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Development of Comprehensive Predictive Models for Evaluating Böhme Abrasion Value (BAV) of Dimension Stones Using Non-Destructive Testing Methods

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Abstract: Due to the global demand for dimension stones, fast and reliable evaluation tools are essential for assessing the quality of dimension stones. For this reason, this study aims to develop comprehensive tools for estimating the abrasion resistance of various dimension stones from Turkey. Non-destructive rock properties, including dry density (ρ_d), water absorption by weight (w_a), and pulse wave velocity (V_p), were determined to build a comprehensive database for soft computing analyses. Three predictive models were established using multivariate adaptive regression spline (MARS), M5P, and artificial neural networks (ANN) methodologies. The performance of the models was assessed through scatter plots and statistical indicators, showing that the ANN-based model outperforms those based on M5P and MARS. The applicability of the models was further validated with independent data from the existing literature, confirming that all models are suitable for estimating varying Böhme abrasion values (BAVs). A MATLAB-based software tool, called Böhme abrasion calculator (v1.00), was also developed, allowing users to estimate BAV values by inputting adopted non-destructive rock properties. This tool is available upon request, supporting the dimension stone industry and fostering future research in this field.

Keywords: dimension stone; abrasion resistance; böhme abrasion value; predictive model; soft computing

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1. Introduction

The suitability of rock materials is significant and varies depending on specific areas of use. Different rock types exhibit unique physical and mechanical properties, making them more or less suitable for numerous engineering applications. Therefore, careful selection of rock materials based on their intended purpose is essential to ensure safety, durability, and cost-effectiveness in engineering and construction projects [1,2].

Numerous physical and mechanical laboratory tests are employed to assess the suitability of rock materials. However, it is important to note that natural weathering processes, such as freezing–thawing, drying–wetting, heating–cooling, and salt crystallization, weaken the structure and fabric of rocks over time [3]. This deterioration in structural integrity not only makes rocks more susceptible to decomposition but also reduces their abrasion/fragmentation resistance as the bonds between grains weaken, allowing for easier material removal.

From the perspective of the dimension stone industry, selecting rock types that can withstand the weathering effects is essential to mitigate wear and maintain material quality. Since the durability of dimension stones is closely linked to their initial physical and mechanical properties [4], comprehensive evaluation methods/models are required to assess rock material quality. Theoretically, rocks with lower strength properties are expected to abrade more easily than those with higher quality.

In general, the abrasion resistance of rock materials is evaluated using standardized tests, such as the Böhme, wide wheel, and Cerchar abrasion tests [5–18]. These abrasion tests provide a solid foundation for understanding the abrasion resistance of rock materials and the wear rate of rock-cutting tools. Among the above-mentioned testing methods, the Böhme Abrasion Value (BAV) is one of the most widely used indicators for assessing rock quality in the dimension stone industry. For this reason, several predictive models have been developed to estimate the BAV of dimension stones (Table 1). As shown in Table 1, the mentioned predictive models are based on linear and nonlinear regression analyses. Apart from these, soft computing algorithms were also utilized to establish several predictive models that can be used to estimate the BAV.

Table 1. Empirical formula for evaluating the BAV of different dimension stones.

Empirical Formula	Number of Datasets, *n*	R^2	Reference
$BAV = -4.64CAI + 25.06$	15	0.83	[9]
$BAV = -1.2363SHV + 94.648$	6	0.66	[19]
$BAV = 579.97V_p - 2.4279$	19	0.85	[20]
$BAV = 69.578PLS^{-1.4807}$		0.76	
$BAV = 8.935\exp(0.0857n_e)$		0.89	
$BAV = 10553SHV^{-1.6868}$		0.92	
$BAV = 50.685\exp(-0.2134PLS)$	14	0.85	[21]
$BAV = 112.87\exp(-0.043SHV)$		0.75	
$BAV = -7.8496\gamma_d + 223.5$	32	0.81	[22]
$BAV = 4.8095n_e + 12.046$		0.83	
$BAV = 143.14\exp(-0.039SHV)$		0.70	
$BAV = -37.17\ln(UCS) + 193.7$		0.70	
$BAV = -37.62\ln(\gamma_d) + 123.21$	22	0.90	[23]
$BAV = 1.0408w_a + 0.5077$		0.94	
$BAV = 1378.4UCS^{-1.76}$		0.65	
$BAV = -210.3\ln(\rho_d) + 229.92$	6	0.81	[24]
$BAV = 1170UCS^{-1.008}$		0.76	
$BAV = -19.167w_a + 17.62$		0.75	
$BAV = 2.697w_a + 14.901$	119	0.74	[25]
$BAV = 1.559n_e + 14.253$		0.73	
$BAV = 0.024SHV^2 - 3.25SHV + 128$		0.72	
$BAV = 280.46 \times SHV^{-0.435} \times {w_a}^{0.1} \times PLS^{-0.572}$		0.88	
$BAV = 173.2CID^2 - 61.0CID + 10.6$	50	0.89	[26]
$BAV = 55.2CAI^{-1.16}$	80	0.67	[27]

Explanations: *SHV*: Shore hardness value; V_p: pulse wave velocity (km/s); *PLS*: point load strength (MPa); n_e: effective porosity (%); *CAI*: Cerchar abrasivity index; *CID*: Cerhar indentation depth (mm); γ_d: dry unit weight (kN/m^3); *UCS*: uniaxial compressive strength (MPa); w_a: water absorption by weight (%); ρ_d: dry density (g/cm^3).

For example, Bayram [14] applied support vector machine (SVM) and random forest (RF) techniques to evaluate varying BAV values. In these soft computing models, dry density (ρ_d), effective porosity (ne), and mechanical rock properties such as tensile strength

(TS), uniaxial compressive strength (UCS), and deformation modulus (Et) were used as input parameters. Similarly, Strzałkowski and Köken [28] used several artificial neural network (ANN) algorithms to develop comprehensive predictive models for BAV. They concluded that the BAV of natural stones from Turkey could be reliably estimated by considering rock properties such as ρ_d, UCS, water absorption by weight (w_a), Shore hardness value (SHV), and pulse wave velocity (V_p).

Based on a comprehensive database for metamorphic rocks in Turkey, Özdemir and Kahraman [29] proposed an ANN-based predictive model to assess BAV. The input parameters used in their model included UCS, flexural strength (FS), ρ_d, w_a, and n_e. Soft computing algorithms have undoubtedly made significant contributions to various engineering disciplines, offering strong predictive capabilities and flexible calculation options. Furthermore, these algorithms are evolutionary tools that can be easily improved by adding new datasets to their databases. Nevertheless, it should be noted that the above-mentioned soft-computing-based predictive models incorporate physical and destructive mechanical properties together. For simplicity and practicality, soft-computing methods should ideally include fewer inputs that can be easily measured in laboratory studies. Here, the hypothesis of the present study is that BAV could also be estimated using non-destructive rock properties, such as w_a, ρ_d, and V_p. Among these, w_a and ρ_d are fundamental physical rock properties that have already been used to estimate the BAV of dimension stones [24,25]. In contrast, V_p, an acoustic rock property, was used by Kılıç and Teymen [20] and Strzałkowski and Köken [28] to assess BAV.

In this direction, the present study aims to develop comprehensive predictive models for assessing the BAV of a wide range of rock types. For this purpose, detailed laboratory studies were conducted to determine the physical and abrasion properties of dimension stones from different regions in Turkey. Based on the collected data, several soft computing techniques were employed to construct comprehensive predictive models for estimating the BAV. The performance of the proposed predictive models was assessed using several statistical indicators.

2. Materials and Methods

Representative rock blocks were collected from various rock exposures and quarries in Turkey (Figure 1). Following the qualitative recommendations of the International Society for Rock Mechanics [30], only unweathered rock types were selected for laboratory analysis. The investigated rock types have been considered dimension stone resources in the surrounding regions. The number of rock blocks obtained and their lithological features are listed in Table 2. Initially, the rock blocks were cut using an industrial rock saw, and cubical samples with dimensions of 70 × 70 × 70 mm were prepared from each block. Non-destructive rock properties were then determined using these cubical samples. All laboratory studies were performed under oven-dried conditions, and the flowchart of the laboratory procedures is illustrated in Figure 2.

Table 2. Details on the number of rock blocks (*n*) collected and their lithologies.

Location	*n*	Rock Lithology	Location	*n*	Rock Lithology
L1	28	Andesite, Basalt, Basaltic andesite	L7	10	Gabbro
L2	16	Tuff, Ignimbrite	L8	3	Gabbro, Diabase
L3	10	Granite, Granodiorite	L9	4	Granodiorite, Granite

Table 2. *Cont.*

Location	*n*	Rock Lithology	Location	*n*	Rock Lithology
L4	12	Andesite, Basaltic andesite, Basalt	L10	25	Limestone, Andesite, Granodiorite
L5	4	Limestone, Phyllite	L11	6	Marble, Dolomite
L6	5	Limestone	Total	123	

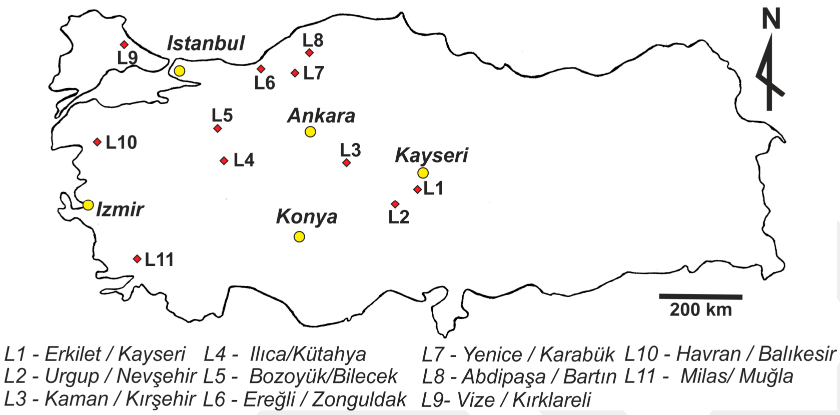

Figure 1. Sampling location map.

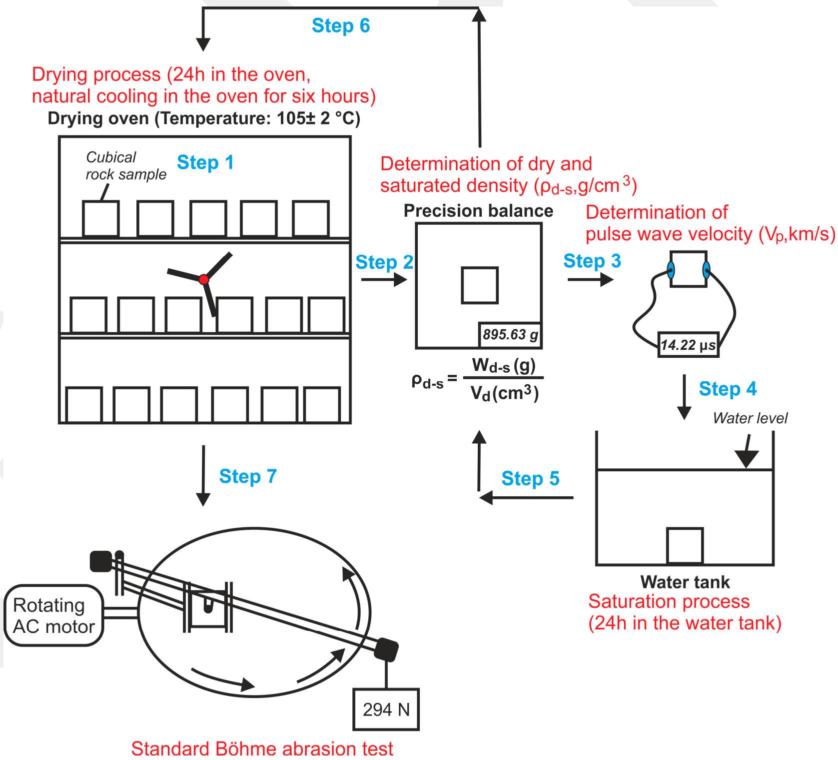

Figure 2. Experimental flowchart for laboratory studies.

3. Laboratory Studies

Firstly, the size of the obtained rock blocks was reduced using an industrial rock saw. After resizing the rock blocks, cubical rock samples with 70 × 70 × 70 mm were cut and trimmed for each rock type. The laboratory tests were performed under oven-dried conditions. Selected rock properties, (i.e., ρ_d, w_a, V_p) were determined following the recommendations of the International Society for Rock Mechanics [30]. These properties are based on non-destructive testing methods, and they may be declared as crucial indicators of a rock's suitability as a dimension stone, reflecting fundamental aspects of its physical and mechanical behavior. Specifically, the ρ_d is used to measure the rock's compactness, w_a indicates a relative measure of rock porosity and resistance to rock weathering processes, and V_p characterizes the internal integrity and a relative measure of rock strength.

In addition to assessing non-destructive rock properties, Böhme abrasion tests were also performed in accordance with the TS EN 14157 [31] standard. This test is widely used in industry to measure the wear resistance of natural stones. In this context, the Böhme Abrasion Value (BAV) is considered an important factor in determining the suitability of natural stones, particularly for flooring and high-traffic applications. BAV also provides a comparative measure of abrasion resistance, indicating that selected dimension stones meet the durability standards required in construction and architectural applications. Some of the laboratory studies are illustrated in Figure 3.

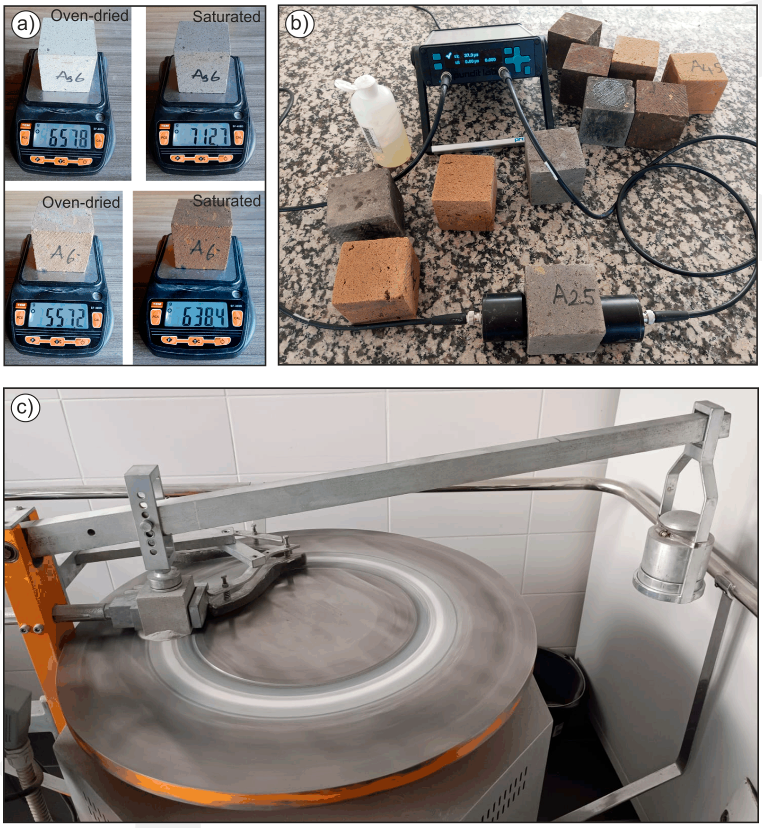

Figure 3. Laboratory studies. (**a**) Determination of ρ_d and w_a; (**b**) pulse wave velocity measurements; (**c**) BAV test.

Soft computing analyses were conducted based on a comprehensive database that included ρ_d, w_a, V_p, and BAV values. Descriptive statistics of the database are presented in Table 3, providing an overview of data distribution and clarifying the range of these rock properties.

The laboratory analyses revealed significant variability in these properties. More profoundly, the ρ_d values ranged from 1.47 to 2.99 g/cm^3, and w_a varied widely from 0.09% to 24.23%, reflecting differences in porosity and their potential durability against drying-wetting and freeze–thaw actions.

Table 3. Descriptive statistics of the rock properties.

Location	ρ_d (g/cm^3)	w_a (%)	V_p (km/s)	BAV (cm^3/50 cm^2)
Min	1.47	0.09	1.23	5.28
Mean	2.49	2.72	4.51	15.37
Max	2.99	24.23	7.36	60.07
Std. dev.	0.262	3.559	1.304	6.686
n	123	123	123	123

The V_p and BAV ranged from 1.23 to 7.36 km/s and from 5.28 to 60.07 cm^3/50 cm^2, respectively. These results provide a comprehensive dataset for further soft computing analyses.

4. Results and Discussion

4.1. Suitability of the Investigated Rocks for Use as Dimension Stones

Dimension stones are highly demanded for their durability, appearance, and ability to be polished, making them ideal for various architectural and decorative applications. In this regard, the investigated rock types were systematically evaluated to determine their suitability for use in the dimension stone industry. To assess the quality of these rock types, the quantitative classification system developed by Strzałkowski et al. [4] was adopted, providing a structured framework for categorizing the materials based on selected rock properties. The analysis results, presented in pie charts (Figure 4), reveal that the majority of the rock materials were classified as high or very high quality, suggesting that most of the investigated rock types have desirable characteristics for commercial use as dimension stones in Turkey. Figure 4 also highlights the potential uses of these rock types, revealing their suitability as valuable resources for construction and decorative stone applications.

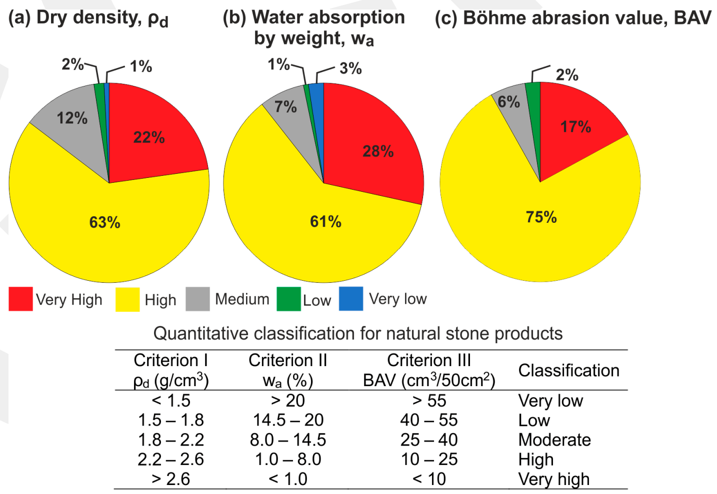

Figure 4. Rock material classification of the investigated rocks depending on different rock properties (**a**) ρ_d, (**b**) w_a, and (**c**) BAV.

A closer examination of specific rock types reveals notable differences in rock quality. For example, gabbro-type rock materials (L7) demonstrated the highest quality across the evaluated rock properties, making them one of the best choices for dimension stone applications.

Similarly, rocks from the L10 location were found to be of high quality for dimension stone applications. In contrast, the quality of tuffs and ignimbrites (L2) showed greater variability, depending on the rock properties assessed. When evaluated by ρ_d, these rocks generally exhibited moderate quality. However, based on their BAV values, they received higher quality ratings, making them suitable for applications that required strong abrasion resistance (Figure 5). Based on the provided information, it is concluded that most of the rock types seem appropriate for dimension stone applications. Therefore, the investigated rock types should be further investigated in more detail from the viewpoint of engineering economics.

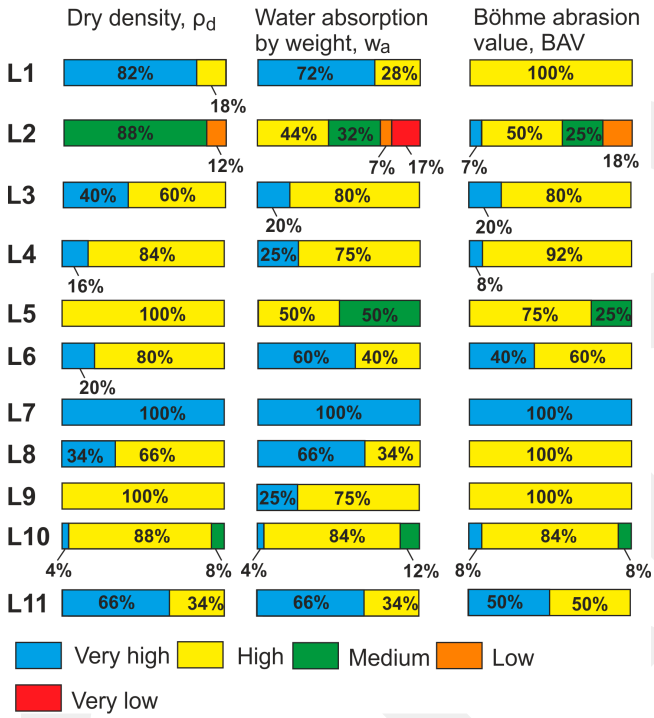

Figure 5. Rock material classification based on sampling locations.

These findings highlight the importance of evaluating rock materials through critical rock properties to forecast their performance and comprehend suitability for use as dimension stones. By using both ρ_d and BAV values, the suitability analyses provide a more comprehensive view of the characteristics of each rock type, ensuring that the selected dimension stones can meet the needs of the dimension stone industry in Turkey.

4.2. Development of Predictive Models for Estimating Böhme Abrasion Value (BAV)

This section introduces soft computing analyses to estimate BAV values. For this purpose, several soft computing techniques, including multivariate adaptive regression splines (MARS), the M5 model tree algorithm (M5P), and artificial neural networks (ANN), were implemented for assessing varying BAV values. Before performing soft computing analyses, the dataset was randomly divided into training (70/100) and testing (30/100) datasets. In other words, the predictive models were first trained using the training datasets (n = 86) and analyzed using the testing datasets (n = 37) for validation.

4.2.1. Multivariate Adaptive Regression Spline (MARS)

The MARS method is a hybrid linear approach designed for nonparametric regression, widely applied in prediction and optimization tasks [32–37]. The method was first proposed by Friedman [38] and consists of two main components: the forward pass and the backward pass. Constant terms called basis functions (BFs) are generated randomly in the forward pass. During the backward pass, these BFs are optimized and combined with linear regression models. In this study, MARS analyses were conducted using the R software (v4-4-2), resulting in an effective predictive model for estimating BAV. As a result of MARS analyses, the BAV can be estimated using Equations (1)–(6).

$$BAV = 26.80 + 2.094BF1 - 0.841BF2 + 18.492BF4 + 3.076BF9 \tag{1}$$

$$BF1 = \max(0; w_a - 18.25) \tag{2}$$

$$BF2 = \max(0; 18.25 - w_a) \tag{3}$$

$$BF4 = \max\left(0; 2.45 - V_p\right) \tag{4}$$

$$BF8 = \max(0; 2.63 - \rho_d) \times BF2 \tag{5}$$

$$BF9 = \max\left(0; V_p - 4.2\right) \times BF8 \tag{6}$$

4.2.2. M5 Model Tree Algorithm (M5P)

The M5 algorithm, originally developed by Quinlan [39], is a powerful and hybrid method for handling complex problems. It combines the advantages of decision trees with the predictive capabilities of linear regression. The M5P analyses were performed in the WEKA (Waikato Environment for Knowledge Analysis) environment. The number of if-then rules was set to between four and six in the M5P analyses. As a result, a simple M5P algorithm was developed for assessing BAV. The decision tree and corresponding linear models (Lm1–Lm3) are presented in Figure 6.

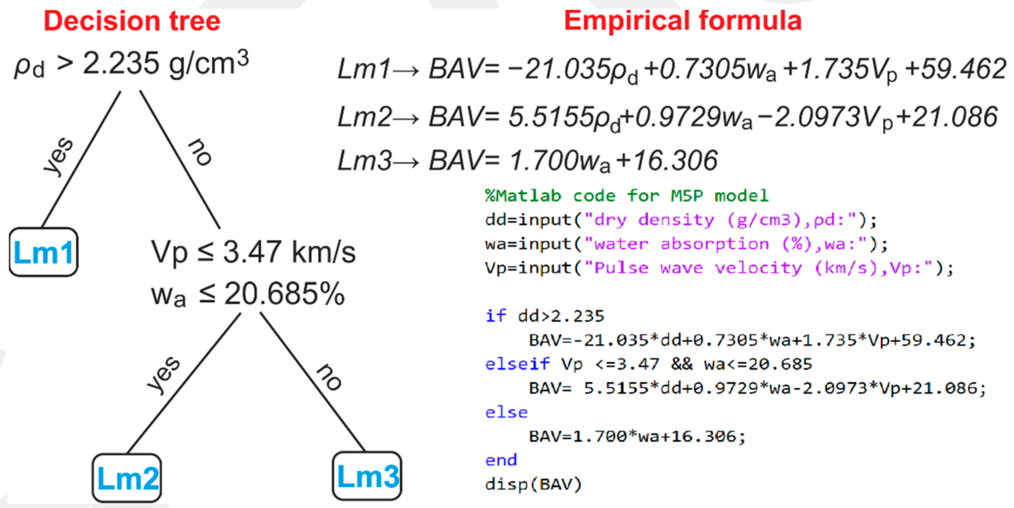

Figure 6. Developed M5P model for evaluating BAV.

4.2.3. Artificial Neural Networks (ANN)

ANN offers distinct advantages, including a straightforward feedforward backpropagation structure and faster training capabilities. These strengths enable ANNs to effectively solve a wide range of problems. In this study, a novel ANN model was developed in the MATLAB (R2021b) environment. Before loading the datasets into the software, they were normalized between −1 and 1 to mitigate overfitting. The normalization was conducted using Equation (7). The input parameters were ρ_d, w_a, and V_p, and various ANN architectures were attempted to develop the optimal predictive model with a simplified structure. As a result, one of the best ANN-based predictive models was found to have a 3–4–1 ANN architecture, indicating that the three input parameters (ρ_d, w_a, and V_p) were processed through four hidden layers to estimate the output (BAV).

$$x_{norm} = 2 \times \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} - 1 \tag{7}$$

where x_{min} and x_{max} are the minimum and maximum values in the relevant datasets, respectively.

The mathematical formulations of the developed ANN model were derived using the deterministic approach proposed by Das [40]. Specifically, the weights and biases obtained from the MATLAB environment were used to reveal the mathematical expressions of the ANN model, which are listed in Equations (8)–(15).

$$BAV = 45.807\tanh\left(\sum_{i=1}^{4} A_i + 2.5158\right) + 47.112 \tag{8}$$

$$A_1 = -4.0751\tanh\left(1.8599{\rho_d}^n + 4.7668{w_a}^n + 8.3054{V_p}^n + 0.6765\right) \tag{9}$$

$$A_2 = 3.7966\tanh\left(-0.0546{\rho_d}^n + 0.7594{w_a}^n - 0.81760{V_p}^n - 1.5816\right) \tag{10}$$

$$A_3 = 0.3332\tanh\left(-0.8108{\rho_d}^n - 9.3598{w_a}^n - 5.3047{V_p}^n - 3.1726\right) \tag{11}$$

$$A_4 = -4.1126\tanh\left(-1.3518{\rho_d}^n - 6.5916{w_a}^n - 8.7894{V_p}^n - 2.467\right) \tag{12}$$

Normalization functions

$${\rho_d}^n = 1.0101\rho_d - 2.0101 \tag{13}$$

$${w_a}^n = 0.0509 w_a - 1.0015 \tag{14}$$

$${V_p}^n = 0.3263 V_p - 1.4013 \tag{15}$$

4.3. Performance Evaluation

The performance of the proposed predictive models was evaluated using scatter plots and statistical indicators such as the coefficient of determination (R2), root mean square error (RMSE), mean absolute percentage error (MAPE), and variance accounted for (VAF). These error metrics may address different requirements depending on the dataset, allowing for a comprehensive evaluation of errors from various perspectives. The mathematical formulae of the above-mentioned error metrics are given by Equations (16)–(19).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_m - y_p)^2}{\sum_{i=1}^{n} (y_m - y_{ave})^2} \tag{16}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_m - y_p)^2}{n}} \tag{17}$$

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \left| \frac{y_m - y_p}{y_m} \right| \tag{18}$$

$$VAF = \left(1 - \frac{\mathrm{var}(y_m - y_p)}{\mathrm{var}(y_m)}\right) \times 100 \tag{19}$$

where y_m, y_p and y_{ave} are measured, predictive, and measured average outputs, respectively.

The scatter plots of the proposed models are shown in Figure 7. The corresponding R2 values range from 0.83 to 0.91, indicating their prediction accuracy. Among these models, the one based on the ANN methodology turns out to provide more balanced outputs when estimating varying BAV values. Based on the statistical indicators listed in Table 4, it was concluded that the ANN-based predictive model (Section 4.2.3) is found to be the most suitable tool for estimating the BAV values of dimension stones. However, additional inputs or new datasets may be required to improve the prediction accuracy of the M5P model, as it shows a clear trend of undulating results at higher BAV values.

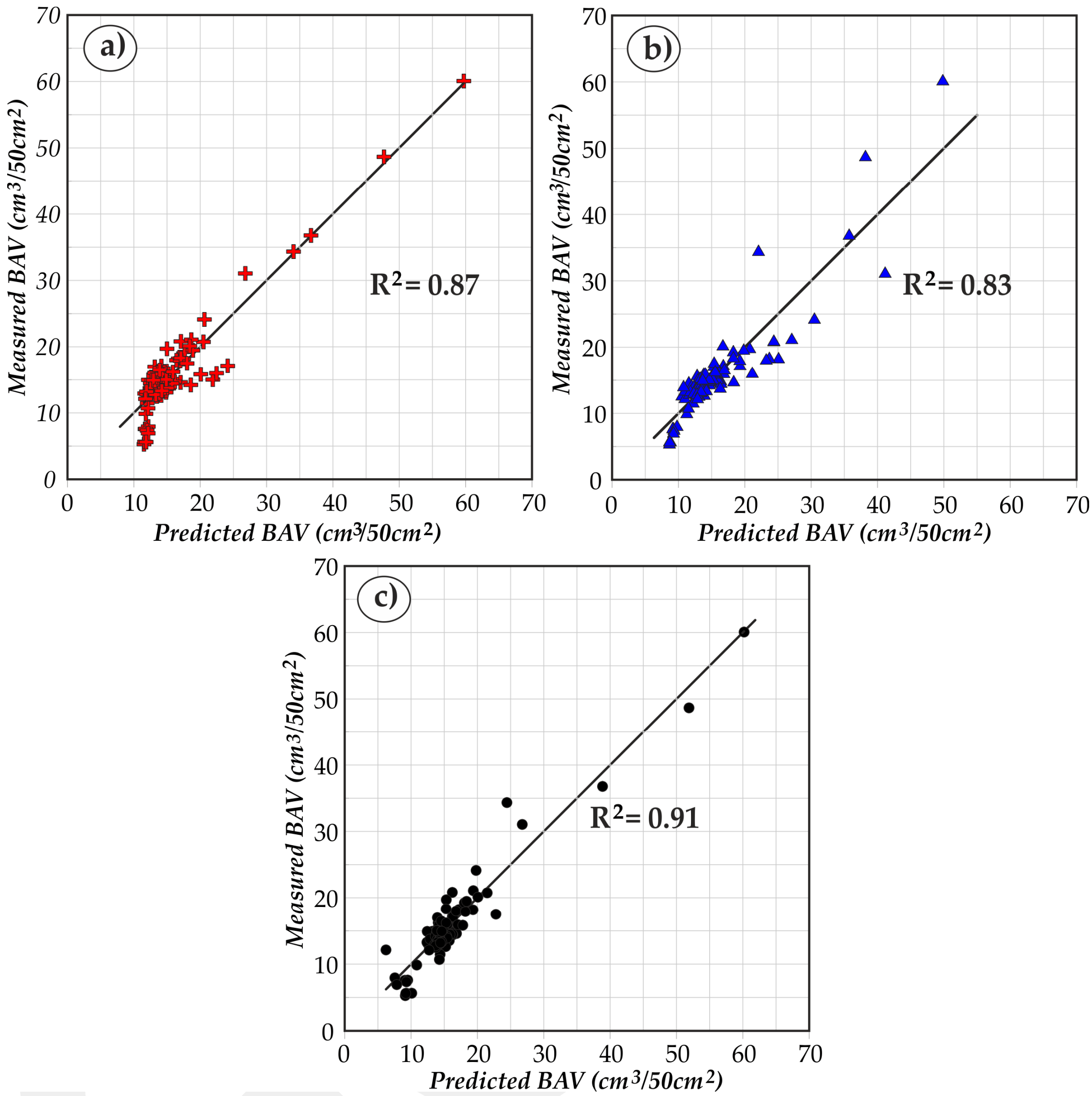

Figure 7. Scatter plots of the predictive models (**a**) MARS, (**b**) M5P, and (**c**) ANN.

Table 4. Statistical indicators for performance evaluation.

Soft Computing Method	R^2	RMSE	MAPE	VAF
MARS	0.876	2.432	14.138	87.72
M5P	0.832	2.726	10.772	83.24
ANN	0.911	1.979	10.463	91.17

The performance of the established predictive models was further evaluated using previously published data. Table 5 lists several dimension stones with associated non-destructive properties gathered through a literature survey. The predictive models were then assessed by implementing them with these data.

Table 5. Performance evaluation of the predictive models based on different datasets.

MAPE			*n*	BAV Range ($cm^3/50\ cm^2$)	Dataset Skewness	Reference
MARS	**M5P**	**ANN**				
39.70	37.49	30.40	30	6.83–89.32 (25.45)	2.46	[22]
15.75	30.65	14.17	17	14.55–80.85 (34.94)	1.34	[41]
29.59	44.64	22.23	9	15.50–92.00 (44.24)	1.07	[42]
43.30	53.01	52.46	13	5.58–87.02 (31.87)	1.24	[43]
33.82	46.50	34.95	22	5.21–46.74 (23.45)	0.31	[44]
14.138	10.77	10.46	123	5.28–60.07 (15.38)	3.93	This study
MAPE (%)	Predictive model performance [45]					
≤10	Very good					
10–20	Good					
20–50	Acceptable					
>50	Unacceptable					

The results indicate that the predictive models can generally be considered acceptable tools for estimating the BAV of various dimension stones. However, it is important to consider the intervals of the non-destructive properties (Table 3) when applying these predictive models. Exceeding the defined intervals of the non-destructive input parameters may lead to undulating results.

4.4. Concluding Remarks

Performance evaluations indicate that the established predictive models can be effectively used to estimate the BAV of various dimension stones. Their accuracy increases significantly when the models are applied within the specified intervals of the non-destructive properties (Table 3). On the other hand, non-destructive rock properties (ρ_d, w_a, and V_p) enable one to implement these models more efficiently. In particular, Figure 8 suggests that w_a may be a critical factor when assessing BAV. Last but not least, for the sake of clarity and ease of use, a novel software application was developed to incorporate the proposed predictive models.

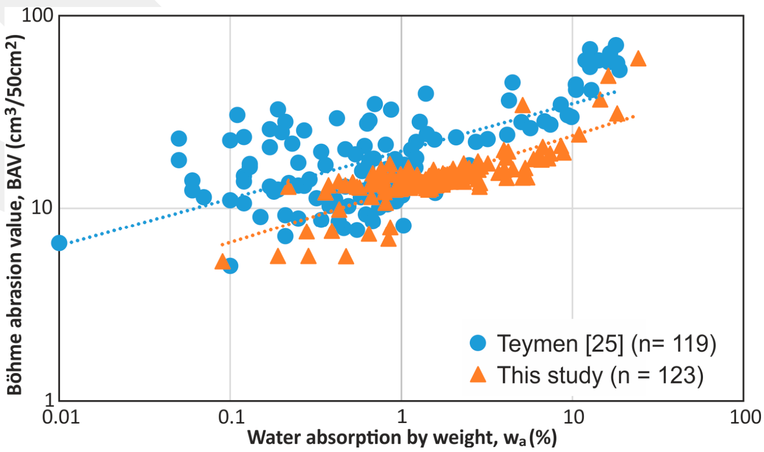

Figure 8. Variation in BAV values with respect to w_a. (revised the x-axis explanation).

This software, called the Böhme Abrasion Value (BAV) Calculator (version 1.0), provides an accessible tool for estimating BAV values. The BAV Calculator was developed using MATLAB (Design App Toolbox), allowing users to easily obtain BAV values by inputting adopted non-destructive rock properties.

Some outputs obtained from the software are illustrated in Figure 9, demonstrating its functionality and potential practicality in the dimension stone industry. The BAV Calculator offers a user-friendly interface, providing quick and reliable BAV outcomes based on the established predictive models.

Figure 9. Some outputs of the developed software.

Thanks to the established predictive models, the present study can provide a significant contribution to the dimension stone industry by facilitating quick and reliable decision-making processes. It is achieved through the utilization of nondestructive rock properties as input parameters, which are not only cost-effective but also highly repeatable in the laboratory. Furthermore, the BAV tests are relatively expensive, time-consuming, and environmentally detrimental because the use of abrasive powders leads to environmental and occupational health concerns. By focusing on nondestructive methods, the present study may reduce the dependency on traditional BAV testing, paving the way for more sustainable and efficient practices in evaluating the abrasion resistance of dimension stones.

5. Conclusions

The present study aims to provide comprehensive predictive models for evaluating the BAV of various dimension stones. For this purpose, critical non-destructive rock properties (ρ_d, w_a, and V_p) were determined in laboratory studies. Based on the collected data (Table 3), several soft computing methods, including MARS, M5P, and ANN, were applied. The soft computing analysis results indicate that the ANN-based predictive model outperforms those based on the MARS and M5P methods.

The performance of these models was further validated with independent data from the existing literature, confirming that all models are suitable for estimating BAV. To facilitate the implementation of these models, a simple software tool was developed in the MATLAB environment (Figure 9). This software requires ρ_d, w_a, and V_p as input parameters to implement the established predictive models. In addition, it is free and available on reasonable request. The outcomes of this study are expected to support the dimension stone industry by providing comprehensive predictive models and fostering the applicability of soft computing methods for further studies.

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Conflicts of Interest: The corresponding author declares no conflicts of interest.

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