sigma_{B,max}$. The ranges of f_B have been reported in the literature [11][22].

The standard deviation can be estimated using the six-sigma rule as follows.

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$$\sigma_{B,\max} = \frac{\mu_{B,\max} - \mu_{B,\min}}{6} \tag{8}$$

Six-sigma rule is adopted to calculate the standard deviation of data when only a range of the data is available, like the range [0.31 N/mm^2, 2.5 N/mm^2] given in Table 2. The maximum standard deviation of f_B is therefore, estimated as $\sigma_{B,max}$ = ($\mu_{B,max}$ - $\mu_{B,min}$)/6 = (2.5 – 0.31)/6 = 0.365 N/mm^2. On the other hand, $f_{B'}$ minimum standard deviation is taken as $\sigma_{B,min}$ = 0 N/mm^2 because of the standard deviation's non-negative physical meaning. This set of ranges (i.e., μ_B [0.31 N/mm^2, 2.5 N/mm^2] and σ_B [0 N/mm^2, 0.365 N/mm^2] is taken as the prior information.

Table 1: Compressive test result of sandcrete blocks collected from Northcentral of Nigeria (after Aderibigbe et al. [10]).

Specimen No	**Compressive strength, f_B**	**Specimen No**	**Compressive strength, f_B**	**Specimen No**	**Compressive strength, f_B**
B1	1.12	B9	1.02	B17	0.74
B2	1.26	B10	0.88	B18	0.80
B3	1.38	B11	0.83	B19	0.99
B4	0.91	B12	0.96	B20	1.31
B5	0.63	B13	1.37	B21	1.24
B6	0.85	B14	1.08	B22	0.93
B7	1.22	B15	1.04	B23	0.96
B8	1.12	B16	1.02	B24	0.92

Table 2: Prior information of the compressive strength, f_B of sandcrete block

Parameter (N/mm^2)	**Prior information**
Minimum mean, $\mu_{B,min}$	0.31
Maximum mean, $\mu_{B,max}$	2.50
Minimum standard deviation, $\sigma_{B,min}$	0
Maximum standard deviation, $\sigma_{B,max}$	0.365

4. RESULTS AND DISCUSSION

The detailed development of the Markov chain Monte Carlo (MCMC)-based Bayesian characterization has been presented in section 2. The proposed method is adopted in this section. Hence, this method can handle a limited number of measured data points. The process can also handle a case where repeated evaluations of the likelihood function $p(\boldsymbol{D}|\mu,\sigma)$, in the probabilistic optimization search is computationally prohibitive. The prior distribution is a systematic way of incorporating initial knowledge about the uncertain f_B in terms of σ and μ, into the identification process. It is subjective because people with different experiences may use various prior, leading to broader ranges of the solution in cases where the lesser amount of prior information is available. The proposed Bayesian method is essential to update prior knowledge about the uncertain model parameters and obtain the posterior probability density functions (PDFs).

Figure 4 shows a scatter plot of 30,000 MCMC samples that were generated for f_B. It is clear from the figure that the parameter space has one important region (i.e., a high PDF value). The figure also includes the mean, 5% percentile, 95% percentile marks at 0.935 N/mm^2, and about 0.737 N/mm^2 and 1.142 N/mm^2. Generally, it would be observed that the generated samples plot sparsely below 0.737 N/mm^2. It was further observed that from 0.737 N/mm^2 upward, the samples plot near and again become sparsely located at the upper region of the plot after it reached 1.142 N/mm^2. About 1,462 samples fall below 0.737 N/mm^2. This value represents 4.87% of the total population. Also, 1,633 samples fall above 1.142 N/mm^2, representing 5.44% of the total population. About 26,905 out of the total 30,000 samples representing about 89.68% are within the range of 0.737 N/mm^2 and 1.142 N/mm^2. The probability density function (PDF) of the posterior samples was concentrated in the most probable model neighborhood since only one important region is in the parameter space of interest. The posterior samples of f_B clearly show the difference from the prior samples (assumes to be uniform) since they are concentrated around a point.

With the generated MCMC samples, the marginal posterior probability density function (PDF) of f_B is calculated, as shown in Figure 5 (solid black line). Simultaneously, the values of the 24 direct measurements by compression test were plotted with an open square. It is clear from the figure that f_B's marginal PDFs are close to Gaussian distribution but not exactly Gaussian distributions. It is also clear from the figure that the spreading of the distribution f_B decay relatively fast from the optimal value (i.e., the most probable value), showing that the associated posterior uncertainty is relatively high. Therefore, this means that there exists a finite number of most probable models. In order words, there is only one solution point led to f_B, which can reproduce the subset of measured test data taken from the complete set of measured compressive test data. The reason for these relatively high uncertainties lies in the fact that the data is inherently uncertain due to the quality of material used for making blocks, curing methods, and mixing techniques. Hence, this shows the importance of using the MCMC-based method in identifying the f_B.

To provide more information about the results' interpretation, conventional statistics are performed on the samples generated to estimate the posterior mean and coefficient of variation (COV) of f_B. The most probable value (MPV) of f_B is summarized in the second column of Table 3, together with the estimated posterior COV. It is clear from the table that the estimated f_B has a large COV. Hence, this may result from higher sensitivity of the f_B to the limited number of data, that is, larger observability of f_B in data. Consequently, this may also result from modeling error and the variability in the measured data caused by environmental conditions and measurement error. The table also includes the values of the mean and COV of the direct measurement of f_B from the sandcrete blocks manufacturers as 1.03 N/mm^2 and 19.20%, respectively. The difference between samples' mean values from the MCMC samples approach and direct measurement by laboratory tests is 0.09 N/mm^2, representing a relative difference of 8.77%.

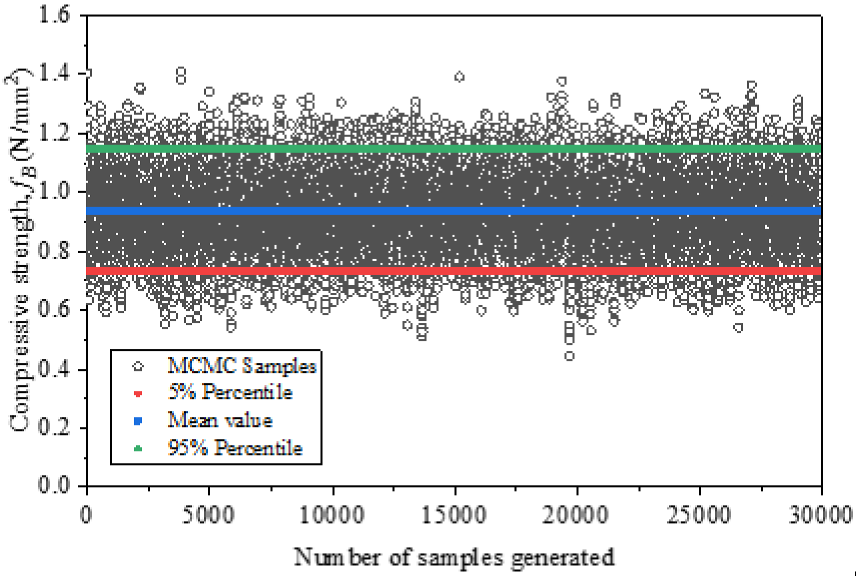

Figure 4: Scatter plot of the Bayesian equivalent samples of f_B.

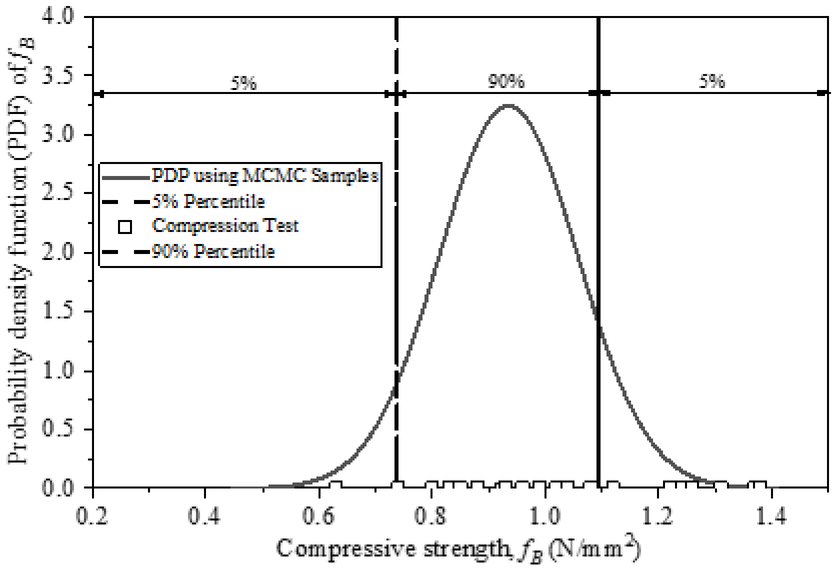

Figure 5: Probability density function (PDF) for compressive strength, f_B.

On the other hand, the COV difference is 6.10%, representing a relative difference of 31.80%. The small difference between the mean values indicates that the mean agrees well, suggesting that the MCMC-based Bayesian method performs satisfactorily. The difference in COV is relatively large. Hence, this might be attributed to the limited number of f_B data from direct measurement.

Figure 6 is the cumulative distribution function (CDF) plot of the f_B, estimated from the MCMC samples generated, and the 24 direct measurement result reported in Aderibigbe et al. [10]. The CDF of the samples generated from the MCMC approach is plotted using a solid line, and it plots closely with the CDF of direct compression test indicated by open squares. There is good agreement between the CDFs of f_B from the direct measurement by compression tests and the MCMC samples. Hence, this shows that the information contained in the samples generated through the MCMC approach is consistent with the one obtained from the direct measurement of f_B.

Finally, f_B samples generated from the MCMC approach contain updated information from the prior information and a limited number of data. It was observed that the prior knowledge includes previous engineering experience, engineering judgment from past similar works, and literature. Based on the initial and measured data from the compression test, the MCMC approach generates samples sufficient for a reasonable f_B statistical distribution estimate. This probabilistic characterization of sandcrete blocks f_B usually requires many data from manufacturer or laboratory tests, which could be expensive, time, and energy-consuming or even impossible because of equipment costs. The proposed full probabilistic distribution of blocks f_B could help the design and construction of the masonry wall.

Table 3: Summary of the estimated statistics of compressive strength f_B.

Estimated statistics	**MCMC generated sample of f_B**	**24 compressive strength test results**	**Difference (N/mm^2)**	**Relative difference (%)**
Mean (N/mm^2)	0.94	1.03	0.09	8.77
COV (%)	13.10	19.20	6.10	31.80

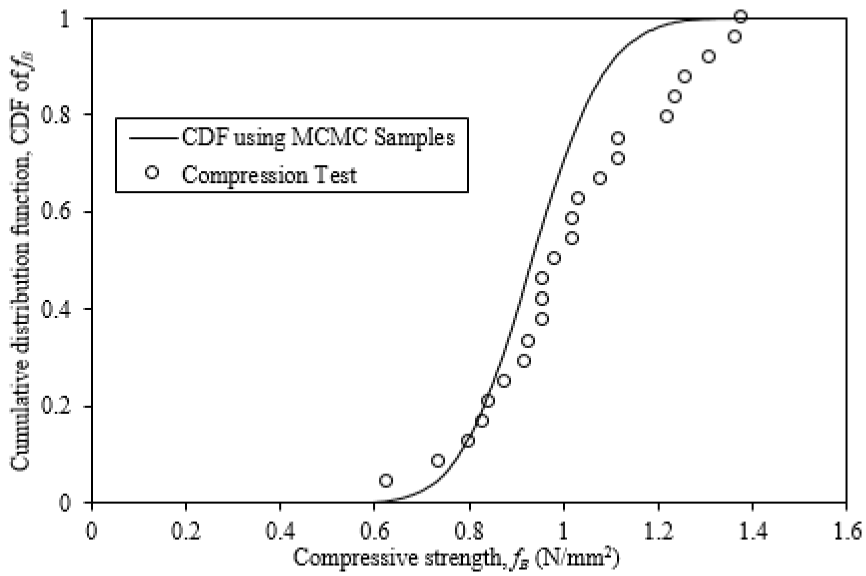

Figure 6: Validation of the CDF of compressive strength from MCMC generated samples.

5. CONCLUSION AND RECOMMENDATION

Based on the limited data samples, this study puts forward the Markov chain Monte Carlo (MCMC)–based Bayesian approach method to characterize the compressive strength of the sandcrete block. MCMC was used to ensure that the proposed method can be applied even when the problem is unidentifiable. The study also successfully incorporated prior knowledge, including previous engineering experience and engineering judgment from the past similar works and literature. The values of the means and coefficient of variations (COVs) of Bayesian equivalent sample and direct measurement of f_B were 0.94 N/mm^2 and 13.10% and; 1.03 N/mm^2 and 19.20%, respectively. The difference between samples' mean values from the MCMC samples approach and direct measurement is 0.09 N/mm^2, representing a relative difference of 8.77%. On the other hand, the COV difference is 6.10%, representing a relative difference of 31.80%. The small difference between the mean values indicates that the mean values agree well, suggesting that the MCMC-based Bayesian method performs satisfactorily.

Most producers of concrete in Nigeria do not have the quality control ability to have small standard deviations. To this end, it is suggested that producers without adequate records start with a standard deviation of 0.12 N/mm^2. If a consecutive result of 30 tests is available, the standard deviation should be based on the 30 straight tests. This statistical quality control method provides a scientific approach to understanding the variations encountered on-site to provide proper tolerance to allow for inevitable variations. Whenever the producer is convinced that the lower standard deviation can be achieved, that new value should be adopted for mix design. Therefore, it can be recommended that the NIS 87 [1] specifications for sandcrete blocks could be improved by requiring that the strength of any sandcrete blocks shall not fall below the specified strength (f_B) by more than 0.015 N/mm^2.

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