Int. J. Econ. Environ. Geol. Vol. 12 (1) 41-45, 2021

Journal home page: www.econ-environ-geol.org

Open Access

ISSN: 2223-957X

Monte Carlo Simulation and Scenario Analysis Based Limestone Quarry Production Planning

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Received: *26 October, 2020* ***Accepted:*** *24 January, 2021*

Abstract: The key factor behind raw mix design in the cement factory is the appropriate production planning, resulting in high-quality raw material. Quarry managers usually come up with uncertainty-related raw materials due to variations in chemical composition. These uncertainties required efficient planning in terms of useful insight into this problem. This research provides a detailed explanation of scenario analysis of raw materials used in cement manufacturing using Monte Carlo simulation (MCS) and indices. Scenario analysis is used to predict the possibility of best, worst and most likely cases of raw material's quality. Whereas, Monte Carlo simulation is used to evaluate the inherent uncertainty associated with chemical composition values in order to analyze the impact of truly unpredictable scenarios. The predictive results help in decisions related to production planning, raw mix design optimization and increasing the probability of designing the best plan.

Keywords: Monte Carlo simulation, scenario analysis, raw mix design, production planning, cement factory.

Introduction

The raw materials commonly used in cement production are limestone, slate, shale, laterite, clay and marl. (Ali and Shah, 2008). The cement production process involves complex operations starting with raw material extraction from the quarry. Raw material extraction from quarry comprise a sustained supply of raw material meeting the quality and quantity requirement (Asad, 2010). Planning and operating cement quarry with optimal production of raw material is associated with challenging issues due to inherent uncertanity related to chemical composition and sufficient quality and quantity of raw material (Rehman and Asad, 2010; Shah and Rehman, 2016; Shah and Rehman, 2020).

The main constituent used in the cement production process is limestone. It contains oxides such as lime (CaO), silica (SiO_2), Alumina (Al_2O_3), iron (Fe_2O_3) and magnesium (MgO) in various quantities (Ali and Shah, 2008). The percent content of oxides varies around the quarry and across different quarries. The clinker quality depends on the provision of optimal raw material in terms of quality and quantity to ensure the quality of the end-product. The optimal quality ensures that the raw material constituents with oxides are within a specific range (Rehman and Asad, 2010). Generally, different grades of raw material within the quarry are blended to meet the raw mix required for the kiln meal. An efficient blending process can be achieved through proper proportioning to obtain good homogeneity to ensure appropriate burnability, plant efficiency and final product quality (Asad, 2011; Chatterjee and Kumar, 2018). Therefore, the blending of raw material with adequate quality and quantity of oxides is essential for the cement manufacturing process. Supplementary materials if required, are provided from the market such as laterite, clay, fly ash, slate, gypsum and sandstone. Proper sampling and chemical analysis are essential to achieve the uniformity and homogeneity of the raw mix for kiln meal (Asad, 2011). Quarry managers usually face uncertainty related to raw materials due to variation in chemical composition. These uncertainties required efficient planning for useful insight into this problem. Monte Carlo simulation is mostly used to achieve the final cement product, and fulfilling the quality and quantity the percentage of various oxides (Silica (SiO_2),calcium (CiO) iron (Fe_2O_3) and alumina (Al_2O_3)). To achieve the quality of the final product following indices are used given in Equations 1, 2 and 3 (Asad, 2010).

$$\text{Lime saturation factor (LSF)} = \frac{CaO}{2.80SiO_2 + 1.18Al_2O_3 + 0.65Fe_2O_3} \quad (1)$$

$$\text{Silica ratio (SR)} = \frac{SiO_2}{Al_2O_3 + Fe_2O_3} \quad (2)$$

$$\text{Alumina ratio(AM)} = \frac{Al_2O_3}{Fe_2O_3} \quad (3)$$

The quality of the end-product is also based on the provision of major oxides within the specific limit (silica (14-15%), calcium (40-42%), alumina (2.7-3.4%) and iron (1.65-2.17%)). After the burning of raw material, the clinker contains compounds such as alite (C_3S) (30-35%), belite (C_2S) (15-20%), celite (C_3A) (6-8%) and brownmillerite (C_4AF) (4-9.6%) (Asad, 2010).

$$C_3S = 4.017 \times CaO - 7.6 \times SiO_2 - 6.718 \times Al_2O_3 - 1.43 \times Fe_2O_3 \quad (4)$$

$$C_2S = 3.071 \times CaO - 8.6 \times SiO_2 - 5.068 \times Al_2O_3 - 1.079 \times Fe_2O_3 \quad (5)$$

$$C_3A = 2.65 \times Al_2O_3 - 1.692 \times Fe_2O_3 \quad (6)$$

$$C_4AF = 3.043 \times Fe_2O_3 \quad (7)$$

Equations 4, 5, 6 and 7 are also employed to ensure the balance of the major oxides.

Bao et al. (2019) developed a novel algorithm to determine the chemical composition of raw material in the quarry. Chatterjee et al. (2015) employed a sequential branch and cut method to model production planning for limestone quarry while keeping quality and quantity requirements. Joshi et al. (2015) presented a long-term production planning with a consistent quality and quantity supply of raw material and used the branch-and-cut algorithm to generate a production sequence. Asad (2011) presented a quarry, production scheduling model to ensure the sustained supply of the raw material from the quarry. Rehman and Asad (2010) developed a mixed-integer linear programming (MILP) model to optimize the raw material blending, ensuring the objective of cost-saving while meeting the required quality and quantity. Almeida (2010) used a joint simulation (CoDSS) and direct sequential simulation (DSS) algorithm to evaluate the distribution of the local factors indices using geostatistical images. The presented literature, however, offers insight into the cement raw material production planning, but scarce with uncertainty incorporation. Jones et al. (2013) used multiple pint statistics (MPS), an emerging spatial simulation framework to evaluate the high-order spatial relationship. MPS uses training images to assess the volumetric and geological uncertainty that can be used for the calculation of grade uncertainty and the uncertainty related to entire deposit. Vu et al. (2020) assessed the geological uncertainty related to cement raw material based on hierarchical simulation.

Materials and Methods

In this study, Monte Carlo simulation was employed to predict the effect of major oxides on indices values, preceding the raw mix design. The chemical composition of limestone dust samples was obtained to carry out scenario analysis. In this analysis best fit probability distributions were analyzed and generated through software package Microsoft Excel and SimulAr, followed by computation of the number of scenarios using Monte Carlo simulation and indices formulas to analyze the factors (LSM, AM and SR). After that, the results of the factors are estimated for each scenario. Finally, the best, most frequent and worst scenarios are estimated on the basis of optimum values of the factors using linear programming formulation (Fig. 1).

In the initial step, the decision-making scenario is completely represented through a mathematical model. In the first step, describe the problem and distinguish the input and output variables. Next, determine the precise relationship between input and output variables and finally, creating a mathematical model using a spreadsheet. The second step involves uncertainty identification-related input variables that are significant for making a decision. Uncertainty is modeled by specifying the most likely probability distribution for the decision variables. In the third step, the model is simulated with hundreds or thousands of iteration (combination) of input variables. These combinations are randomly selected from the predefined distribution of input variables. These simulations result in potential outcomes and their distributions are obtained. From the simulation results and obtained distributions in the third step, the quarry manager may able to choose the best course of action. Therefore, simulation results also provide an effective understanding related to resource allocation.

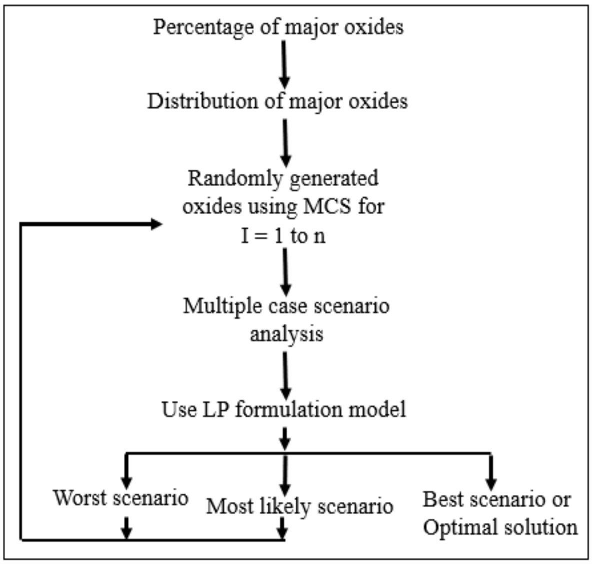

Fig. 1 Framework for the prediction of the best and worst scenario.

In this study a detailed application of scenario analysis is presented in cement raw material production planning using data from FECTO cement, located about 1.6 km north of the Sangjani, Islamabad, Pakistan. The clinker production capacity of FECTO cement is 2600 tons/day. The required raw material is transported from limestone dust stocks produced by crushing of limestone for aggregate production because the Capital Development Authority (CDA) banned the quarry operation at Margalla hills.

During planning for raw mix design, scenario analysis is used to find out the best, worst and most likely case scenarios possibility. From the projection of distribution, the likelihood of best, worst and most likely results of LSF, SR and AM is observed. This case study is aimed to find the effect of variation in major oxides on the LSF, AM and SR or Raw mix design. For the Monte Carlo simulation, the data given in Tables 3.1, 3.2 and 3.3 were used. Monte Carlo simulation uses random numbers to generate random data.

Results and Discussion

The percent content of oxides obtained from chemical analysis of the limestone dust samples is used to estimate the descriptive statistics and evaluate the best fit probability distributions. Probability and frequency distribution is a reliable approach to explain the trend of the data. The statistics of the major oxides are provided in Table 1, and the probability distributions plots are presented in Fig. 2.

Table 1**.** Summary of major oxides and MgO descriptive statistics.

Statistics	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	K_2O
Sample size	30	30	30	30	30	30
S D	4.77	1.32	0.646	3.746	1.51	0.144
Average	7.359	1.62	0.851	49.086	1.123	0.211
Skewness	1.5	1.59	1.40	-1.35	5.49	0.910
Kurtosis	2.28	2.5	0.86	1.22	30.91	0.29
Mode	9.09	1.76	0.30	9.17	0.79	0.02
Median	6.31	1.19	0.62	6.29	0.791	0.161
Mean	7.34	1.51	0.85	7.29	1.18	0.220
Confidence level	95%	95%	95%	95%	95%	95%

Based on the goodness of fit test, distributions followed by major oxides are SiO_2 (largest extreme value), CaO (smallest extreme value), Fe_2O_3 (lognormal), Al_2O_3 (Weibull), K_2O (Weibull) and MgO (Weibull) (Fig. 4).

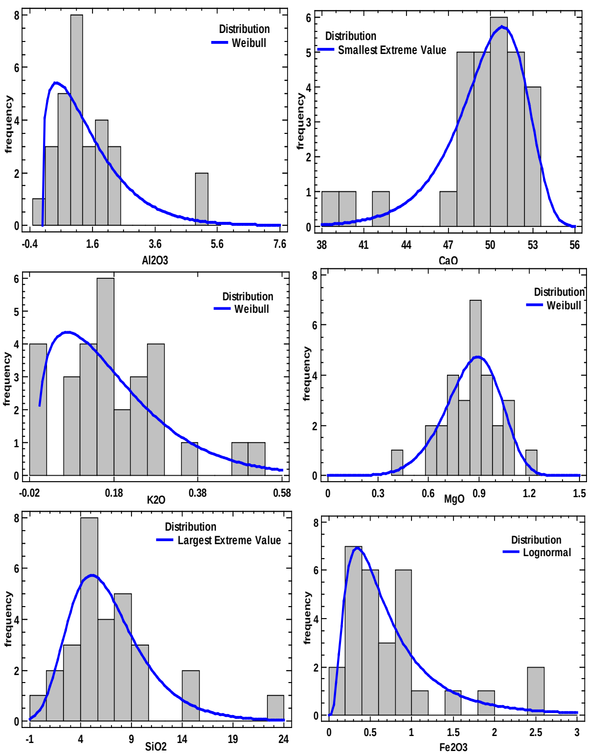

Fig. 2 Probability distributions of major oxides and MgO of limestone dust.

Monte Carlo simulation is used to model sample data using indices formulas given in Equations 1, 2, and 3 to address the possible best, worst and most likely case scenarios for raw mix design. Indices parameters (major oxides) are used to achieve the statistical models of indices. The existing data are simulated up to 500 alterations using Monte Carlo simulation. The results from the simulation were used to find out the possible scenarios and possible indices that require raw material blending to fulfill the quality requirements.

From the scenario analysis, it is revealed that about 35.4% of scenarios are best-case scenarios and 41.6% are worst case, while 23 % are most likely case scenarios. The results of the predictive values of indices in percentage are given in Table 2.

Table 2. Percentage and probability of predictive values in the range.

Indices	Values in Range	Probability
LSF	82%	0.82
AM	58.4%	0.584
SR	52.1%	0.521
C_2S	89.5%	0.895
C_3S	83%	0.83
C_4AF	95.8%	0.958
MgO	60.4%	0.604
C_3A	60.4%	0.604

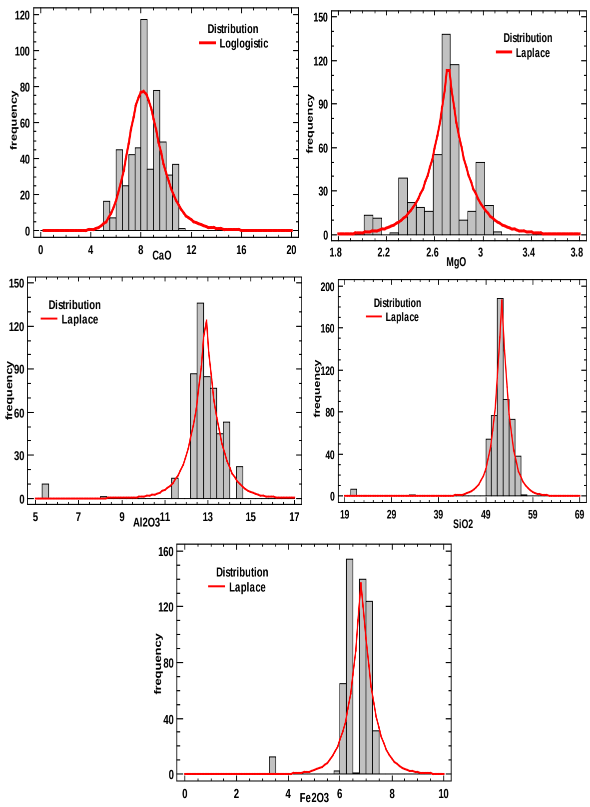

Fig. 3 Frequency distribution of major oxides and MgO of shale.

It is predicted that limestone dust used for cement manufacturing in this case study is of average quality using scenario analysis. It is suggested to fulfill the CaO for quality requirement using high-quality limestone with limestone dust as a raw material. Laterite with low MgO content < 10% should be provided to maintain MgO content up to an acceptable level. Similarly, to keep silica at a smooth level, shale with high silica content should be provided. Hence preceding to raw mix design using Monte Carlo simulation for scenario analysis, can help in the decision about production planning.

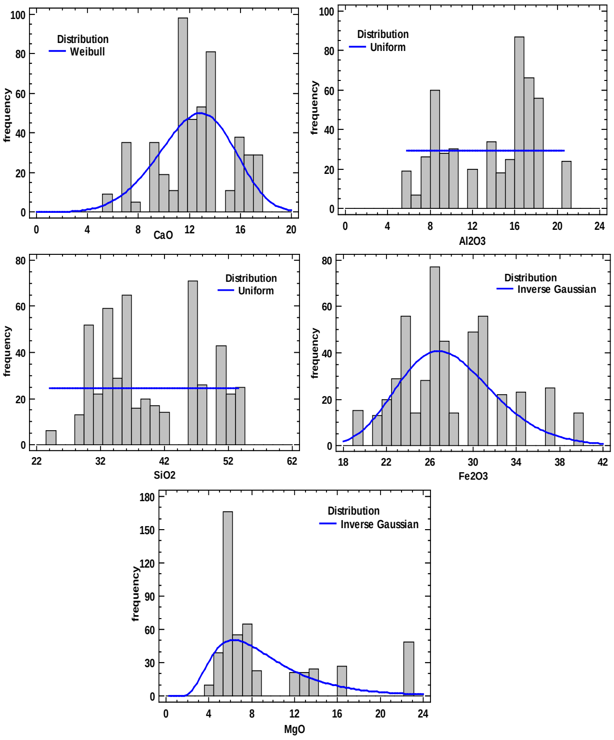

Fig. 4 Histogram of the observed distribution of major oxides and MgO of laterite.

In this study short-term production planning is done based on the optimized raw mix which is designed to find the optimum short-range production plan for this case study. The optimum production plan should ensure the stockpile capacity of 26000 tons. The cost of limestone dust and additives acquired from the market is given in Table 3.

Table 3. Purchased cost and required quantity limits of the raw material.

Raw material	Purchased Cost ($/ton)	Required quantity (tons)	
		Minimum	Maximum
Limestone D 1	0.8	0	20,000
Limestone D 2	0.85	0	20,000
Limestone D 3	0.9	0	20,000
Shale PC	0.66	300	6000
Laterite-I	2.42	10	1500

The variation in the purchasing cost of limestone dust is due to variation in transportation cost because the raw material is transported from various locations. Manual planning involves a trial and error approach which is impractical in this case study and also may be time-consuming. Linear programming (LP) model indices are used to achieve optimum blending. Excel solver was used to developing an LP model. Linear programming-based optimization ensures the required quality and quantity of raw material for blending at minimum cost. Therefore, two optimized scenarios are presented out of 500 scenarios to evaluate the applicability of the proposed approach. The purchasing cost of raw material for scenario-I is 19285 dollars and for scenario-II is 19265 dollars given in Table 4.

Table 4. Raw material and their optimum cost for scenario-I and II.

Raw material	Sample	Raw material (tons)	
		Scenario-I	Scenario-II
Limestone D 1	N 9	19,150	18,961
Limestone D 2	NE 09	0	0
Limestone D 3	NE 9	0	0
Shale PC	SPC	5,670	5,855
Laterite-1	935	170	174
	overall cost ($)	19285	19265

Scenario analysis revealed that scenario-I and scenario-II provide 19150 tons and 18961 tons of raw material to fulfill the stockpile requirement. The optimum values of the indices of both scenarios are given in Table 5. Therefore, the optimum planning ensures the maximum use of limestone dust to avoid the maximum additives purchased from the market.

Table 5. Quality parameters of raw material blending in scenario-I and II.

Quality Parameters	Lower limit	Upper limit	Optimized values for Scenario-I	Optimized values for Scenario-II
Silica ratio (SR)	2.5	2.9	2.66	2.6
Alumina modulus (AM)	1.5	1.8	1.80	1.80
Celite (C_3A)	6	8	6.22	6.37
Alite (C_3S)	30	35	30.75	32.7
Belite (C_2S)	15	20	20.00	20.00
Brownmillerite (C_4AF)	4	9.6	6.15	6.29
Lime saturation factor (LSF)	0.86	0.97	0.89	0.86
Magnesium oxide (MgO)	1%	2%	1.15	1.17
Required raw material (tons)	25,000	30,000	25,000	25,000

The cement industry in Pakistan usually used 73% limestone, 23% clay and 2% laterite to manufacture the final product of cement. In the case of FECTO cement 85% limestone dust, 9% shale and 6% laterite are used to meet the kiln need. By using the proposed approach for FECTO cement the results revealed that 77% limestone dust, 22% shale and 1% laterite for scenario-I, while for scenario-II, 76% limestone dust 23% shale and 1% laterite provides optimum raw material blending. The results also revealed that according to the chemical composition of raw material and additives, at an optimum cost the quantity of limestone varies from 76% to 90%, shale from 8% to 13% and laterite from 0.055% to 1.25% respectively.

The difficulty in modeling the available raw material is the variation in chemical composition, where the limestone dust pile is an essential factor influencing the distribution. The design of the resource model without this relation may be unrealistic. In some places the laterite composition is extremely high that is unacceptable, while in some scenarios the CaO grade is lower that is unreasonable. Therefore, due to these variations, most of the scenarios deviate from the required quality. The quality deviation also provides a better picture to understand the ground reality before quarry planning. In this study, a Monte Carlo simulation-based scenario analysis has been proposed to overcome the challenge related to uncertainty based on the chemical composition of raw material. The MCS reproduces the chemical composition based on their real-time chemical composition probability distribution. Despite this, there is some criticism on MCS, such as abominable contact relation among rock type and deficiency of image or simulation-based results.

Conclusion

Adequate production planning from the quarry and raw material purchased from the market has a key role in optimizing the raw material blending. The results of Monte Carlo simulation and scenario analysis presented in this paper induct standards that could assist FECTO cement managers in ascertaining the appropriate strategy for production planning. It is evident from the Monte Carlo simulation that 500 scenarios are addressed for raw mix design using scenario analysis. The results revealed that 35.4% of scenarios exhibit the optimum values for indices fulfilling the quality and quantity requirements. Monte Carlo simulation not only randomly sample data but also cope with the uncertanity related to raw material chemical composition. Therefore, this approach ensures not only optimum raw material blending but also provides detailed background by prediction to choose ideal blocks for raw material extraction. The results revealed that these models and techniques help in better decision-making related to production planning of cement quarry operations.

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