

**MIXTURE DESIGN OF EXPERIMENT FOR MULTICRITERIAL
OPTIMIZATION OF POLYMER CONCRETE**

Marinela Bărbuța¹⁾, Daniel Lepădatu²⁾ and Bogdan Marcel Patras³⁾

*¹⁾Concrete, Material, Technology and Organization Department, Technical University
"Gh. Asachi", Iasi - Romania*

²⁾Civil Engineering Department, Technical University "Gh. Asachi", Iasi - Romania

*³⁾Hydrotechnical Structures and Sanitary Engineering Department, Technical University
"Gh. Asachi", Iasi - Romania*

Abstract: *The aim in this paper is the multicriterial responses optimization of mechanical characteristics of polymer concrete. Polymeric concrete mixes based on epoxy resin as binder, silica fume (SUF) as filler and crushed stone as aggregate have been prepared. The main objective of the multicriterial responses optimization is to improve the quality of a product or process by minimizing the effects of variation without eliminating the causes. Properties such as density and adherence to cement concrete support have been optimized by varying the level of resin and SUF.*

1. INTRODUCTION

The usual building material, namely Portland cement concrete is prepared by binding aggregates with Portland cement paste. In time cement concrete has been improved by adding polymeric additives and polymeric materials were used for substituting the hydraulic cement binder. Polymer concrete differs from typical Portland cement concrete, polymer-cement concrete and polymer-impregnated concrete. Polymer concrete contains no cement or water. Polymeric concrete is a composite material in which the aggregates are included in a polymer matrix. The use of polymer resin instead of Portland cement in the concrete mix improves the mechanical behavior, durability properties such as abrasion resistance and impermeability to water and salts [1].

Today, polymer concrete is used in precast components for building, bridge panels, machine bases and due to its corrosion resistance, it is also used as repair material for pavements, buildings, bridges, floors and dams.

The main objective of this study is to investigate the optimum mix for polymer concrete by analyzing the densities and the adherence of polymer concrete to the layer support, considering the polymer concrete as a repair material.

Typically, in the analysis of industrial data there are many responses (variables) that are under investigation at the same time. Relationships between these responses are quite common, and the analyst must decide which responses are most important, usually at the expense of the other responses. Additionally, to optimize these responses individually may yield different and conflicting process output. For the optimization of multiple responses [2], in this paper we propose the widely used Desirability Function (DF) approach [3]. It is based on the idea that the "quality" of a product or process that has multiple quality characteristics, with one of them outside of some "desired" limits, is completely unacceptable. The method finds operating conditions (optimum process variables) that provide the "most desirable" response values.

2. EXPERIMENTAL PROGRAM

The materials used were: epoxy resin (X_1), SUF (X_2) and crushed aggregates of two grades 0-4 mm (Sort I – X_3) and 4-8 mm (Sort II - X_1) and the mechanical characteristics such as: adhesion stress (Y_1) and density (Y_2) of polymer concrete was analyzed (Table1). The epoxy resin in combination with the hardener forms the binder of the PC. The SUF is a by-product that results from ferrosilicon production having the following characteristics:

- particle sizes of 0.01...0.5 μ ,
- shape of particles is spherical,
- specific surface is between 13000 and 23000 m^2/kg ,
- density between 2.1 and 2.25 g/cm^3 [4].

The aggregates were obtained from river gravel by crushing. A minimum resin content of 12.4% was adopted from the workability conditions and the maximum dosage of 18.8% was imposed by the segregation of the mix. PC of different compositions as is given in Table 1 was prepared by mixing required quantities of epoxy resin firstly with aggregates, than with the filler (SUF) that was added slowly in a mechanical mixer. Than the casting of specimens: cubes of 70.7 mm sides were prepared for determining the densities and for the adhesion stress the sample was realized by casting PC circular tablet on an usual concrete cube surface (Figure1).

Table 1. Mixture design combinations for PC and the analyzed responses

Mixture	Epoxy resin X_1 (%)	SUF X_2 (%)	Aggregate Sort I X_3 (%)	Aggregate Sort II X_4 (%)	Adhesion stress - Y_1	Density Y_2
PC1	18.8	6.48	37.4	37.4	7,27	2,03
PC2	12.4	12.8	37.4	37.4	5,18	2,08
PC3	12.4	6.4	43.8	37.4	5,67	2,1
PC4	12.4	6.4	37.4	43.8	6,57	2,12
PC5	15.6	9.6	37.4	37.4	8,45	1,97
PC6	15.6	6.4	40.6	37.4	10,25	2,01
PC7	15.6	6.4	37.4	40.6	9,01	2,06
PC8	12.4	9.6	40.6	37.4	7,56	2,04
PC9	12.4	9.6	37.4	40.6	7,66	2,00
PC10	12.4	6.4	40.6	40.6	9,06	2,13
PC11	16.4	7.2	38.2	38.2	5,87	1,96
PC12	13.2	10.4	38.2	38.2	5,47	2,05
PC13	13.2	7.2	41.4	38.2	5,77	2,12
PC14	13.2	7.2	38.2	41.4	7,96	2,06
PC15	14.0	8.0	39	39,0	10,15	2,02



Figure 1. Test samples of PC

3. MIXTURE DESIGN OF EXPERIMENT AND RESPONSE SURFACE METHODOLOGY

3.1. Mixture design of experiment

Research in many disciplines frequently involves blending two or more ingredients together. The design factors in a mixture experiment [1, 5~8] are the proportions of the components of a blend, and the response variables vary as a function of these proportions making the total and not actual quality of each component. The total amount of the mixture is normally fixed in a mixture experiment and the component settings are proportions of the total amount. The component proportions in a mixture experiment cannot vary independently as in factorial experiments since they are constrained to sum to a constant (1 or 100% for standard design). Imposing such constraint on the component proportions complicates the design and the analysis of mixture experiments. Although the best-known constraint in a mixture experiment is to set the sum of the components to one (100%) additional constraints such as imposing a maximum or minimum value on each mixture component may also apply. In the mixture design approach the total of amount of the input variables was fixed and constrained to sum 100.

3.2. Response surface methodology

Response Surface Methodology (RSM) consists of a group of empirical techniques devoted to the evaluation of relations existing between a cluster of controlled experimental factors and the measured responses, according to one or more selected criteria [6,7]. Prior knowledge and understanding of the process and the process variables under investigation is necessary for achieving a realistic model.

RSM provides an approximate relationship between a true response y and p design variables, which is based on the observed data from the process or system [9,10]. The response is generally obtained from real experiments or computer simulations, and the true response y is the expected response. Thus, real experiments are performed in this paper. We suppose that the true response Y_t can be written as:

$$Y_t = F(x_1, x_2, \dots, x_p) \quad (1)$$

where:

the variables x_1, x_2, \dots, x_p are expressed in natural units of a measurement, so are called as the natural variables. The experimentally obtained response Y_t differs from the expected value y

due to random error. Because the form of the true response function F is unknown and perhaps very complicated, we must approximate it and y can be written as:

$$y = F(\zeta_1, \zeta_2, \dots, \zeta_n) + \varepsilon \quad (2)$$

where, ε denotes the random error, which includes measurement error on the response and is inherent in the process or system and the variables $\zeta_1, \zeta_2, \dots, \zeta_n$ are the coded variables of the natural variables. We treat ε as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2 .

4. MULTICRITERIAL RESPONSES OPTIMIZATION

Generally, the total cost of production is expressed as the sum of the non quality and the manufacturing cost. In addition, the Multicriterial Response Optimization (MRO) measures the sensitivity of the responses for the final quality of products. The procedure calls for introducing for each response $Y_j(x)$, $j = 1, 2, \dots, p$, a function $d_j(Y_j(x))$ with a range of values between 0.0 and 1.0 that measures how the desirable response $Y_j(x)$ takes on a particular value. Here x denotes the vector of factors or independent variables $x^T = (x_1, x_2, \dots, x_n)$. Once this function is defined for each of the n responses of interest, an overall objective function (*the total desirability*) is defined as the geometric mean of the individual desirabilities:

$$D(x) = [d_1(Y_1(x)) \cdot d_2(Y_2(x)) \cdot \dots \cdot d_p(Y_p(x))]^{1/p} \quad (3)$$

The rationale behind using the geometric mean is that if any quality characteristic has an undesirable value (i.e. $d_j(Y_j(x)) = 0$) at some operating conditions $x = x_0$ then the overall result is usually a product which is wholly unacceptable, regardless of the value taken on by the other responses. The form of the $d_j(Y_j(x))$ function was originally proposed by Harrington [2] as:

$$d_j(Y_j(x)) = e^{Y_j(x)} \quad (4)$$

for the one-sided specification case, and

$$d_j(Y_j(x)) = e^{-|Y_j(x)|} \quad (5)$$

for the two-sided case.

As indicated by Castillo, Montgomery and McCarville [1], the existence of a breakpoint in the desirability function does not allow the use of gradient-based optimization algorithms. Thus, Castillo, Montgomery and McCarville [1] proposed the Modified Desirability Function to solve this breakpoint problem so that the Generalized Reduced Gradient (GRG) algorithm can be applied.

5. RESULTS AND DISCUSSIONS

The optimization of several responses at the same time is of great interest, for obvious reasons of cost reduction. Multicriterial optimization techniques [11 - 13] are used in this work to identify settings of process parameters that make the product's performance close to target values in the presence of multiple quality characteristics.

The variables that affect the responses, specially the adherence or density of PC are the epoxy resin, SUF and crushed aggregates. A GRG algorithm coupled with Ch'ng's technique [13] is used here to find the best combination of the process parameters to ensure an acceptable adherence and to enable optimization of the other responses simultaneously.

In order to handle a process or product with p quality characteristics, we use the Total Desirability proposed by Ch'ng [13], which is the optimization criterion in this paper, as follows:

$$TotalDesirability = \frac{\sum_{i=1}^p e_i \cdot |d_i^*(Y_i) - d_i^*(T_i)|}{p} \quad (6)$$

where: $d_i^*(Y_i)$ is the desirability value of Y_i of quality characteristic i , $d_i^*(T_i)$ is the desirability value of T_i of quality characteristic I , e_i is the degree of importance or priority of quality characteristic i , and

$$\sum_{i=1}^p e_i = 1 \quad (7)$$

In this work we consider that the two responses are not equally important. The importance priority for each response is as follows: $e_1 = 70\%$, $e_2 = 30\%$, Using the "Solver" option in Microsoft Excel, to optimize the two response we obtain the following desirability function (Table 2).

Table 2 Optimal solutions given by Ch'ng's technique

Variables X	Responses		Total desirability
	Y₁	Y₂	
12.407			
8.118			
39.752	7.04	2.04	
39.722			
Individual desirability D(Y)	1.02	0.72	0.021

Table 2 shows the Total Desirability Function for a multiple response optimization. In this paper we combined the response Y_1 , and Y_2 and treated them as one response. Using the Ch'ng's technique the optimum setting was $X = (12.407, 8.118, 39.752, 39.722)$ in the real values and $Y = (7.04; 2.04)$. The method of optimization gives the mixture that is responding to the required properties related to density (high density) and good adherence to the support that is with the following compounds proportion: epoxy resin -12.407%, SUF - 8.1118%, aggregate sort I-

39.752% and aggregate sort II- 39.722%. This mix will be analyzed in the repair and consolidation works of concrete structures.

6. CONCLUSIONS

In this paper a multicriterial response optimization methodology has been used to identify robust design parameters setting to minimize the variation of mechanical characteristics to increase of the quality of the polymer concrete. We were interested in obtaining the mixture suitable for repair and consolidation of reinforced concrete structures, for that the adherence and compaction of polymer concrete were optimized.

Finally with the multiple responses optimization a new mix was obtained that satisfies the desired mechanical characteristics.

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