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Evaluate the Granite Waste Efficiency in the Construction Using Statistical Indicators

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ABSTRACT

Due to the expansion of industrial operations globally in recent years, waste output has rised. So these wastes must redused by recycle and reuse to acheive environmentally friendly buildings and find various alternatives materials in critical cases. The statistical indicators is used as practical study including Multiple linear regression (MLR) and artificial neural network (ANN) models. The study's goals were to assess the effectiveness of granite waste (GW) as a replacement to cement, sand, plastic, and binder in specific building applications as well as the relationships between MLR and ANN approaches. Results shows the efficiency of adding granite waste to some construction stages and replacing it with cement in the mixture and examining its strength, it gave excellent results in addition to good results for its use as a binder in cement mortar, while the results were weak when used as a substitute for sand and plastic in insulator because its classified as fine sand, Therefore, it cannot be used as a substitute for sand in the construction. The statistical models give an effictive indicators to use GW as asalternative material (binder and cement) based on the coefficient of correlation (R^2) for the two models MLR and ANN equal to 83.4 % and 80 % respectively.

1. Introduction

Many different test methods have been developed in attempts to characterize the properties of bulidings construction. So far, no single method or combination of methods has achieved universal approval and most of them have their adherents. Similarly, no single method has been found which characterizes all the relevant workability aspects so each mix design should be tested by more than one test method in order to obtain different workability parameters[1], [2]. A new alternative to support sustainable development is the incorporation of waste from granite rock processing in manufacture of building. Granite has diverse applications because of its versatile characteristics, such as high durability and resistance to scratches, stains, cracks, spills, heat, cold, and moisture. Unfortunately, a considerable and increasing number of solid wastes from granite industries are generated in cutting and polishing, these wastes are currently disposed in landfills with increasing cost and

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negative environmental impact, which affects the economic and environmental sustainability of such industrial productions, as well as public health. In recent decades, environmental considerations have become a main concern, and efforts to reuse granite wastes have been undertaken. The main aim of sustainable development is to reduce the usage of natural resources by proper recycling,the wastes of Granite factories are divided into: Large solid waste of marble, Heavy viscous liquid waste consisting of particles, granular particles, sand and Sawdust (these curtains are assembled residues in natural or synthetic rates causing many environmental and health problems on the healthy environment animal and plant), Dense emissions of dust, and Factory sewage waste, which is drained into the sewage network local[3].

Recently, the use of recycled materials in rigid and flexible pavements, including granite, coal, and recycled polyethylene terephthalate, has been researched (PET). In research by Fakhri and Saberi (2016), cement and certain aggregates were replaced with crumb rubber and silica fume [4], [5]. The utilization of Granit waste in place of cement will reduce the cost of concrete significantly because cement is costliest ingredients also solve the problem of energy as production of cement requires very high energy demand[6]. (Savadkoohi and Reisi, 2020) examined the utilization of stone-cutting residue in the production of reactive powder concrete using 90 RPC mix designs. The results indicate improvements in the mechanical properties of the concrete when silica sand is replaced in the RPC by up to 30% granite waste[7].

Lopes et al. (2021) assess and improve the performance of building paints for coverage power and abrasion resistance, granite debris is used as a pigment, the performance of the paints was optimized by the use of performance indicators and a statistical desirability function. In addition to the inclusion of this industrial waste improves the physical and mechanical properties of these applications, according to experimental studies[8].

that have been conducted on the utilization of granite waste in a variety of construction applications, including mortar, cement, ceramics, concrete, and composite materials. Since granite waste lacks silt and organic pollutants and can be made to satisfy specific gradation and fineness standards, it may also be used as a replacement for natural sand. The effectiveness of applying this product in place of cement is described, along with the properties of fresh and hardened concrete made from granite waste, environmental advantages and cost. Available experimental research employing the granite slurry waste have also been evaluated. The critical review's final observations are presented at the end [9].

Sufficient literature is available and it indicates that granite waste can be used in place of fine Aggregate or cement, the use of this waste in place of cement will reduce energy demand, CO2 emission and consumption of natural resources. A salient available experimental study using the granite waste have been reviewed by Chouhan et al. 2017 and it is shown that the granite waste reduces the workability whereas compressive strength of granite concrete is improved[9]. Also, the potential of achieving carbon mitigation and energy efciency in the building sector is greater than in the industry and transportation sectors, respectively (Ma et al. 2018).

The engineering properties of solid waste were studied through a laboratory experiment on several samples taken from marble factories to determine the usability these wastes are used to improve facilities or as alternatives to building materials.

Through the recycling of granite waste in construction materials, the research's main goal is to eliminate the environmental pollution brought on by granite wastes. By explaining the connection between two or more variables, statistical analysis may be used to process data. As a result, this study is focused on evaluating the effectiveness of the GW in construction and predicting the most important parameters that influence it using SPSS simulation algorithms.

2. Materials and methods

2.1. Case study description

Granite powder (comes from cutting granite by cutting machine then granules grinding) was brought from the marble factory in the city, and it was sieved on sieve No. 111, and an X-ray diffraction (XRD) test was performed to determine the proportions of the basic compounds constituting the GW sample. Table (1) shows the mineral analysis of GW, Figure (1) shows the Granite cutting machine and its dust before grinding.

Figure 1. Granite cutting machine and marble granules before grinding [10]

Table 1. percentage of minerals in granite powder [10]

Mineral Name	Chemical Formula	Compound	Semi Quan.
Calcite	$CaCO_3$	Calcium Carbonate	86
Dolomite	$CaMg(CO_3)$	Calcium Magnesium	11.5
Quartz	SiO_2	Silicon Oxide	2.5

2.2. Gathering and processing of data

In this study, data were measured and collected from laboratory experiments included adding granite waste and testing its efficiency in construction. Data were taken and tabulated by Excel 2019 software were used for data analysis. The regression analysis and multilayer prediction artificial neural network assessments were carried out by software (IBM SPSS 24)[11].

3. Statistical indicators

3.1. Multiple Linear Regression model (MLR)

The function of multiple linear regression can be used by a statistician or researcher to predict the value of one variable based on information about another variable. Linear regression can only be used when there are two continuous variables (independent variable) and a dependent variable. A multiple regression model has several variables (dependent and independents). The factor used to calculate the value of the dependent variable or result is referred to as the independent variable.**[12]**

Whereas the equation for the MLR model depends on the connection between the variables (independent and dependent variables):

$$Y_i = B + b_1x_1 + b_2x_2 + \cdots + b_nx_n \quad (1)$$

Where:

[B] means the constant term (offset).

[bi] coefficients of classification, [x] independent variables (1 – n), and
[Y_i] Represents the function of classification for i = 1 to j.
To determine the extent to which the variation in the independent variables may explain the variance in the outcome, a statistical measure known as the coefficient of determination (R-squared) is employed. R2 always increases when additional predictors are added to the MLR model, even if the variables may not be related to the outcome variable. The assumptions which the MLR model based on are: The independent variables are not overly correlated with one another, the independent variables and the observations (yi) are chosen independently, the dependent and independent variables have a linear relationship, and the residuals should have a normal distribution [13].

3.2. Artificial neural network (ANN)

The structure (neurons) of a biological nervous system is modeled by artificial neural networks (ANNs) algorithms. Dense Parallel in connections make up ANN Networks. The cells use an activation function to collect signals from neurons in the form of weight inputs and transmit that weight to other neurons. There are one or more multilayers in the neutral activities. There is a lot of application of the Multilayer Perceptron Network in neural activities. The number of input parameters, input layers, and output are what determine the perception response. There are three layers in every network: input, hidden, and output layers as shown in Figure 2 **[14]**.

The ANN is a tool of mathematical modelling based on the following equation[8]:

$$x_r = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Where:

(Xr) is the normalize rate; (xi) the initial dats; (xmin) (xmax) the minimum and maximum values respectively.

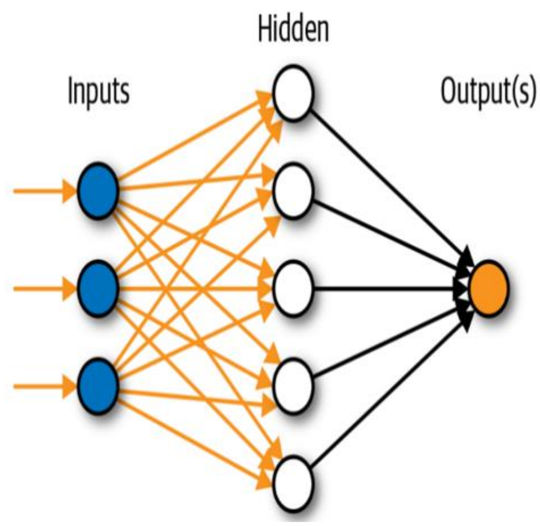

Figure 2. Major and minor components of ANN technique.

4. Results and discussions

4.1. Distribution of data

The parameterized mathematical function of the distribution may be used to compute the probability for each data points in the parameter space. SPSS is a summary of a statistical application that uses a series of lists and tools to input data.

This distribution is useful for testing the data before entering it into the regression and ANN models to give efficiency in the results. Once a function of distribution is determined, it may be used for defining and computing associated values, such as observations, and displaying the connection between observations in the domain [15].The dots are clearly close together, and in this instance the data are distributed normally as shown in Figure 3 with a mean of (104.49) and a standard deviation of (16.446), the relationship between the observed cumulative probability and the expected cumulative probability for the best fit has been discovered.

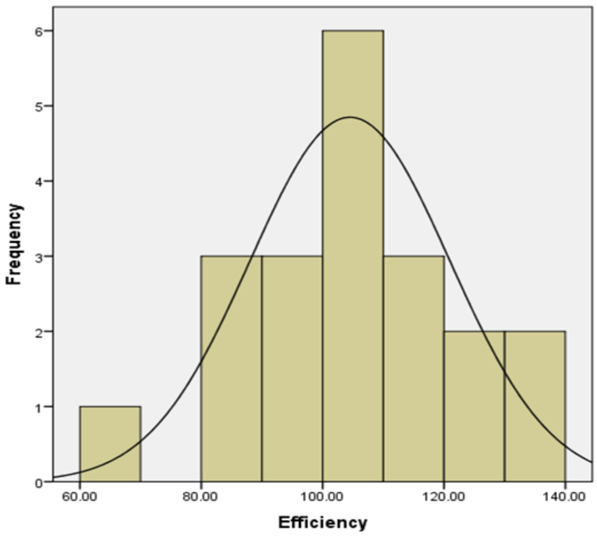

Figure 3. Histogram of relationship between regression and frequency standardized

4.2. Neural network formulation

To build and improve the ANN accuracy over time, neural networks need training data sets. So, these learning algorithms start to work as good instruments that may be used to any system after they have been accurately tuned. A collection of measured data that entered to the neural network model. In order to identify a collection of model variables that enables the model with the given function form to be presented in an effective fashion, several ANN trainings with desirable input and output connections have been developed. **[13]**. The values are pooled in one batch to see if a neural network model for predicting GW efficiency can be developed. Equation 3 shows the correlation coefficient (R^2) for the function of ANN function model which was 80 percent. As demonstrated in Figure 4, using the GW as cement and binder have a greater impact on the efficiency forecasting model than other factors.

$$Y=24.57 + 0.77 x \tag{3}$$

Where:

(Y) means the absorbance, (x) means the other input parameters.

Furthermore, Equation 3 represents the model's fitting line, which may be usrd at point to get the efficiency value based on another input parameter.

Table 2 shows the full parameters of the suggested model for the ANN estimation including output, hidden and input layers.

Table 2. The prediction variables of hidden and output layers

Predictor		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	Efficiency
Input Layer	(Bias)	-1.162	1.033	-.452	-
	Cement	-.981	-.302	.105	-
	Sand	-.283	-.286	-.454	-
	Plastic	-.607	-.124	-.311	-
	Binder	-.623	-.573	-.018	-
Hidden Layer1	(Bias)	-	-	-	.131
	H(1:1)	-	-	-	-.634
	H(1:2)	-	-	-	-.899
	H(1:3)	-	-	-	.132

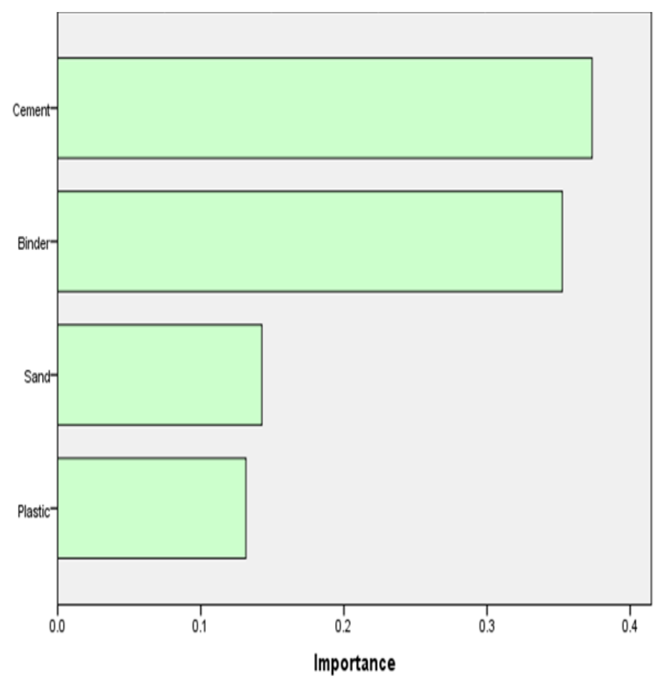

Figure 4. Importance of an independent Variables.

Where the second hidden layer is H (1:2), the first hidden layer is H (1:1), the third layer is H (1:3) and the constant element is (Bias).

The close of the ANN model to a set of data points is calculated by Mean square error (MSE) taking the average, specifically the mean, of errors squared from data as it relates to a function which is shown:

$$MSE = \frac{51.58}{12} = 4.3$$

The ANN network was utilized to assemble the synthetic neurons that linked and changed in a different layer, which helped to lessen the complexity and the model detailes are shown in Table 3. The connection weights are determined by minimizing the difference between the predicted and actual output values under experience information.

Table 3. model details

Mean		102.2814
95% Confidence Interval for Mean	Lower Bound	91.0574
	Upper Bound	113.5055
Median		105.1316
Variance		312.064
Std. Deviation		17.66534
Minimum		69.00
Maximum		130.95
Range		61.95
Interquartile Range		26.80
Skewness		.637
Kurtosis		1.232

4.2. Formulation of Multiple Linear Regression (MLR) models

As a data set, there are 48 experiments values available. Table 4. shows the results of using the SPSS regression tool and following the stepwise approach in the variable selection process. In the last model, the greatest coefficient of determination (R2) was shown to be 83.4 percent

Table 4. The models of MLR

Model	R^2	R	Adjusted R^2
1	.834	.913[a]	7.55052

a. Predictors: (Constant), Sand

5. Conclusions

This research work is an attempt to:

The granite waste powders increase the compressive strength of concrete, as recycledpowder's fineness gets finer, its reactivity gets more and more reactive. the relationship between the observed cumulative probability and the expected cumulative probability for the best fit has been discovered with a normal distributed, using the ANN and MLR model, identify a number of influence parameters that are utilized to create a solution that has improved the current effectiveness of using GW in the construction especially when it used as binder or cement enhancement,the use of statistical indicators showed good results in the two mathematical models and the MLR gave a better correlation coefficient (R2) than the ANN model which achieve 83.4%, while 80% for the ANN. Finally, the paper methodology may be used in another number of construction materials such as used it in the self-compacted concrete.

References

[1] A. Karmegam, A. Kalidass, and D. Ulaganathan, “Utilization of granite sawing waste in self compacting concrete,” *Građevinar*, vol. 66, no. 11., pp. 997–1006, Dec. 2014.

[2] S. C. H and D. Venkatesh, “Optimization of Granite Powder used as Partial Replacement to Cement in the Design of Ready Mix Concrete of M20 Grade using IS10262:2009,” *Int. J. Eng. Res. Technol.*, vol. 4, no. 1, Jan. 2015, doi: 10.17577/IJERTV4IS010142.

[3] Z. Al-Adeeb, “Feasibility study of recycling waste from marble and stone factories in the

building materials industry," Damascus university, 2015.

[4] M. Fakhri and F. Saberi. K, "The effect of waste rubber particles and silica fume on the mechanical properties of Roller Compacted Concrete Pavement," *J. Clean. Prod.*, vol. 129, pp. 521–530, Aug. 2016, doi: 10.1016/j.jclepro.2016.04.017.

[5] A. Albassrih and Z. K. Abbas, "Properties of Roller-Compacted Concrete Pavement Containing Different Waste Material Fillers," *J. Eng.*, vol. 28, no. 9, Art. no. 9, Sep. 2022, doi: 10.31026/j.eng.2022.09.06.

[6] Z. Z. Woźniak, A. Chajec, and Ł. Sadowski, "Effect of the Partial Replacement of Cement with Waste Granite Powder on the Properties of Fresh and Hardened Mortars for Masonry Applications," *Materials*, vol. 15, no. 24, Art. no. 24, Jan. 2022, doi: 10.3390/ma15249066.

[7] M. S. Savadkoohi and M. Reisi, "Environmental protection based sustainable development by utilization of granite waste in Reactive Powder Concrete," *J. Clean. Prod.*, vol. 266, p. 121973, Sep. 2020, doi: 10.1016/j.jclepro.2020.121973.

[8] M. M. S. Lopes *et al.*, "Optimization of performance of sustainable paints using granite waste through the variation of particle size and pH," *J. Clean. Prod.*, vol. 326, p. 129418, Dec. 2021, doi: 10.1016/j.jclepro.2021.129418.

[9] D. S. Chouhan, Y. Agrawal, and T. G. and R. K. Sharma, "Utilization of Granite Slurry Waste in Concrete: A Review," *Indian J. Sci. Technol.*, vol. 10, no. 6, pp. 1–9, Feb. 2017, doi: 10.17485/ijst/2017/v10i6/88279.

[10] J. A. J., F. F. Gh., and A.-B. N. M., "Effect of marble powder on the properties of self-compacting concrete," in *29-31*, 2019.

[11] G. Pirmohammadi and M. Mast, "Comparison of Artificial Neural Network and SPSS Model in Predicting Customers Churn of Iran's Insurance Industry," *Int. J. Comput. Appl.*, vol. 176, no. 32, pp. 14–21, Jun. 2020, doi: 10.5120/ijca2020920345.

[12] A. M. Salal and B. H. Khudair, "Influent Flow Rate Effect On Sewage Pump Station Performance Based On Organic And Sediment Loading," *J. Eng.*, vol. 25, no. 9, Art. no. 9, Aug. 2019, doi: 10.31026/j.eng.2019.09.1.

[13] M. Kıranşan, A. Khataee, S. Karaca, and M. Sheydaei, "Artificial neural network modeling of photocatalytic removal of a disperse dye using synthesized of ZnO nanoparticles on montmorillonite," *Spectrochim. Acta. A. Mol. Biomol.* Spectrosc., vol. 140C, pp. 465–473, Jan. 2015, doi: 10.1016/j.saa.2014.12.100.

[14] L. K. Abidoye, F. M. Mahdi, M. O. Idris, O. O. Alabi, and A. A. Wahab, "ANN-derived equation and ITS application in the prediction of dielectric properties of pure and impure CO2," J. Clean. Prod., vol. 175, pp. 123–132, Feb. 2018, doi: 10.1016/j.jclepro.2017.12.013.

[15] F. Farooq, W. Ahmed, A. Akbar, F. Aslam, and R. Alyousef, "Predictive modeling for sustainable high-performance concrete from industrial wastes: A comparison and optimization of models using ensemble learners," J. Clean. Prod., vol. 292, p. 126032, Apr. 2021, doi: 10.1016/j.jclepro.2021.126032.