Chemometrics and Intelligent Laboratory Systems 136 (2014) 1–9

Contents lists available at ScienceDirect

Chemometrics and Intelligent Laboratory Systems

journal homepage: www.elsevier.com/locate/chemolab

Development of a graphical user interface for determining the optimal mixture parameters of normal weight concretes: A response surface methodology based quadratic programming approach

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ARTICLE INFO

Article history:
Received 7 June 2013
Received in revised form 23 April 2014
Accepted 2 May 2014
Available online 10 May 2014

Keywords:
Graphical user interface
Normal weight concrete
Response surface methodology
Quadratic programming

ABSTRACT

The optimization of a normal weight concrete mixture proportions for determination of the desired concrete quality is an important issue for concrete manufacturers and users. In this study, the constrained quadratic programming methodology is based on meta-models developed by using response surface methodology for determining optimal normal weight concrete mixture proportions. We developed a graphical user interface to take the burden of numerous experiments and complex mathematical calculations away from laboratory experts and manufacturers. However, we developed a graphical user interface based on MATLAB® toolbox which allows performing optimization of normal weight concrete mixture proportions interactively. The GUI was tested through real case studies and satisfactorily results were obtained. The results showed that developed graphical user interface was functional, effective and flexible in solving the optimization problems of normal weight concrete mixture proportions.

1. Introduction

Such expression programming applications as artificial neural networks and fuzzy logic, genetic algorithm and gene expression programming are widely used in literature, in order to estimate the optimal factor levels in concrete quality. For instance, Topcu and Sarıdemir [27] carried out a study to estimate rubberized concrete properties using artificial neural network and fuzzy logic. Özcan et al. [19] compared the artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete. Tanyıldızı [25] proposed a fuzzy logic model for the prediction of bond strength of high-strength lightweight concrete. Baykaşoğlu et al. [4] estimated and optimized high strength concrete parameters via soft computing approaches such as gene expression programming and neural network. Yeh and Lien [35] proposed a novel knowledge method to estimate compressive strength of high performance concrete using genetic algorithm. Erdem [11] analyzed mechanical behavior of concrete at high temperatures through neural network. Tsai [28] introduced a weighted operation structures to program strengthener of concrete-typed specimens using genetic algorithm. Demir et al. [9] modeled some properties of the crushed tile concretes exposed to elevated temperatures through neural network. Atıcı [1] predicted the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network. Sarıdemir [22] modeled empirically the splitting tensile strength from cylinder compressive strength of concrete by genetic programming. Özgan [20] modeled the Marshall Stability of asphalt concrete using neural network. Güler et al. [12] modeled stress–strain of high strength concrete by fuzzy logic approach. Bal and Bodin [2] estimated drying shrinkage of concrete.

The RMC's (Ready Mixed Concrete Plant) mixture proportion optimization process is time consuming and difficult task for the decision makers. In Turkey, during the last six years, C30/37 concrete class or higher durability concrete production rate (see Tables A1–A2) increased from 17.77% to 38.40% [29]; [33]. In the ready mixed concrete mixture optimization process, decision makers or laboratory technicians need expert systems which accelerate the concrete production process and make laboratory technicians' work easier due to increase in concrete production. Although there are a vast amount of studies to predict optimal mixture parameters of concrete using expert systems such as fuzzy logic, neural network, genetic algorithm and genetic programming, there is still a need for an easy-to-use, flexible, modifiable and user-friendly tools such as graphical user interface (GUI) that help the decision makers to identify optimal mixture proportions of RMCs.

The proposed methodology in this paper aims to fill this gap in RMC mixture optimization process. This paper proposes such an experimental

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http://dx.doi.org/10.1016/j.chemolab.2014.05.001
0169-7439/

design based graphical user interface for determining optimal mixture proportions of normal weight concrete (NWC). The main contribution of this study demonstrates the development of easy to use GUI in order to determine optimal mixture proportion of NWCs. The developed GUI allows laboratory technicians to analyze relationship between the required responses and required factors by three-dimensional plots. Other contribution of this article shows the application of RSM based quadratic programming (QP) in order to optimize NWCs' properties. The developed GUI is quite flexible in terms of assigning different weights to quality criteria and selecting properties of concrete type. The developed methodology not only relieves the user from numerous calculations but also provides excellent graphical user interfaces (GUIs) through which the user can enter various input combinations and have the results calculated.

2. Materials and methodologies

2.1. Materials

The cement used in this research is a "CEM I 42.5 R" and weighs 350 kg. It has a specific gravity of 3.08 and Blaine fineness of 3540 cm^2/g. Fly ash was used with a specific gravity of 2.46 and weighs 80 kg [23]. Chemical composition of the binder materials is given in Table 1 [24].

A novel polycarboxylate ether type super plasticizer (PCE) was used in concrete mixtures. The physical and chemical properties of PCE are shown in Table 2. Crushed sand, which has particle size smaller than 4 mm (I), was used as the fine aggregate. Aggregate number (II) with a size between 4 mm and 11.2 mm and aggregate number (III) with a size between 11.2 mm and 22.4 mm were used as coarse aggregate in the concrete mixtures [24]. Table 3 presents the aggregate sieve analysis. The fine and coarse aggregates have specific gravities of 2.65 g/cm^3 and 2.70 g/cm^3 and mean water absorptions of 1.5% and 0.9%, respectively. Well water was used for the test [23]. The fine aggregate ratio was fixed at 50% in all experiments. Also, mixture time of fresh concrete was fixed at 120 s.

2.2. Response surface methodology

RSM is an experimental design methodology for determining the optimum factor levels for a multi-level system [7,10]. Although it is possible to use either a first-order model or a second-order model, in RSM the second order model is more common due to its flexibility and ease of estimation of the optimal factor levels in that model [34]. There are practical experimentations indicating that second-order models are sufficient in solving real word multi-response problems [6]. First-order models are inadequate modeling the complex systems. Therefore, optimization with the first-order models is not very successful. However, second-order models such as quadratic models are successful modeling the complex systems including various material interactions. One of the most useful second-order designs in RSM is Central Composite Design (CCD) ([6]; Myers, and Montgomery, [36]). In our study, rotatable experimental design is carried out as CCD which consists of 20 experiments [2^n ($2^3 = 8$: factor points) + 2n ($2 * 3 = 6$: axial points) + 6 (center points: six replications)] [7].

In this study a second-order RSM was obtained by regression analysis for three factors by using MINITAB®. In the regression equation developed by Box-Hunter, the test factors are coded according to the following equations (Eq. (1)) [7]:

$$x_i = \frac{X_i - X_{i0}}{\Delta X_i} \tag{1}$$

where in Eq. (1) x_i is the coded value of the ith independent variable, X_i is the natural value of the ith independent variable, X_{i0} is the natural value of the ith independent variable at the center point, and ΔX_i is the step change value [7].

The three significant independent variables A, B, and C and the mathematical dependency of the response Y to these variables can be approximated by second-order polynomial equation as given below [7]:

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_{11} A^2 + \beta_{22} B^2 + \beta_{33} C^2 + \beta_{12} AB + \beta_{13} AC + \beta_{23} BC \tag{2}$$

where Y is the predicted response, β_0 is the constant, β_1, β_2, and β_3 are the linear coefficients, β_{12}, β_{13}, and β_{23} are the cross-product coefficients, and β_{11}, β_{22}, and β_{33} are the quadratic coefficients [7].

2.3. Quadratic programming

Quadratic programming is one of the most important optimization techniques in operations research. It has led to a number of interesting applications and the development of numerous useful results. The inventory management, engineering design, molecular study, economics, and portfolio selection are some examples [15]. Quadratic programming is a mathematical modeling technique designed to optimize the use of limited resources. In vector–matrix notation, it may be written as [15]:

$$\text{Min } Z = \mathbf{cx} + \mathbf{x}'\mathbf{Qx} \tag{3}$$

$$\text{s.t.} \quad \mathbf{Ax} \le \mathbf{b}, \quad \mathbf{x} \ge \mathbf{0}, \tag{4}$$

where $\mathbf{x} = (x_j, j = 1,\dots, n)$ is the vector of decision variables to be determined. The other parameters given by the problem $\mathbf{c} = (c_j, j = 1,\dots, n)$ is vector of cost coefficients, $\mathbf{Q} = \|q_{ij}\|$ is the matrix of the quadratic form $\mathbf{b} = (b_i, i = 1,\dots, m)$ is vector of right-hand sides, and $\mathbf{A} = \|a_{ij}\|$ is the matrix of constraint coefficients [15]. In our study, $\mathbf{Q}$ is symmetric and semi-definite. The optimal values of the decision variables x_j, $j = 1, \dots, n$ are functions of the parameters a_{ij}, b_i and c_j, $i = 1, \dots, m$, $j = 1, \dots, n$.

Table 1
Chemical composition of binder materials [23,24].

Chemicals	CEM I 42.5 R (%)	Fly ash (%)
CaO	66.25	4.76
SiO_2	21.79	56.21
Al_2O_3	5.98	23.1
Fe_2O_3	2.51	6.51
SO_3	1.54	0.73
MgO	1.15	2.11
K_2O	0.61	2.53
Na_2O	0.15	0.27
Cl	0.0071	0.0018
Loss of ignition	3.71	2.24

Table 2
Properties of the PCE at 20 °C [23].

Properties	Superplasticizers
Chemical description	Polycarboxylic type polymer
Color	Brown
Specific gravity (kg/L)	1.059–1.099
Chlorin content % (EN 480-10)	<0.1
Alkaline content% (EN 480-12)	<3
Phase	Liquid