WEBSJOURNAL OF SCIENCE AND ENGINEERING APPLICATION

WESEA ISSN: 1974-1400-X,

Vol 12, No 1, 2023,-666-671

LATERITE-CEMENT COMPONENT MIXTURE SELECTION USING GENETIC ALGORITHM

T. O Alao[1], A. A. Adedeji[2] and V. Kamara[3]

[1]Department of Building, Federal University of Technology, Minna. Nigeria

[2]Department of Civil Engineering, University of Ilorin, Ilorin, Nigeria

[3]Department of Civil Engineering, Namibia University of Science and Technology

ABSTRACT

Meeting specification requirements at first attempt in mixture proportioning are difficult to achieve without employing a carefully designed process. Such a method is regarded to, as an experimental design process. A Genetic Algorithm (GA) seamless process is carried out here for a laterite-cement brick component selection process for use, particularly in mass housing project. It involved firstly, by developing a prediction equation described here as the objective/cost function achievable within a constrained design domain for component mixture quantities using the Scheffe mixture design process. Secondly, the relationship of component mixtures which yields responses such as cost were modelled as equality or inequality constraints. The choice of the GA procedure employed was based on the feasibility of the solution and convergence rate to obtain solutions meeting the specification requirement desired. This method enabled obtaining combinations of mixture quantities in an effortless way to meet the desired user requirement.

Key words: component selection, genetic algorithm, variables

1. INTRODUCTION

Mixture experimental designs are usually employed with an assurance that specification requirements are met with utmost reliability of prediction in an on-site or off-site production processes. Generally, a diverse range of choice of methods are available depending on practice procedures often referred to as standards varying from one country to another. These include methods ranging from absolute volume method, experimental methodologies such as the Taguchi's method, Classical Mixture Approach, Factorial experimental design method and other analytical experimental approaches, (Alao and Jimoh, 2017; Alao and Jimoh, 2018).

In the development of procedures capable of arriving at solutions yielding the quantities of component mixtures, it is usually necessary to formulate problem statements referred to as the objective function. This problem statement in itself is incapable of yielding a seamless solution and therefore a number of equality or inequality constraints may enhance re-defining the problem statement. These may take the form of a linear or quadratic expressions which can further be defined by boundary conditions often referred to as limits or a domain of component proportions selection. The aim being to obtain constituent mixture proportions capable of meeting a desired or a specified performance criterion.

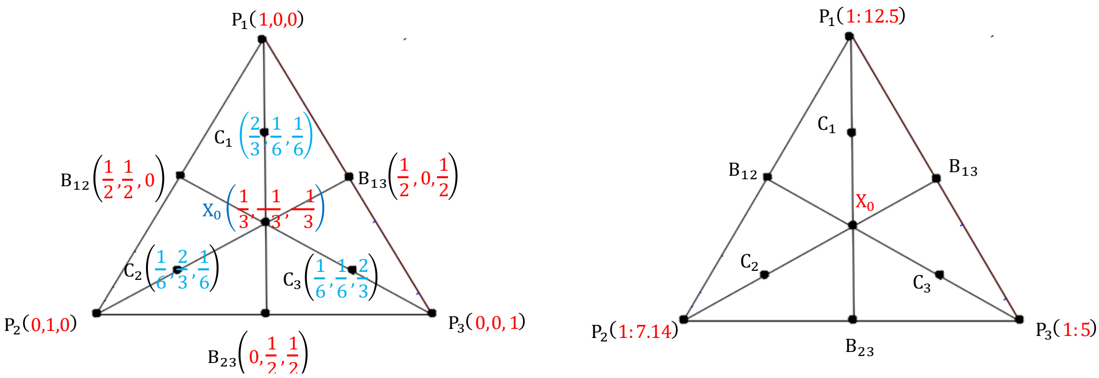
2. MODEL FORMULATION USING THE MIXTURE APPROACH

A Scheffe's method of mixture polynomial which is implementable using Design Expert 12 Software (Design Expert, 2000) is capable of predicting properties of a mixture within a simplex design. In this method of response prediction, the constituent proportions, estimated in absolute volume is fixed and constrained to be summed equal to unity. This is a pre-condition of this solution procedure where one of the constraints must be equality (Montgomery, 2001; Simons et al, 1999). For an n-number of components, the perfect expression of all absolute volumes of the materials equal to unity can be expressed with a constraint equation written out as:

$$\sum_{i=1}^{n} x_i = 1 \qquad (1)$$

and $x_i \geq 0$

Graphically, the experimental points show the vertices which represent the pure blends, the mid-points represent the binary blends on each of the three sides of the triangle. To enable a better prediction of the properties of the mixture, control points are added and a single centre-point. This is shown in Figures 1(a) and 1(b). The vertices P_1, P_2, and P_3 are fitted with cement:laterite ratio 1:12.5, 1:7.14 and 1:5 representing 8%, 14% and 20% cement content respectively at optimum moisture content.



(a) (b)

Figure 1(a), b) : An augmented Simplex design (Alao and Jimoh, 2018)

The number of design points is represented by the expression in Equation (2), (Montgomery, 2001):

$$N = \frac{(p+m-1)!}{m!(p-1)!} \qquad (2)$$

The design is however, further augmented with additional points in the interior of the region. This enables making the prediction equation about all the properties of the complete mixture possible within the simplex. This quadratic model is shown in Equation (3):

$$y = \sum_{i=1}^{p} \beta_i x_i + \sum \sum_{i<j}^{p} \beta_{ij} x_i x_j \qquad (3)$$

2.1 GA principles and process

GAs, formulated as an optimization problem are usually not solved on real materials but rather on formulated models as in Equation (3). Empirical models yielding responses of interest offers objective functional expressions and their reliability are often improved by removing all insignificant terms having probalility $p < 0.05$. This resulting functions or response model is called, the response prediction equation or objective/cost function representing at least 95 percent of the results falling within the normal distribution curve. The GA concept is an evolutionary method that is usually based on a population of solutions which can be improved progressively thus leading to a number of optimal solutions of the continuous variables input. Subsequent runs in the iterative process can yield a global minimum of the component variables combinations, called improvements, (Amouzgar, 2012; Carr, 2014). This method essentially mimics the natural evolutionary process of humans for reproduction and natural selection of genes and chromosomes to yielding the best or optimum. Constraints are often inevitable just as in all practical engineering problems, which are needed to improve the chances of arriving at solutions for both single and multi-objective functions. In this iterative process, the solution is updated in each generation which eventually converges to a single optimal solution. (Gen and Cheng, 1997; Deb, 2001).

The genetic operators perform the objective of duplicating and keeping only the fit solutions, thereby eliminating poor or unfit chromosomes, (Carr, 2014). Chromosomes can be referred to in this context here, as individuals or a vector of variables which carry inherited cell information.

2.2 GA coding methods

GA parameters can be coded using binary strings or where this can cause some computational difficulties, real or floating-point numbers could be used to represent the variable. Using floating point numbers is however considered more logical and there is no need for decoding before fitness evaluation (Carr, 2014). When solving non-integer floating point numbers, it is expedient to make the chromosomes for reproduction, as an array of real numbers. This implies that the chromosomes are presented as an $N_{parameter}$ element array (Carr, 2014) of the form in Equation (4)

$$chromosome = \left[P_1,\ P_2, P_3, \ldots, P_{N_{par}}\right] \qquad (4)$$

Where each P_i represents a particular value of the i^{th} parameter of the floating-point numbers.

2.3 Selecting initial population of chromosomes and evaluating its function

The method employed here uses a set of initial populations of chromosomes which are selected at random and this represents the first generation. This initial population of chromosomes are tested for its fitness, referred to as the fitness functional evaluation. The next chromosomes that will reproduce are then selected based on the estimation of their fitness values using a probability distribution, (Carr, 2014) defined in the Equation (5) as:

$$P(chromosome\ i\ reproduce) = \frac{f(x_i)}{\sum_{k=1}^{N} f(x_k)} \quad (5)$$

This probability distribution is described as the proportion of its fitness function to the sum of the fitness functions of all the individuals in the current generation. Therefore, the fitter the chromosome is, the more likely it is to be selected. Functional evaluation at each iteration tests and quantifies the fitness of each of the potential solution in the iterative history, thus showing each of the candidate solutions for each of the selection process. In the Haupt's method (Haupt & Haupt, 1998), it uses a selection of random parameters where the entire populations with new offspring are not replaced completely but rather a fitter half of the current population is kept and the other half generated. The probability that the new set of chromosomes in the nth place will be a parent for reproduction is re-evaluated and ranked, (Haupt & Haupt, 1998) as in shown in Equation (6):

$$P_{(C_n)} = \frac{N_{keep} - n + 1}{\sum_{i=1}^{N_{keep}} i} \quad (6)$$

2.4 Handling of the fitness functions with imposed constraints

Constraints handling methods for both single and multi-objective functions are based on adaptability and convergence in the particular circumstance. These include methods based on preserving feasibility of solutions, methods based on penalty functions, methods biasing feasible over infeasible solutions, methods based on decoders and the hybrid methods, (Deb, 2001; Amouzgar, 2012). A penalty functions can transform a constrained problem into an unconstrained one by simply adding a multiplier into the equation as a penalty for the addition of artificial variables which does not initially exist in the fitness function. Penalties serve several functions and are similarly categorized by Deb (2001) as: Death Penalties, Static Penalties, Dynamic Penalties, Annealing Penalties, Adaptive Penalties and Segregated GA.

3. METHODOLOGY

Problem formulation that yields a solution of this type are usually not solved on real materials. Instead, prediction models refered to as objective functions are required which can be further re-defined by imposed constraints.

3.1 Response prediction for 28-day strength

The quadratic (inverse) relationship for response prediction for strength is shown in Equation (8). All constant terms have been eliminated, yielding a statistical significance with probability $p \leq 0.05$. The variables x_1, x_2 and x_3 represents the quantity of water, cement and laterite respectively, (Alao and Jimoh, 2017).

$$Strength, \frac{1}{(fc)_{28}} = -3.54724x_1 + 0.10341x_2 + 1.53865x_3 \quad (8)$$

3.2 Response prediction for Cost

Similarly, relationship for response prediction for cost, yielding a statistical significance with probability $p \leq 0.05$ is shown in Equation (9), (Alao, 2018):

.

$$Cost, \quad C = -9.48243x_1 + 236.04554x_2 + 1.53865x_3 \quad (9)$$

Again, the variables x_1, x_2 and x_3 represents the quantity of water, cement and laterite respectively.

3.3 Construction of a Ratio for cement:laterite mixture

In building an equality constraint for ratio of the component mixture, the ratio of cement to laterite using for example, an 8% cement content representing a ratio 1:12.5 within the limits considered, the procedure is:

$$\frac{x_3}{x_2} = 12.5; \quad (9a)$$

where x_2 = cement and x_3 = laterite

This can be re-written as: $x_3 = 12.5x_2$, and re-arranging gives: $-12.5\,x_2 + x_3 = 0$. Multiplying by the respective unit weights of 3150kg/m^3 and 2640kg/m^3 for cement and laterite respectively yields the expression in Equation (10):

$$Cement\!:Laterite\ ratio = -39375x_2 + 2640x_3 = 0 \quad (10)$$

3.4 The lower and upper limits on the component mixes

In building the limits on the component mixture proportions, the considerations on this domain of component mixture combinations were between 8 and 20% cement content. This domain is represented in absolute volumes as shown in Equation (11)

$$\begin{bmatrix}0.261\\0.046\\0.633\end{bmatrix} \le \begin{matrix}x_1\\x_2\\x_3\end{matrix} \le \begin{bmatrix}0.266\\0.106\\0.688\end{bmatrix} \quad (11)$$

3.5 Building the objective function and constraints for the GA process

The general formulation of the problem is written thus:

$$\text{Maximize/Minimize} \quad f(x) \quad (7)$$

$$\text{Subject to} \quad h_k(x) = 0 \quad , \; g_j(x) \le 0 \quad , \; x^l \le x_i \le x^u \quad (7a)$$

In which $j = 1,2,3,\dots,J$ and $k = 1,2,3,\dots,K$

These equality, inequality and limits constraints restrict the decision variables and also within a lower and upper limit. When a solution satisfies all these constraints, then it is referred to as a feasible solution (Brandt and Marks, 1993).

3.6 GA problem formulation Validation

Quantities of constituent proportions of the materials can be validated using the Design Expert software by simply imputing the desired strength, which in this case is the reciprocal of the strength, the objective function. The values of the constituent proportions can also be read from either the trace or contour plots, which are graphical reproductions of the relationship of the variable inputs to yield the desired strength satisfying all the constraint input. An approximate method specified by (Alao and Jimoh, 2018) which uses in addition, a linear relationship called quantity of laterite based on the cement quantity assumed. The method also uses an additional equation relating quantity of mixing water at maximum dry density to the ratio of cement: laterite obtained in a regression equation. The results compared favourably.

4. DISCUSSION OF RESULTS

The building up for the solution process are listed which include defining the objective function, the linear equality of all the absolute volumes equal to unity which is a pre-condition for the Simplex method and limitation on the cost.

4.1 GA problem formulation

$$Minimize\ f(x) = a_{1i}x_{1i} + a_{2i}x_{2i} + a_{3i}x_{3i} \qquad objective\ function, strength$$

Subject to inequality constraint:

$$x_{il} \le x_i \le x_{iu} \qquad upper\ and\ lower\ limits\ on\ the\ variables$$

$$\sum_{i=1}^{3} a_i x_i \le c_i \qquad cost$$

Subject to equality constraint:

$$\sum_{i=1}^{3} x_i = 1 \qquad sum\ of\ absolute\ volumes\ must\ be\ equal\ to\ 1$$

$-a_i x_{2i} + x_{3i} = 0$ ratio of cement: laterite

$i = 1, 2, 3$ *number of component variables*

4.2 Problem setup and results

```
i) function z = ((x(1).*(-3.54724))+(x(2).*(0.10341))+(x(3).*(1.53865)))as in
Equation (9)
ii) Linear inequalities for Cost, (Equation (9):
```

$$[-9.48243 \quad 236.04554 \quad 24.41443] \leq [30]$$

iii) *linear equality for all the absolute volumes equal to unity (Equation (1) is:* $[x_1 \quad x_2 \quad x_3] = [1]$

iv) Linear equality for Ratio of cement:laterite, (Equation (10)

$$[0 \quad -39375 \quad 2640] = [0] \qquad (10)$$

v) Bounds (Equation (11)):

$$[0.261 \quad 0.046 \quad 0.633]^T \leq x_i \leq [0.266 \quad 0.106 \quad 0.688]^T$$

v) The solution is shown in Figure (2)

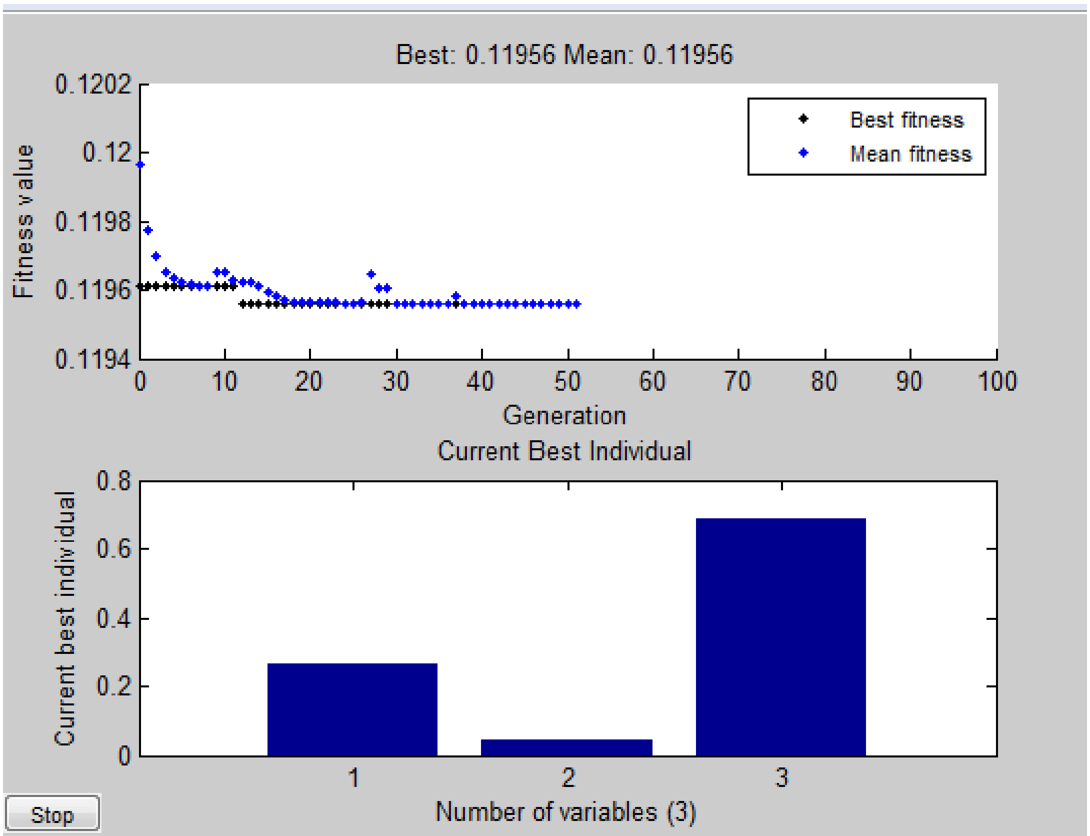


Figure 2: Fitness plot from GA Solver

The solution satisfying the fitness function is: x1 = 0.266, x2 = 0.046, x3 = 0.688

Or by multiplying by their respective unit weights: x1 = 266, x2 = 145, x3 = 1816.32kg/m³ representing water, cement and laterite respectively, with functional evaluation $\frac{1}{f(x)}$ *= 0.11956 and the inverse is 8.364N/mm²*

5. CONCLUSION

An advantage of the GA method is that it does not require any extra information such as search direction. There is also no evaluation of derivatives of the objective functions at every iteration. It also progresses from a population of candidate solution instead of a single point search thereby reducing the likelihood of searching for a local minimum. It also does not require numerous prediction equations or other relationships to arrive at solutions thereby offers a seamless process.

REFERENCES

Alao, T. O. and Jimoh, A. A. (2017). Performance Criteria design of mixture proportions for laterite-cement bricks using the Schéffé Mixture Approach. Journal of Research Information in Civil Engineering. 14 (3), 1626-1649.

Alao, T. O. and Jimoh, A. A. (2018). Response prediction for strength and Durability properties of laterite-cement bricks using the Scheffe Mixture Approach. Nigerian Journal of Engineering and Applied Sciences.4(2), 120-136.

Alao, T. O. and Jimoh, A. A. (2018). Development of specifications writing procedure for mixture proportions for laterite cement bricks using the Central Composite Design Approach.Nigerian Building and Road Research Institute.12th – 14th June, Abuja, Nigeria. 180 -190

Alao, T. O. (2018). A rational approach to estimating the cost of laterite-cement bricks. Journal of Research Information in Civil Engineering. 15(1), 2071-2082.

Amouzgar, K. (2012). Multi-objective Optimization Using Genetic Algorithm. Master's Thesis Dissertation on Product Development and Materials Engineering. Tekniska Högskolan, Högskolan. http://www.diva-portal.org/smash/get/diva2:570751/FULLTEXT01.Pdf

Brandt, A. M. and Marks, M. (1993). Examples of the Multicriteria Optimization of Cement-Based Composites. Composite Structures. 25, 51-60. Elsevier Science Publishers Ltd, England.

Carr, J. (2014). An Introduction to Genetic Algorithms. https://www.whitman.edu/documents/academics/mathematics/2014/carrjk.pdf

Deb, K. (2001). Multi-objective Optimization Evolutionary Algorithms. John Wiley & Sons Ltd. The Atrium, Southern Gate, Chichester, West Sussex, England. https://www.semanticscholar.org/paper/Multi-objective-optimization-using-evolutionary-Deb/f51afa2745947c11300c65ce001dc6fb2ddd5c2e

Design-Expert, (2012). Stat-Ease Corporation. https://www.statease.com › docs

Gen, M. and Cheng, R. (1997). Genetic Algorithms and Engineering Design. New York, Wiley Inter science. https://www.wiley.com/en-us/Genetic+Algorithms+and+Engineering+Design+-p-9780471127413

Haupt, R. L. and Haupt, S. E., (1998). Practical Genetic Algorithms. New York: Wiley-Inter Science. https://www.wiley.com/en-us/Practical+Genetic+Algorithms,+2nd+Edition-p-9780471455653

Montgomery, D. C (2001). "Design and Analysis of Experiments". 5th Edition, John Wiley & Sons, New York. 427-473.

Simon, M.; Snyder, K. and Frohnsdorff, G. (1999). "Advances in Concrete Mixture Optimization". Advances in Concrete Durability and Repair Technology Conference, University of Dundee, Scotland, UK. Thomas Telford Publishing. 21-32.