# Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 8 (15): 2732-2738, 2008
ISSN 1812-5654


# Response Surface Methodology and Genetic Algorithm in Optimization of Cement Clinkering Process

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**Abstract:** In this study, two techniques for optimization of the cement clinkering process are presented. We apply the Response Surface Methodology (RSM) and the Genetic Algorithm (GA). The response surface methodology is a traditional technique and the genetic algorithm is a new technique for experimental process optimization. The situation is to choose the best values of 4 control variables (calcium oxide, silicon dioxide, aluminum oxide and iron oxide) based on 6 quality variables (lime saturation factor, silica modulus, alumina iron modulus, hydraulic modulus, minimum burning temperature and coating index), inside a previous delimited experimental region. The techniques are performed and results compared. Results indicate that both techniques are capable of locating good conditions, but the RSM relatively reach to better solution.

**Key words:** Response surface methodology, experimental optimization, genetic algorithm, cement, clinker

## INTRODUCTION

Quality control experiments in cement industry are so important, especially quality control of raw materials in clinkering process and in stage of furnace feed. These controls not only due to achieve a high quality product but also it is due to achieve a balance producing line. Incompetent of furnace feed and variation in its compounds is equivalent to change furnace working balance and failure rate of the furnace will be increase.

A usual problem in quality control of the cement clinker producing process involves selecting a set of input variables (control variables) which will result in a product with a desirable set of outputs (response variables). Essentially, this becomes a problem in the simultaneous optimization of the response variables, each of which depends upon a set of quality characteristics. The goal is to find the levels of the input variables of the process so that the quality of the product or responses has the desired characteristics.

In this research, it is trying to find the levels of main input variables of cement clinkering process in stage of furnace feed so that the quality of the product or responses has the desired characteristics. We define Calcium oxide, Silicon dioxide, Aluminum oxide and Iron oxide as input variables and lime saturation factor, silica modulus, alumina iron modulus, hydraulic modulus, minimum burning temperature and Coating index as response variables.

The experimental optimization of clinkering process is a very costly and time consuming task, due to many kinds of nonlinear events involved. One of the most widely methods to solve this problem is RSM. Response surface methodology is one of statistical method for modeling and analyzing the relationships between several individual variables and response variable(s).

Response surface methodology is an empirical modeling approach using polynomials as local approximations to the true input/output relationship. This empirical approach is often adequate for process improvement in an industrial setting. By careful design of experiments, the objective is to optimize response (output variable) that is influenced by several independent variables (input variables). An experiment is series of tests, called runs, in which change are made in the input variables in order to identify the reasons for changes in the output response. The relationship between the response variables of interest and the input variables is usually not known. In general, the experimenter approximates the system function with an empirical model. The successful application of RSM relies on the identification of suitable approximation for the function. The necessary data for building the response models are generally collected by an experimental design. One of the most popular of classes of the RSM designs is the central composite design, or CCD.

RSM is an effective statistical approach, because it designs properly experiments to determine optimum of

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several variables. Main advantage of the RSM is reduce experiment repetitions for evaluate multiple factors and their interaction relationships. Identifying and fitting from experimental data a good response surface model requires some knowledge of statistical experimental design fundamentals, regression modeling techniques and elementary optimization methods. For a comprehensive survey of RSM refer to Myers and Montgomery (1995) and Khuri and Cornell (1996).

Many of the recent researches in cement researches area focuses on the RSM.

Cau Dit Coumes and Courtois (2003) investigated a cement-based grout formulation to immobilize low-level radioactive evaporator concentrates with widely variable chemical composition. The objective was to determine the sensitivity of the solidified waste forms characteristics on a variation in the concentrations of four components of the waste. Providing adequate changes of variables, the problem was shown to amount to a mixture study with constraints placed on each factor. Experimental design methodology enabled to build empirical models, which gave a satisfactory description of the responses within the region of the experimental data and which could be used as prediction tools. High contents of phosphate in the waste were shown to improve most properties of the elaborated materials. In particular, setting time, rate of heat production and swelling under water were decreased, while grout workability was enhanced.

Kunhanandan Nambiar and Ramamurthy (2006) discussed the development of empirical models for compressive strength and density of foam concrete through statistically designed experiments. The response surface plots helped in visually analyzing the influence of factors on the responses. The relative influence of fly ash replacement on strength and density of foam concrete was studied by comparing it with mixes without fly ash and brought out that replacement of fine aggregate with fly ash will help in increase in the strength of foam concrete at lower densities allowing high strength to density ratio. Confirmatory tests had shown that the relation developed by statistical treatment of experimental results can act as a guideline in the mixture proportion of foam concrete.

Mandal and Roy (2006) investigated on generation of models for predicting the properties of the sand mix from the composition. Central composite design was used to develop regression equations for predicting compressive strength of the sand mix when molasses is varied between 5.5 and 7.5% and cement between 2 and 4%.

Grabiec and Piasta (2004) applied response surface methodology for studies on the influence of water-to-cement ratio, amount of melamine type of superplasticiser and cement type (with different amount of C3A) on some properties of cement pastes. The most useful combination of w/c, amount of superplasticiser and C3A was determined. Improved cement paste characteristics were obtained in the case of pastes made with a cement having lower amount of C3A.

Recently, some studies have tried to establish a new approach for experimental optimization. They suggest using genetic algorithms to sweep a region of interest and select the optimal (or near optimal) setting to a process. It was found that the GA can be a powerful tool in experimental optimization, even when the experimenter does not have a model for the process. The GA is an optimization algorithm and objective function does not need to be differentiable. This allows the algorithm to be used in solving difficult problems, such as multi model, discontinuous or noisy systems. The great advantage of the GA technique over the RSM especially in irregular experimental regions is that the GA doesn't need to generate models and Forbidden or unreachable combination of the factor settings can be simply put aside with another run of the program. For related studies in the GA approach for experimental optimization see for example Ozcelik and Erzurumlu (2005), Koksoy and Yalcinoz (2006), Correia *et al*. (2005), Suresh *et al*. (2002) and Oktem *et al*. (2005).

## MATERIALS AND METHODS

The aim of this research is to select a set of input variables which will result in a product with a desirable set of response variables in quality control of the cement clinker producing process in an Iranian cement producing company. The goal is to find the levels of the input variables of the process so that the quality of the product is optimized. Calcium oxide, Silicon dioxide, Aluminum oxide and Iron oxide are considered as input variables. For the experimental execution, experimental region of input variables is limited by the search ranges as shown in Table 1.

Also, Lime saturation factor, silica modulus, alumina iron modulus, hydraulic modulus, minimum burning temperature and coating index are defined as the response variables. In the research, the range and target value of the responses variables are considered as shown in Table 2. Many defects such as hard burning, high fuel consuming could occur if the responses variables becomes out of the range.

Table 1: Search range of input variables

| Parameters | Range (%) |
|---|---|
| Calcium oxide (CaO) | 39.0-42.0 |
| Silicon dioxide ($SiO_2$) | 13.0-14.5 |
| Aluminum oxide ($Al_2O_3$) | 3.0-4.5 |
| Iron oxide ($Fe_2O_3$) | 1.5-3.0 |

**RSM optimization:** The experimental design chosen for the RSM optimization is a CCD composed of a full factorial $2^4$ (four factors, two levels), eight axial points and seven central points. The axial points were chosen by an $\alpha$ equal to 2.0, which makes this a rotatable design. The values of the input variables are coded as shown Table 3, in order to facilitate the data treatment and analysis.

According to Table 3, The value of CaO, $SiO_2$, $Al_2O_3$ and $Fe_2O_3$ are coded as $X_1$, $X_2$, $X_3$ and $X_4$ respectively, in order to each of them is between -1 and 1.

Table 2: The range and target value of response variables

| Response | Range | Target |
|---|---|---|
| Lime Saturation Factor ($Y_1$) | 90.0-98% | 94.0% |
| Silica Modulus ($Y_2$) | 2.0-3.0 | 2.5 |
| Alumina Iron Modulus ($Y_3$) | 1.3-2.5 | 1.9 |
| Hydraulic Modulus ($Y_4$) | 1.7-2.4 | 2.0 |
| Minimum Burning Temperature ($Y_5$) | - | 1275°C |
| Coating Index ($Y_6$) | 17.0-25% | 20% |

Table 3: Input variables levels of cement clinkering process

| | Levels (%) | | |
|---|---|---|---|
| Parameters | -1 | 0 | 1 |
| Calcium oxide (CaO) | 39.0-39.999 | 40.0-40.999 | 41.0-41.999 |
| Silicon dioxide ($SiO_2$) | 13.0-13.499 | 13.5-13.999 | 14.0-14.499 |
| Aluminum oxide ($Al_2O_3$) | 3.0-3.499 | 3.5-3.999 | 4.0-4.499 |
| Iron oxide ($Fe_2O_3$) | 1.5-1.999 | 2.0-2.499 | 2.5-2.999 |

Table 4 shows the input variables, the measured responses of each run. Data presented in Table 4 is used for developing of six models related to the each response.

In this study, it use is second-order model for fitting models. This model has R-square ($R^2$) better than first-order model and first-order model with interaction relations and it has the Mean Square Error (MSE) lower than both of the models.

The fitted second-order models are shown in the following equations. Table 5 shows the MSE and $R^2$ of the fitted models.

$$\hat{Y}_1 = 91.75\% + 2.10\%X_1 - 2.34\%X_2 - 0.94\%X_3 - 0.41\%X_4 - 0.08\%X_1^2 + 0.03\%X_2^2 + 0.26\%X_3^2 - 0.14\%X_4^2 - 0.41\%X_1X_2 + 0.05\%X_1X_3 - 0.14\%X_1X_4 - 0.73\%X_2X_3 + 0.35\%X_2X_4 + 0.17\%X_3X_4 \tag{1}$$

$$\hat{Y}_2 = 2.27 + 0.001X_1 + 0.11X_2 - 0.17X_3 - 0.15X_4 + 0.01X_1^2 + 0.02X_2^2 + 0.03X_3^2 - 0.004X_4^2 + 0.02X_1X_2 + 0.02X_1X_3 - 0.03X_1X_4 - 0.02X_2X_3 - 0.01X_2X_4 + 0.002X_3X_4 \tag{2}$$

$$\hat{Y}_3 = 1.59 + 0.05X_1 + 0.02X_2 + 0.25X_3 - 0.37X_4 + 0.02X_1^2 - 0.01X_2^2 + 0.05X_3^2 + 0.09X_4^2 + 0.02X_1X_2 + 0.03X_1X_3 - 0.13X_1X_4 - 0.02X_2X_3 - 0.01X_2X_4 - 0.09X_3X_4 \tag{3}$$

Table 4: Results of the RSM experiments for cement clinkering process

| | Real values (%) | | | | Responses | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Runs | CaO | $SiO_2$ | $Al_2O_3$ | $Fe_2O_3$ | $Y_1$ (%) | $Y_2$ | $Y_3$ | $Y_4$ | $Y_5$ | $Y_6$ (%) |
| 1 | 39.31 | 13.26 | 3.24 | 1.95 | 93.1 | 2.5 | 1.7 | 2.1 | 1259 | 17.5 |
| 2 | 39.75 | 14.16 | 4.27 | 2.65 | 85.6 | 2.0 | 1.6 | 1.9 | 1282 | 25.0 |
| 3 | 41.58 | 13.15 | 4.17 | 2.93 | 95.3 | 1.8 | 1.4 | 2.0 | 1208 | 23.0 |
| 4 | 41.62 | 14.25 | 3.10 | 2.59 | 92.0 | 2.5 | 1.2 | 2.1 | 1246 | 19.5 |
| 5 | 41.95 | 14.44 | 4.23 | 1.56 | 90.3 | 2.5 | 2.7 | 2.1 | 1291 | 20.1 |
| 6 | 39.86 | 13.25 | 4.09 | 2.60 | 91.4 | 2.0 | 1.6 | 2.0 | 1203 | 22.5 |
| 7 | 41.89 | 13.34 | 3.35 | 2.91 | 97.0 | 2.1 | 1.1 | 2.1 | 1224 | 19.9 |
| 8 | 41.12 | 14.04 | 3.39 | 1.55 | 92.8 | 2.8 | 2.2 | 2.2 | 1276 | 16.8 |
| 9 | 39.47 | 14.45 | 4.19 | 1.86 | 84.7 | 2.4 | 2.2 | 1.9 | 1252 | 22.6 |
| 10 | 41.96 | 13.11 | 4.41 | 1.52 | 97.8 | 2.2 | 2.9 | 2.2 | 1272 | 18.3 |
| 11 | 39.99 | 14.21 | 3.02 | 2.50 | 88.9 | 2.6 | 1.2 | 2.0 | 1254 | 19.9 |
| 12 | 39.56 | 13.31 | 3.12 | 2.61 | 89.5 | 2.3 | 1.2 | 2.1 | 1210 | 19.3 |
| 13 | 41.91 | 13.49 | 3.27 | 1.95 | 97.7 | 2.6 | 1.7 | 2.2 | 1275 | 16.4 |
| 14 | 39.57 | 14.12 | 3.05 | 1.86 | 89.2 | 2.9 | 1.6 | 2.1 | 1292 | 17.8 |
| 15 | 39.79 | 13.33 | 4.19 | 1.98 | 91.3 | 2.7 | 2.1 | 2.0 | 1268 | 20.9 |
| 16 | 41.98 | 14.41 | 4.22 | 2.70 | 89.2 | 2.0 | 1.6 | 2.0 | 1267 | 24.1 |
| 17 | 38.99 | 13.55 | 3.85 | 2.21 | 88.8 | 2.2 | 1.7 | 2.0 | 1233 | 21.3 |
| 18 | 42.00 | 13.76 | 3.60 | 2.27 | 94.9 | 2.3 | 1.6 | 2.1 | 1238 | 19.2 |
| 19 | 40.78 | 12.99 | 3.75 | 2.36 | 96.3 | 2.1 | 1.6 | 2.1 | 1256 | 19.4 |
| 20 | 40.84 | 14.50 | 3.51 | 2.30 | 88.3 | 2.5 | 1.5 | 2.0 | 1242 | 20.9 |
| 21 | 40.95 | 13.59 | 2.99 | 2.18 | 95.2 | 2.6 | 1.4 | 2.2 | 1275 | 17.0 |
| 22 | 40.87 | 13.63 | 4.50 | 2.02 | 91.2 | 2.1 | 2.2 | 2.0 | 1258 | 22.0 |
| 23 | 40.55 | 13.71 | 3.99 | 1.49 | 92.0 | 2.5 | 2.6 | 2.1 | 1280 | 18.6 |
| 24 | 40.73 | 13.66 | 3.78 | 3.00 | 91.2 | 2.0 | 1.3 | 2.0 | 1233 | 23.0 |
| 25 | 40.35 | 13.54 | 3.86 | 2.15 | 92.0 | 2.2 | 1.8 | 2.1 | 1263 | 20.3 |
| 26 | 40.29 | 13.62 | 3.95 | 2.24 | 91.0 | 2.2 | 1.7 | 2.0 | 1264 | 21.1 |
| 27 | 40.60 | 13.99 | 3.83 | 2.41 | 89.7 | 2.2 | 1.6 | 2.0 | 1250 | 21.7 |
| 28 | 40.91 | 13.82 | 3.59 | 2.36 | 92.0 | 2.3 | 1.5 | 2.1 | 1247 | 20.2 |
| 29 | 40.75 | 13.50 | 3.61 | 2.49 | 93.3 | 2.2 | 1.4 | 2.1 | 1238 | 20.3 |
| 30 | 40.68 | 13.77 | 3.53 | 2.22 | 92.1 | 2.4 | 1.6 | 2.1 | 1256 | 19.5 |
| 31 | 40.45 | 13.62 | 3.57 | 2.38 | 92.1 | 2.3 | 1.5 | 2.1 | 1249 | 20.1 |

Table 5: MSE and $R^2$ of the fitted models

| Responses | Fitted model | $R^2$ (%) | MSE |
|---|---|---|---|
| Lime saturation factor ($Y_1$) | Eq. 1 | 93.0 | 1.33 |
| Silica modulus ($Y_2$) | Eq. 2 | 94.6 | 0.005 |
| Alumina iron modulus ($Y_3$) | Eq. 3 | 93.3 | 0.025 |
| Hydraulic modulus ($Y_4$) | Eq. 4 | 95.6 | 0.0005 |
| Minimum burning temperature ($Y_5$) | Eq. 5 | 73.0 | 70.7 |
| Coating index ($Y_6$) | Eq. 6 | 95.35 | 0.38 |

$$\hat{Y}_4 = 2.05 + 0.04X_1 - 0.04X_2 - 0.05X_3 - 0.04X_4 + 0.0004X_1^2 + 0.0003X_2^2 + 0.01X_3^2 - 0.002X_4^2 - 0.002X_1X_2 + 0.01X_1X_3 - 0.01X_1X_4 - 0.01X_2X_3 - 0.005X_2X_4 - 0.004X_3X_4 \quad (4)$$

$$\hat{Y}_5 = 1252.4 + 2.04X_1 + 8.87X_2 - 0.12X_3 - 16.04X_4 - 3.72X_1^2 - 0.34X_2^2 + 4.02X_3^2 + 1.53X_4^2 - 2.44X_1X_2 + 1.69X_1X_3 - 2.94X_1X_4 + 2.56X_2X_3 + 10.44X_2X_4 2.81X_3X_4 \quad (5)$$

$$\hat{Y}_6 = 20.48\% - 0.49\%X_1 + 0.46\%X_2 + 1.64\%X_3 + 1.31\%X_4 - 0.05\%X_1^2 - 0.07\%X_2^2 - 0.24\%X_3^2 + 0.09\%X_4^2 - 0.11\%X_1X_2 - 0.24\%X_1X_3 + 0.41\%X_1X_4 + 0.39\%X_2X_3 - 0.02\%X_2X_4 + 0.15\%X_3X_4 \quad (6)$$

Now, the optimal value of variables must be obtained. To do this, we apply the LP-metric method. This method is used for measuring variance of a solution from desirable solution. This variance from desirable solution is shown following model:

$$\text{Min} \quad Z = \sum_{j=1}^{n} W_j \left( \frac{Y_j^* - Y_j}{Y_j^*} \right)^P \quad (7)$$

Subject to

$$g_i(X_1, X_2, ..., X_n) \le b \qquad i = 1, 2, ..., m \quad (8)$$

In this case, $Y_j$ states value of the response variable j. $Y_j^*$ and $W_j$ are desirable value and weight factor of the response variable j. Variable P specify assertion degree on deviations.

The responses evaluated in this work do not have equal importance. The most important variable is the lime saturation factor, followed by the silica modulus, minimum burning temperature, alumina iron modulus, hydraulic modulus and coating index. In order to transpose these statuses to the objective function, weight factors are included and their values are 0.3 (lime saturation factor), 0.2 (silica modulus), 0.2 (minimum burning temperature), 0.1 (alumina iron modulus), 0.1 (hydraulic modulus) and 0.1 (coating index).

Study solves, the model with considering the different amount P and obtain the minimum point of Z in P = 2 and in this case all amount of the response variables set at the range too. Therefore, it can be chosen a desirable solution and we obtain final solution of the RSM as shown Table 6 and 7.

Table 6: Input variable for optimal point by the RSM

| $X_1$ | $X_2$ | $X_3$ | $X_4$ | CaO | $SiO_2$ | $Al_2O_3$ | $Fe_2O_3$ |
|---|---|---|---|---|---|---|---|
| 0.023 | 0.036 | 0.138 | 0.404 | 41.1% | 13.8% | 3.8% | 2.3% |

Table 7: Responses for optimal point by the RSM

| $Y_1$ | $Y_2$ | $Y_3$ | $Y_4$ | $Y_5$ | $Y_6$ |
|---|---|---|---|---|---|
| 92.20% | 2.3 | 1.6 | 2.1 | 1263 | 20.40% |

Table 8: Parameters of GA computation

| | |
|---|---|
| Population size (POP) | 6 |
| No. of generation (GEN) | 5 |
| Mutation probability ($P_{mu}$) | 1% |
| Crossover probability ($P_{cr}$) | 90% |

**GA optimization:** Genetic Algorithms (GA) have been originally developed by John Holland as artificial adaptive systems simulating natural evolution and have proven themselves as powerful search algorithms. They have been employed to attack many difficult problems from a variety of fields, especially, combinatorial optimization problems.

In this study, it is proposed that a GA approach to solve the problem. The GA starts by generation of an initial population, i.e., the first generation. It is assume that the initial population contains POP individuals. We generates initial population randomly. In order to create the next generation, after computing the fitness values of the individuals, the population is randomly partitioned into pairs of individuals. To each resulting pair of (parent) individuals, next we apply the crossover operator with probability $P_{cr}$ to produce two new (children) individuals. After applying the crossover operator, each individual is considered for mutation operation with probability $P_{mu}$. The algorithm stops if a pre-specified number of generations, denoted by GEN, are created.

We build a chromosome to contain 4 genes, one gene for each input variable. Therefore, a chromosome is formed by coded values of the Calcium oxide ($X_1$), the silicon oxide ($X_2$), the aluminum oxide ($X_3$) and the iron oxide ($X_4$) that each of them is between -1 and 1. The chromosome is decoded when the experiments have to run and the response variables and the fitness value could be determined.

The fitness value is measured through an objective function similar to the used in the RSM optimization. After a chromosome creating, the input variables could be determined then an experiment must be run and response variables are obtained, finally, the fitness value is calculated.

The used GA parameters are shown in Table 8. The population size, crossover and mutation probability and number of generation are important factors to performance of the algorithm. The large size of population results the better searching of the solution space and reduces the

Table 9: Results of the GA experiments

| | Input variables (coded) | | | | Response variables | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Ind. No. | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $Y_1$ (%) | $Y_2$ | $Y_3$ | $Y_4$ | $Y_5$ | $Y_6$ (%) | Fitness value |
| 1 | 0.38 | 0 | -0.02 | -0.54 | 92.7 | 2.3 | 1.9 | 2.1 | 1262 | 19.5 | 0.95 |
| 2 | 1 | -0.78 | -0.02 | -0.25 | 93.1 | 2.2 | 1.8 | 2.1 | 1252 | 19.2 | 0.41 |
| 3 | -0.45 | 0.17 | 0.07 | -0.75 | 90.5 | 2.4 | 1.9 | 2.0 | 1262 | 20.1 | 0.93 |
| 4 | 0.42 | 0.89 | 0.73 | 0.57 | 89.3 | 2.1 | 1.6 | 2.0 | 1259 | 22.7 | 0.89 |
| 5 | -0.37 | 0.21 | -0.25 | -0.73 | 90.9 | 2.4 | 1.8 | 2.0 | 1264 | 19.5 | 0.81 |
| 6 | 1 | 0.86 | 0.14 | -0.41 | 91.2 | 2.5 | 2.0 | 2.1 | 1261 | 19.7 | 0.63 |
| 7 | -0.37 | -0.2 | -0.06 | -0.99 | 91.7 | 2.4 | 2.0 | 2.1 | 1268 | 19.4 | 0.87 |
| 8 | 0.78 | 0.56 | 0.17 | -0.26 | 91.1 | 2.4 | 1.9 | 2.1 | 1259 | 20.1 | 0.91 |
| 9 | 0.81 | 0.64 | 0.87 | 0.54 | 90.6 | 2.1 | 1.7 | 2.0 | 1256 | 22.5 | 0.78 |
| 10 | -0.75 | 0.57 | 0.1 | 0.2 | 88.8 | 2.3 | 1.6 | 2.0 | 1253 | 21.5 | 0.65 |
| 11 | -0.19 | 0.85 | 0.75 | 0.0 | 88.4 | 2.2 | 1.8 | 2.0 | 1262 | 22.3 | 0.49 |
| 12 | 0.29 | 0.0 | 0.71 | 0.0 | 91.8 | 2.1 | 1.9 | 2 | 1254 | 21.3 | 0.44 |
| 13 | -1.0 | 0.25 | 0.0 | 0.0 | 89.1 | 2.3 | 1.6 | 2 | 1250 | 21.1 | 0.55 |
| 14 | 1.0 | 0.05 | -0.93 | -0.04 | 94.7 | 2.4 | 1.5 | 2.1 | 1254 | 18.3 | 0.64 |
| 15 | -0.26 | -0.75 | 0.0 | -0.06 | 92.9 | 2.2 | 1.6 | 2.1 | 1245 | 20.1 | 0.57 |
| 16 | 1.0 | -0.55 | 0.0 | -0.07 | 90.3 | 2.2 | 1.7 | 2.1 | 1248 | 19.6 | 0.43 |
| 17 | -0.85 | 0.0 | -0.12 | -0.06 | 90.1 | 2.3 | 1.6 | 2.0 | 1249 | 20.5 | 0.51 |
| 18 | -0.49 | -0.31 | 0.5 | -1.0 | 91.2 | 2.3 | 2.1 | 2.0 | 1265 | 20.2 | 0.34 |
| 19 | -0.48 | -0.64 | 0.8 | -0.26 | 91.9 | 2.1 | 1.9 | 2.0 | 1248 | 21.1 | 0.48 |
| 20 | -0.5 | 0.5 | 0.23 | -0.04 | 89.3 | 2.3 | 1.7 | 1.9 | 1255 | 21.3 | 0.44 |
| 21 | -1.0 | -1.0 | -0.01 | -0.51 | 90.8 | 2.3 | 1.8 | 2.0 | 1247 | 20.8 | 0.33 |
| 22 | -0.84 | 0.15 | -0.24 | -0.33 | 89.9 | 2.3 | 2.0 | 1.9 | 1258 | 20.1 | 0.29 |
| 23 | -0.94 | 0.42 | 0.71 | -0.98 | 87.9 | 2.3 | 2.1 | 1.9 | 1260 | 21.5 | 0.15 |
| 24 | -0.92 | 0.45 | 0.69 | -1.0 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.6 | 0.11 |
| 25 | -0.95 | 0.48 | 0.75 | -0.95 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.7 | 0.11 |
| 26 | -0.98 | 0.47 | 0.78 | -0.95 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.7 | 0.11 |
| 27 | -0.96 | 0.46 | 0.78 | -0.95 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.7 | 0.11 |
| 28 | -0.96 | 0.47 | 0.77 | -0.93 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.7 | 0.11 |
| 29 | -0.96 | 0.47 | 0.78 | -0.95 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.7 | 0.11 |
| 30 | -0.96 | 0.47 | 0.78 | -0.95 | 87.7 | 2.3 | 2.1 | 1.9 | 1261 | 21.7 | 0.11 |

Table 10: Input variable for optimal point by the GA

| $X_1$ | $X_2$ | $X_3$ | $X_4$ | CaO | $SiO_2$ | $Al_2O_3$ | $Fe_2O_3$ |
|---|---|---|---|---|---|---|---|
| -0.96 | 0.47 | 0.78 | -0.95 | 39.1% | 14.1% | 4.3% | 1.6% |

Table 11: Responses for optimal point by the GA

| $Y_1$ | $Y_2$ | $Y_3$ | $Y_4$ | $Y_5$ | $Y_6$ |
|---|---|---|---|---|---|
| 87.7% | 2.3 | 2.1 | 1.9 | 1261 | 21.7 |

chance of getting poor solution, but it results more number of experiments and its costs. In this case, the experiments of clinkering process are very costly and time consuming task, hereupon the population size and number of generations are limited. Table 9 presents obtained results by the GA while we obtain the optimal point of Z by the GA as shown Table 10 and 11.

## RESULTS AND DISCUSSION

Here, we discuss and compare on the experiment results obtained by the GA and the RSM. Regarding to the results, the response variables of final solution in both method are within defined range in Table 2 and have a relatively good quality. Though, the RSM and the GA did not achieve the desired targets of the response variables, but the RSM relatively reach to better solution. Table 12 presents comparison between the results obtained by each approach.

Now, we analyze search space of the approaches. Fig. 1 shows used design by the RSM to investigate the experimental region. This design covers majority of experimental region.

Figure 2 shows the experimental region that investigated and the points suggested by the GA. The points are not equally distributed in the search space and many of the points are coincident.

As shown in Fig. 1 and 2, the RSM search region is more effective than the GA. Therefore, it can be increase chance of the RSM to achieve better solutions. In the GA approach difference between target and final values cannot be credited to insufficient generations, since the GA result become convergence after some generations. It can be seen in Fig. 3.

Table 12: Comparison between target and obtained values

| | | RSM optimization | | GA Optimization | |
|---|---|---|---|---|---|
| Responses | Target | Final values | Difference (%) | Final values | Difference (%) |
| Lime saturation factor ($Y_1$) | 94.0% | 92.2% | 1.9 | 97.5% | 3.7 |
| Silica modulus ($Y_2$) | 2.5 | 2.3 | 8.0 | 2.4 | 4.0 |
| Alumina iron modulus ($Y_3$) | 1.9 | 1.6 | 15.7 | 1.8 | 5.2 |
| Hydraulic modulus ($Y_4$) | 2.0 | 2.1 | 5.0 | 2.2 | 10.0 |
| Minimum Burning temperature ($Y_5$) | 1275.0 | 1263.0 | 0.9 | 1281.0 | 0.5 |
| Coating Index ($Y_6$) | 20.0% | 20.4% | 2.0 | 17.2% | 14.0 |

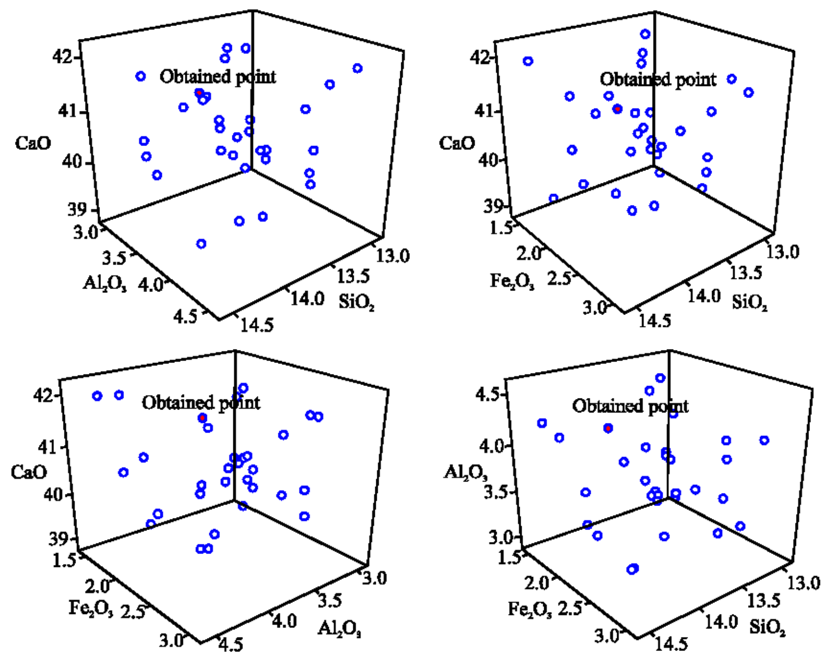


Fig. 1: Search space and the points analyzed by the RSM

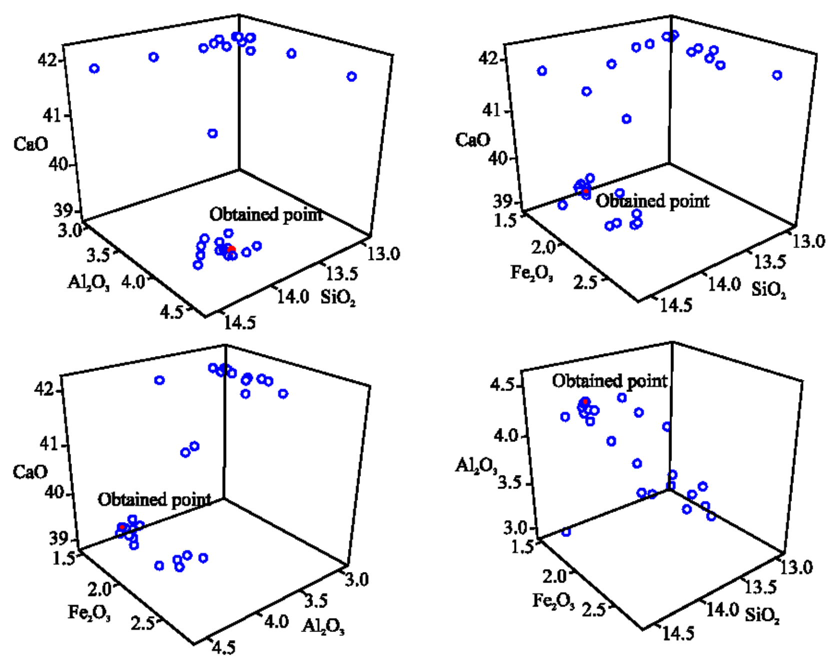


Fig. 2: Search space and the points analyzed by the GA

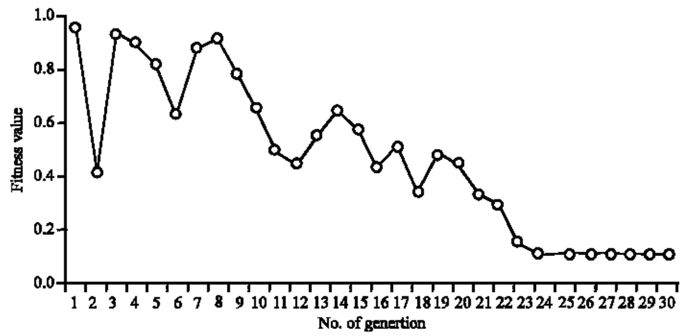


Fig. 3: Convergence of the GA

## CONCLUSIONS

In this research, we investigated setting of cement clinkering process parameters. Therefore, four input variables and six response variables were considered. For setting the process optimizing, two approaches named RSM and GA were applied. Then, results of the approaches applied were obtained and compared. The RSM generated models that can be useful in further investigations of the search space, avoiding the experiments with undesired predicted responses. But the great advantage of the GA technique over the RSM especially in irregular experimental regions is that the GA doesn't need to generate models and Forbidden or unreachable combination of the factor settings can be simply put aside with another run of the program. Results indicate that both techniques are capable of locating good conditions, but the RSM relatively reach to better solution. Finally, we obtained value of setting of cement clinkering process parameters, in order to response variables of the process improved.

Some future areas of research are application of RSM and GA in other processes of cement producing and using of Taguchi method in clinkering process for robustification. One of the other potential interests would be to develop other algorithms, such as simulated annealing, neural networks, ant colony algorithm, etc., to solve the problem.

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