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Development of a Simplified Methodology for British DoE Concrete Mix Design Procedure using python

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ABSTRACT

Most of the methods of concrete mix design developed over the years were geared towards manual approach. Apart from being characterized by rigorous complication in computation, manual concrete mix design is prone to errors and mistakes inherent in the calculation during interpolations and reading of charts. Thus, this research introduces an innovative integration of Python algorithms into mobile applications for concrete mix design. The tables used in this algorithm are the same as those used in the British Method, however, Charts or Figures in the British method were converted into linear and polynomial equations. Python program was written to ease the use of the algorithm and it was also configured into the backend of a mobile application for user-friendliness. The results obtained from the algorithm were compared with those obtained based on the British method manual calculations and available datasets. The percentage errors between the algorithm results and manual calculations were found to range from 0.65% to 3% across all examples. The developed algorithm is a reliable tool for automating DoE concrete mix design computations.

KEYWORDS: British Method, Concrete Mix Design, Mobile App, Python-Based Algorithm.



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41

1 | INTRODUCTION

Concrete is one of the most consumable construction materials on the earth [1]. When concrete ingredients are mixed in proportion it undergoes a chemical reaction called hydration, where the water reacts with the cement particle. It hardens with time and become a durable, strong and versatile construction material. According to Olugbenga [10], concrete is the most popular construction material in the world. It is made up of cement, water, coarse and fine aggregates, and possibly additives or admixtures. Each component plays a specific role in the overall engineering, mechanical and chemical properties of the concrete mixture.

Concrete mix design is one of the most critical issues in concrete technology. This process aims to create a concrete mix which helps deliver concrete with desired features and quality [16]. According to Bansal [3], Concrete mix design is basically the process of selecting suitable ingredients and determining their relative proportions with the objective of having minimum workability, strength and durability as economically as possible.

British department of environment concrete mix design was created in The United Kingdom's Department of Environment, and is well-known as DOE method for designing concrete based on empirical data that are provided to designers in the form of curves [15]. This method can also be called British standard method and the latest version was released in 1988.

The traditional method of concrete mix design has been a lengthy, time-consuming, and requiring high level of expertise or professionalism to be carried out. Additionally, in times of practice in the field, carrying out department of environment (DoE) concrete mix design methodology manually can be highly human error prone due to the use of its complex charts and tables leading to miscalculations and numerous assumptions that may result in poor quality concrete. Hence, there is a need for a more simplified methodology for DoE concrete mix design.

Some researchers have developed simplified methodologies and algorithms for concrete mix proportioning to address the cumbersome nature of traditional methods. Ezeh et al [5] proposed a mathematical algorithm based on the British Method by converting charts into polynomial equations and automating the process using QBASIC, achieving a 10% error margin. Similarly, Arimanwa et al [2] utilized a computer worksheet for automated mix design, although the procedure often resulted in deviations due to computational constraints.

Other approaches include machine learning integration. Tran [14] developed Excel-based models for mix optimization using gradient boosting, while Penki et al. [11] employed Solver to optimize aggregate proportions efficiently. Najam and Khushnood [8] highlighted interactive computing for iterative optimization in concrete proportioning. Kasperkiewicz [6] introduced early computational frameworks for mix design.

While previous works have automated the process using QBASIC, worksheets or Machine learning, they often resulted in higher error rates (>10%). This study leverages Python's advanced libraries to reduce error margins and enhance accuracy.

This is a worthy task because it would be useful in estimating the proportions of concrete constituents that will be required to attain a desired concrete property faster and accurately without the use of complex charts and tables. The resulting mobile application software will be useful to both structural engineers and practitioners in the construction to design concrete of a specific strength accurately on site with ease and also to validate their results.

2 | BRITISH STANDARD METHOD OF CONCRETE MIX DESIGN

British standard method of concrete mix design has been an important aspect of structural engineering that involves exploring the principles of concrete mix design to develop a standard that fits the environment conditions. The method of concrete mix design applied here is in accordance to the method published in year 1988 by the Department of Environment, United Kingdom.

The method consists of the following procedures. Required design mix data:

Specified characteristic strength (fc).

Grade of concrete.

Degree of workability desired Slump or Vebe test (using 0 - 10).

Degree of quality control expected to be exercised at the construction

Exposure condition at the construction site

Type and maximum size of aggregate to be used (using 20mm).

Standard deviation of compressive strength of concrete samples

Specific gravity of aggregate.

Cement type = Ordinary Portland cement, sulphate resisting (OPC)	Sulphate resisting cement crushed 28 36 49				
Sieve analysis test (percentage of fine aggregate)					
2.1 Determining the water/cement ratio:	Hence, strength at 28 days = 49 N/mm2				
Margin (M), $M = k \times s$	Calculating target mean strength:				
Various values of K are as showed in Table 1.	$fm=fc+1.64 \times s$				
Fc = the specified characteristic strength	$fm = 49 + (1.64 \times 4) = 55.6 \text{ N/mm2}$				
s = The standard deviation ($s = 4$ is assumed)					
k = normal distribution.					
Table 1: The value of k based on the percentage defective	Figure 2: relationship between compressive strength and				
Percentage Defective Value of K	water / cement ratio				
10% 1.28					
5% 1.64	Figure 2 $(FWR) W/c= 0.46$ is obtained				
2.5% 1.96					
1% 2.33	Table 3: Approximate free-water contents (kg/m3)				
K = 1.64 (specified in BS 5328. for illustration, will use this)	Agg size Agg type Slum(mm)				
The characteristic strength can be gotten from the	Vebe time(s) 0-10, >12 10-30				
standard deviation(s) using Figure 1	6-12 30-60				
	3-6 60-180				
Figure 1: Relationship between standard deviation and characteristic strength	0-3				
	20mm uncrushed 135 180 180 195				
2.2 Calculation of the target mean strength (fm):	crushed 170 190 210 225				
$Fm = Fc + k \times s \tag{1}$					
The approximate or characteristic strength (Fc) in eqn (1) of the concrete is obtained from Table 2.	From Table 3 There required $FWC = 170 \text{ kg/m3}$ was obtained from the aggregate size, type and slump value.				
	2.3 Determination of the cement content (Cc):				
Table 2: Approximate compressive strength (N/mm2)	Cement Content = Free Water Content / water-Cement Ratio				
Cement type Type C. A Compressive strength					
at age (Mpa) 3 7 28	Cc =FWC/FWR=170/0.46= 369.6				

Total volume of aggregate = Wet density - Cc - FWR

where;

Ac = total volume of aggregate (in kg/m3)

D = The wet density of concrete (in kg/m3)

C = The cement content (in kg/m3)

W = The free-water content (in kg/m3)

Hence, to determine wet density of concrete (Wdcc). This can be achieved from Figure 3 base on FWR of 0.46 and 2.7 specific density of aggregate from Figure 3.

Therefore, Wdcc = 2490 kg/m3

Finding Total volume of aggregate is thus calculated

Ac = 2500 - 369.6 - 170 = 1960



Figure 3: Estimated wet density of fully compacted concrete

2.5 Determination of the fine and coarse aggregate content:

Fine aggregate content (Fac) = Total aggregate content (Ac) x Proportion of Fines (Pfa).

Coarse Aggregate content (Cac) = Total Aggregate Content – Fine Aggregate. 2.6 Determination of volume of Fine aggregate content (Fac):

Based on aggregate size 20mm, w/c 0.46 and grading zone of sand (40% passing through 600um sieve).

The fine aggregate proportion (Pfa) is obtained using Figure 4.

33% of Fine aggregate from Figure 4.

 $Fac = 0.33 \times 1960 (Ac) = 646.93$

Cac = 196.04 - 646.93 = 1313.47

2.7 Determination of the concrete mix ratio:

The total volume of various constituent of mix design is,

Cement = 369.56kg/m3

Cement ratio = 369.56/369.56= 1

Fine agg. = 646.93 kg/m3

Fine agg. ratio $=\frac{646.93}{369.56} = 1.75$ Coarse agg. = 1313.47 kg/m3 Coarse agg. ratio $=\frac{1313.47}{369.56} = 3.55$ Free water content = 170kg/m³ Mix ratio (approximately) = 1:2:4

The manual approach to concrete mix design requires interpolations in determining intermediate values of variables for the concrete mix design, which is prone to human errors when tracing out, estimating and recording values. The development of a simplified procedure and methodology using python can reduce the complexity of this design process using Python, a popular high-level, interpreted programming language that is mostly preferred over other programming language due to its versatility, readability and simplicity [13]. Python was developed in the late 1980s by Guido van Rossum.



Figure 4: Recommended proportions of fine aggregate according to percentage passing a 600 µm sieve

3 | METHODOLOGY

3.1. Data Collection

Data collection of important parameters such as target mean strength, water/cement ratio, cement content, aggregates and other material properties and concrete characteristics of British standard concrete mix design. This data was gathered from manual calculations and laboratory test carried out. This data is further subjected to analysis to study them and know the important, dependent and key parameters in the data.

3.2 Data Extraction and Transformation

Extraction of the coordinates from the DoE concrete mix design charts, and tables into coordinates with the use of plot digitizer and python libraries as seen in Figure 5. Python codes were used to convert charts and tables to coordinates.



Transformation of the coordinates into linear or polynomial equations by the use of python libraries which includes Sk-learn, Pandas and NumPy. This process was repeated for relationship between Figure 1 the standard deviation and characteristic strength chart, Figure 2 the relationship between compressive strength and water / cement ratio, Table 3 the approximate freewater contents (kg/m3) required to give various levels of workability table, Figure 3 the estimated wet density of fully compacted concrete chart and Figure 4 the Recommended proportions of fine aggregate according to percentage passing a 600 μ m sieve chart. The transformation process is as shown in Figure 6.



Figure 6: Transformation of Traditional DoE Charts into equations

3.4 Python script programming:

Python script was programmed to completely automate the entire procedure in such a way that when the required inputs are provided correctly, the calculation is done and the require output will be returned to the user. The procedure flow is as shown in Figure 7.



Figure 7: Flow chart of concrete mix design

4 | RESULT AND DISCUSSION

Linear and polynomial equations obtained from the simplification of DoE concrete mix design charts and tables as follows:

Target mean strength equation (Fm) as in eqn 1 remains the same.

$$Fm = F + K \times S \tag{1}$$

4.1 Free water/cement ratio equation (Fw/c):

The Transformation of Figure 2 the relationship between compressive strength and w/c free water-cement ratio chart into two parabolic equations for uncrushed and crushed stones as follows:

$$Fw/c = 0.0002952Fm^2 - 0.0312Fm + 1.291$$
 (2)

$$Fw/c = 0.00008519157 Fm^2 - 0.01571 Fm + 1.0097$$
(3)

$$Fw/c = 0.000295 Fm^{2} - 0.0312 Fm + 1.351$$
(4)

$$Fw/c = 0.000008519157 Fm^2 - 0.01571 Fm + 1.0697$$
(5)

Equations (2) and (3) are for uncrushed stone with compressive strength of (10 - 42) N/mm² and (42 - 80) N/mm² respectively. Equations (4) and (5) are for crushed stone with compressive strength of (10 - 42) N/mm² and (42 - 80) N/mm² respectively.

4.2 Free water content equation (Fwc)

Table 3 the approximate free-water contents (kg/m³) For the required workability was programmed using python conditional statements into a program script.

4.3 Cement content equation:

The cement content equation as shown in eqn 6 is the ratio between the free water content and the free water ratio.

$$Cc = \frac{Fwc}{Fw/c} \tag{6}$$

4.3 Wet density of concrete equation (Wdcc):

. _ . . . _

Figure 3, the Estimated wet density of fully compacted concrete chart was transformed into six linear equations.

_ _ _ _ _ _ _ _ _

Wdcc = -1.7440 Fwc + 2898.4795	(7)
Wdcc = -1.5961 Fwc + 2802.5554	(8)
Wdcc = -1.4480 Fwc + 2702.8337	(9)
Wdcc = -1.2492 Fwc + 2410.3614	(10)
Wdcc = -1.0996 Fwc + 2500.6876	(11)
Wdcc = -0.9809 Fwc + 2410.3614	(12)

Equations (7), (8), (9), (10), (11) and (12) were equations obtained for saturated surface dry densities (SSDD) of 2.9, 2.8, 2.7, 2.6, 2.5 and 2.4 respectively.

4.4 Aggregate content equation (Ac):

The total aggregate content equation remains the same.

$$Ac = Wdcc - Cc - Fwc \tag{13}$$

4.5 Proportion of fine aggregate equation (Pfa):

Recommended proportions of fine aggregate according to percentage passing a 600 μ m sieve chart in Figure 4 was transformed into 60 linear equations as follows:

Where:

Pfa is percentage passing of fine aggregate.

Fw/c is the free water ratio

Each of the group of equation represents each segmented chart in Figure 4 based on the maximum aggregate size.

4.5.1 Maximum aggregate size of 10mm:

Slump of 0 - 10mm

 $100\% Pfa = 13.18908 \times Fw/c + 19.8728$ (14)

 $80\% Pfa = 16.16210 \times Fw/c + 22.6454$ (15)

 $60\% Pfa = 17.771430 \times Fw/c + 28.6479$ (16)

 $40\% Pfa = 26.4602 \times Fw/c + 32.2883$ (17)

 $15\% Pfa = 29.4189 \times Fw/c + 43.7290$ (18)

Slump of 10 – 30mm

$100\% Pfa = 11.7061 \times Fw/c + 21.4389$	(19)
$80\% fa = 13.6133 \times Fw/c + 25.1982$	(20)
$60\% Pfa = 18.7888 \times Fw/c + 29.1995$	(21)
$40\% Pfa = 26.4551 \times Fw/c + 33.6037$	(22)
$15\% Pfa = 28.1448 \times Fw/c + 45.2898$	(23)

Slump of 30 – 60mm

$100\% Pfa = 17176 \times Fw/c + 21.9764$	(24)
$80\% Pfa = 17873 \times Fw/c + 26.8855$	(25)
$60\% Pfa = 15.9632 \times Fw/c + 33.1685$	(26)
$40\% Pfa = 23.5540 \times Fw/c + 37.3736$	(27)
$15\% Pfa = 27.5801 \times Fw/c + 49.3627$	(28)

Slump of 60 – 180mm	
$100\% Pfa = 13.2146 \times Fw/c + 26.0036$	(29)
$80\% Pfa = 15.1139 \times Fw/c + 30.0719$	(30)
$60\% Pfa = 17.9339 \times Fw/c + 36.4952$	(31)
$40\% Pfa = 23.9291 \times Fw/c + 43.3777$	(32)
$15\% Pfa = 29.2583 \times Fw/c + 55.0112$	(33)

4.5.2 Maximum aggregate size of 20mm:	
Slump of 0 – 10mm	
$100\% Pfa = 12.7119 \times Fw/c + 13.7892$	(34)
$80\% Pfa = 13.9989 \times Fw/c + 16.7774$	(35)
$60\% Pfa = 19.0900 \times Fw/c + 18.9410$	(36)
$40\% Pfa = 23.6469 \times Fw/c + 22.0002$	(37)
$15\% Pfa = 27.6044 \times Fw/c + 29.3724$	(38)

Slump of 10 – 30mm

$100\% Pfa = 13.3050 \times Fw/c + 15.1615$	(39)
$80\% Pfa = 16.4544 \times Fw/c + 17.0508$	(40)
$60\% Pfa = 20.0436 \times Fw/c + 19.7431$	(41)
$40\% Pfa = 251666 \times Fw/c + 22665$	(42)
$15\% Pfa = 28.7500 \times Fw/c + 31.7355$	(43)
Slump of 30 – 60mm	

 $100\% Pfa = 11.7402 \times Fw/c + 17.5560$ (44)

 $\begin{array}{ll} 80\% Pfa &=& 17124 \times Fw/c \,+\, 19.8785 & (45) \\ 60\% Pfa &=& 19.1263 \times Fw/c \,+\, 23.3679 & (46) \\ 40\% Pfa &=& 23.6930 \times Fw/c \,+\, 27.7049 & (47) \\ 15\% Pfa &=& 30.9438 \times Fw/c \,+\, 35.5925 & (48) \end{array}$

Slump of 60 – 180mm	
$100\% Pfa = 10334 \times Fw/c + 19.9064$	(49)
$80\% Pfa = 16.9835 \times Fw/c + 22.1607$	(50)
$60\% Pfa = 20.7198 \times Fw/c + 26.1337$	(51)
$40\% Pfa = 22.9208 \times Fw/c + 32.9819$	(52)
$15\% Pfa = 29.3257 \times Fw/c + 41.2271$	(53)

 $\begin{array}{ll} 4.5.3 \ Maximum \ aggregate \ size \ of \ 40mm: \\ Slump \ of \ 0 - 10mm \\ 100\%Pfa \ = \ 13.0640 \ \times \ Fw/c \ + \ 9.9264 \\ 80\%Pfa \ = \ 15.0040 \ \times \ Fw/c \ + \ 12.2357 \\ 60\%Pfa \ = \ 17.9476 \ \times \ Fw/c \ + \ 12.6535 \\ 40\%Pfa \ = \ 25.5045 \ \times \ Fw/c \ + \ 15.9692 \\ 15\%Pfa \ = \ 27.6787 \ \times \ Fw/c \ + \ 22.2533 \end{array} \tag{54}$

Slump of 10 – 30mm	
$100\% Pfa = 11.2332 \times Fw/c + 12.4117$	(59)
$80\% Pfa = 12.8358 \times Fw/c + 14141$	(60)
$60\% Pfa = 16.61589 \times Fw/c + 16.3139$	(61)
$40\% Pfa = 23.3234 \times Fw/c + 18.6401$	(62)
$15\% Pfa = 27.7727 \times Fw/c + 23.9597$	(63)

 $\begin{array}{ll} Slump \ of \ 30-60mm \\ 100\% Pfa \ = \ 10.8513 \ \times \ Fw/c \ + \ 18334 \\ 80\% Pfa \ = \ 10.6332 \ \times \ Fw/c \ + \ 18.0029 \\ 60\% Pfa \ = \ 16657 \ \times \ Fw/c \ + \ 20.0989 \\ 40\% fa \ = \ 19.13231 \ \times \ Fw/c \ + \ 23.9366 \\ 15\% Pfa \ = \ 29165 \ \times \ Fw/c \ + \ 28.7106 \\ \end{array} \tag{64}$

 $\begin{array}{ll} Slump \ of \ 60-180mm \\ 100\% Pfa \ = \ 13.2440 \ \times Fw/c \ + \ 17.1058 \\ 80\% Pfa \ = \ 15.2712 \ \times Fw/c \ + \ 19.9462 \\ 60\% Pfa \ = \ 19.4269 \ \times Fw/c \ + \ 22.4551 \\ 40\% Pfa \ = \ 22.8452 \ \times Fw/c \ + \ 27.980 \\ 15\% Pfa \ = \ 29.2544 \ \times Fw/c \ + \ 34333 \\ \end{array} \tag{69}$

4.4 Fine aggregate content (Fac)

Fac remains the same as specified

$$Fac = Pfa \times Ac$$
 (74)

4.5 Coarse aggregate content (CAC)

Cac remains the same as specified

$$Cac = Ac - Fac \tag{75}$$

Comparing the result obtained from manual calculations using DoE Charts and tables to result obtained from the

python algorithm as shown in Table 4, the values of percentage error obtained was minimal.

These equations (1 - 75) gathered was programmed into a Python single script and validated with the data **Table 4**: Percentage difference of the transformed collected as shown in Table 4. This comparison served as a test on the reliability of the model. This algorithm was integrated in mobile app as shown in Figure 8, build with flutter framework.

Parameters	Manual Calculation	Python Algorithm	Manual Calculation	Python Algorith	Manual Calculation	Python Algorithm	Mean error	%
				m				
Target Mean Strength	46	45.7	42	40.7	55.6	55.6	1.23	
W/C Ratio	0.47	0.47	0.57	0.51	0.46	0.46		
Cement Content	340	340.5	320	313.75	369.6	369.6	0.69	
Wet Density	2400	2327	2325	2327	2490	2457	1.53	
Total Agg	1900	1822	1845	1850.9	1960.4	1917	2.16	
Fine Agg Content	515	452.06	405	406.2	646.93	630.18	5.03	
Coarse Agg Content	1385	1372.1	1440	1448	1313.47	1286.7	1.1	

Hence the overall mean error after numerous trials was at an overall mean error percentage is between 0.65% to 3% as in Table 4.



Figure 8: DoE concrete mix design mobile

the

5 | CONCLUSION

The development of a Python-based algorithm for automating the British Department of Environment (DoE) concrete mix design procedure has successfully addressed the challenges of complexity, inefficiency, and human errors inherent in traditional manual methods. By transforming DoE charts and tables into equations and integrating them into a user-friendly mobile application, the study significantly enhances the accuracy and efficiency of mix design computations, achieving error margins as low as 0.65% to 3%. This innovation bridges theoretical and practical gaps, offering engineers and practitioners an accessible tool for on-site applications while improving accuracy in structural projects. Based on the study, it is recommended that the developed algorithm and mobile application be adopted as a standard tool for civil engineering practice to improve efficiency, minimize human errors, and ensure consistency in concrete mix design across the construction industry

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References

1. Ashish Chhachhia (2020). Concrete Mix Design by IS, ACI and BS Methods: A Comparative Analysis. Lecturer, GGS Govt. Polytechnic Education Society, Cheeka, Haryana, 136034, India. Journal of Building Material Science, Volume 02, Issue 01

2. Arimanwa, J., & Arimanwa, M. C. (2017). Computer aided concrete mix design. ResearchGate. Retrieved from

https://www.researchgate.net/publication/331471242

3. Bansal, G. (2007). Concrete technology. Indian Railways Institute of Civil Engineering.

4. Chhachhia, A. (2020). Concrete mix design by IS, ACI, and BS methods: A comparative analysis. Journal of Building Material Science, 02(01).

5. Ezeh, J. C., & Ibearugbulem, O. M. (2009). Algorithm for concrete mix design based on the British method. Nigerian Journal of Technology, 28(1).

6. Kasperkiewicz, J. (1998). Advances in mix design methods: Early computational frameworks. In Concrete Technology (pp. 45–65). CRC Press.

7. Mitchell, T. M. (1997). Machine learning. McGraw-Hill.

8. Najam, F. A., & Khushnood, R. A. (2016). Paradigms for employing interactive computing tools and GUIs in structural engineering problems. International Journal of Advanced Structural Engineering, 8(1), 1–10.

9. Neville, A. M. (2011). Properties of concrete. Pearson Education.

10. Olugbenga, I. O., Seun, D. O., & Sunmbo, P. A. (2018). Investigation of properties of concrete using sawdust as partial replacement for sand. Civil and Environment Research, 6(12), 35–40.

11. Penki, R., Rout, S. K., & Das, A. K. (2024). Computational techniques for proportioning of aggregates in bituminous mix design. International Journal of Pavement Research and Technology, 16(3), 65–75. https://doi.org/10.1007/s42947-022-00264-w

12. Python Software Foundation. (2019). Python developers survey 2019. Retrieved from https://www.python.org/dev/peps/pep-9999

13. Python Software Foundation. (2021). The Python programming language. Retrieved from https://www.python.org/

14. Tran, V. Q. (2022). Machine learning approach for investigating chloride diffusion coefficient of concrete. Construction and Building Materials, 348, 128642. https://doi.org/10.1016/j.conbuildmat.2022.128642

15. Teychenne, D. C., Franklin, R. E., & Erntroy, H. (1996). Design of normal concrete mixes. Department of Environment Building Research Establishment Transport and Road Research Laboratory.

16. Ziolkowski, P., Niedostatkiewicz, M., & Kang, S. (2021). Model-based adaptive machine learning approach in concrete mix design. Materials, 12(8), 1256. https://doi.org/10.3390/ma12081256