University of Sistan and Baluchestan

Chemical Process Design

Available online at http://cpd.usb.ac.ir/



Modeling the Effect of Chemical Modules LSF, SM, AM, LP, and Residual on the Sieve 90-micron Factors on Fuel Consumption of Preheater and Kiln of Zabol Cement Industries Company using Design Expert Software

Mohammad Amin Mokhtari*, Masoud Keikhaei

Technical Office Group, Zabol Cement Factory, Hamgaman Tose'e S&B Holding, PO Box: 14155-1955

ARTICLE INFO

Article history:
Received: 2024-08-28
Received in revised form: 2024-11-04
Accepted: 2024-11-27
Published online: 2024-11-27

Keywords:
Modeling; Optimizing; Preheater & Kiln; RSM; Fuel consumption; Chemical Modules

DOI: *10.22111/cpd.2025.50143.1042*

ABSTRACT

Today, the issue of optimizing fuel consumption in cement plants is considered an effective factor in determining the cost price of the product and is being pursued more seriously by energy management organizations. Optimizing and reducing fuel consumption, especially to preserve national economic resources, is one of the important goals of every country. In recent years, this issue has also received special attention in Iran and industries are looking for effective economic solutions in this field. One of the solutions to reduce energy consumption is to examine the relationship between chemical Modules and their effect on fuel consumption, which has not been studied and investigated much to date. In this article, the effect of chemical Modules LSF, SM, AM, LP and Residual on the 90-micron sieve of the kiln feed on the fuel consumption of the Zabol Cement Industries Company's firing system has been investigated using mathematical modeling, response surface methodology, and Design Expert software. The method studied is for optimizing fuel consumption in the preheater and cement kiln, and kiln fuel consumption is considered as the response variable. The results of this research show that among the chemical Modules used for Kiln feed analysis, LSF and AM values have the greatest impact on fuel consumption (the more these two parameters tend to increase, the more kilocalories are consumed, but the LP parameter has the opposite effect, meaning that as it increases, fuel consumption decreases, and the 90-micron sieve Residual is not seen in the model due to its constant range of changes.

1. Introduction

As an energy-intensive industry, the cement industry accounts for about 7% of the world's total fuel consumption [1, 2] and averages about 100kWh/ton of cement and 790 to 820kcal/kg of clinker energy. Heat consumption and

Corresponding author. Tel: +989106963628
E-mail address: m.mokhtari@zabolcement.com (M.A. Mokhtari).

costs account for 30 to 40% of the total production cost [3]. In this area, several studies and investigations have been conducted, which have played an effective role in reducing energy consumption in the cement industry. Fellaou et al. [4] used an advanced energy analysis tool to assess the real potential of thermodynamic changes in the energy system. Taweel et al. [5] presented an analysis based on the temperature of the clinker leaving the cooler. Using experimental studies and numerical simulations, Shao et al. [6] studied the heat distribution in the entire cooling system. In addition, Shao et al. [7] presented an air distribution model for heat recovery from the clinker cooling system using optimization techniques. Utlu et al. [8] evaluated the energy efficiency of raw material grinding in this context. Atmaca [9] summarized the cement production process from the perspective of energy balance and pointed out that increasing the energy efficiency of fuel can help reduce energy consumption. In the mentioned studies, mechanical models were used to verify performance and energy optimization, but the development of these models can be complex and time-consuming.

The increasing energy consumption and the limitation of fossil fuels, which are the main source of energy production in cement plants, have led industrial societies to look for other ways to meet their energy needs. In addition, the cement industry plays a significant role in global CO_2 emissions (about five to seven percent [10]. Since 1950 and 1990, respectively, cement production has become the third largest source of anthropogenic CO_2 emissions [11-12]. During the years 1760 to 1840, atmospheric CO_2 concentration increased from 280 mg/L to 370 mg/L, followed by an increase in the average global temperature in the range of 0.6 and 1 ℃ [13]. A large number of studies have been conducted on CO_2 removal based on various methods such as membrane separation, adsorption, absorption and distillation processes [14].

Carbon capture methods mainly include pre-combustion, oxy-fuel combustion and post-combustion processes [15]. Greenhouse gases, especially CO_2, are increasing [16]. In 2019, the atmospheric CO_2 concentration reached 410mg/L [17]. In the study of Mansouri et al. [18] in 2024, the changes in the compressive strength of Portland pozzolanic cement, energy rate and CO_2 emissions due to the increase in additives were investigated. Compressive strength was evaluated at time intervals of 2, 7 and 28 days. The results of this study showed that the use of natural pozzolan powder in cement production significantly reduces greenhouse gas emissions and also the addition of additives to cement ultimately leads to a reduction in energy consumption. In addition, the use of these materials can reduce the clinker factor by up to 50%. In this way, the capacity of production lines can be increased by up to twice the current capacity and the cost of cement production can be reduced. Also, the use of blended cement helps to reduce dust and environmental problems.

In another study conducted by Mansouri et al. [19] in 2024, the response surface methodology (RSM) approach was used to model and optimize seven variables affecting temperature and carbon monoxide (CO) reduction in the cement kiln combustion process. The aim of this research was to create two models to reduce the kiln body temperature (y_1) and CO production (y_2) in the cement kiln combustion process using RSM. The results showed that carbon monoxide and kiln body temperature were considered as response variables in RSM. The mean absolute error of the model prediction for kiln body temperature was estimated to be about 1.6% and for carbon monoxide, about 15.5%. Due to population growth and global demand for concrete as a major construction material, cement production is expected to increase by 0.8–1.2% per year, reaching 3.7–4.4Gt by 2050, highlighting the need for further research into CO_2 reduction or sequestration by the cement industry [13].

Given that limited research has so far examined the effect of chemical modules on preheater fuel consumption, in this study we have used the RSM model and analyzed this relationship using the actual data generated through Design Expert software. A random statistical population of kiln feed was studied over a six-year period (2018-2024). The range of fuel consumption can be measured experimentally and operationally, which parameter has the greatest impact on fuel consumption, and the impact of each can be calculated and measured in the operational phase. Table 1 shows the numerical characteristics of the chemical analysis of kiln feed of Zabol Cement Industries Company over a six-year period. Part of the data received from the X-ray laboratory of Zabol Cement Industry is given in Table B of the appendix [20].

Table 1. Numerical characteristics of chemical analysis of Zabol cement Industries Company kiln feed during (2018-2024)

Parameter	Range of changes
Lime Saturation Factor (%)	90-96
Residual on the sieve 90-micron (%)	8-11
Silica Modulus (%)	2.24-2.48
Alumina modulus (%)	1.19-1.46
Liquid Phase (%)	26-28

2. RSM method

A preliminary one-factor test yielded approximations for the range of five factors: LSF, Residual on the sieve 90-micron, SM, AM, and LP. A Full Factorial Design test with five factors at three levels was conducted using Design-Expert 13.0 software to investigate the effects of five factors on kcal. The response was evaluated using the mean of DEM results and analyzed using analysis of variance (ANOVA) to determine the main effects and interaction variables for each response. To indicate the desired ranges for response, a multiple-response approach using the utility method was described [21-22]. Multivariate statistical techniques are preferred as a tool to identify the optimal combination of factors and their interactions, since these cannot be identified by traditional methods [23-24].

Among these techniques, RSM is known as an efficient tool for optimizing multiple variables affecting the results [25]. This method is designed to predict the relationships between the input and output of an engineering system and optimize it [26]. RSM has been widely used in various manufacturing fields for process optimization [27-28]. In this study, the quadratic RSM model associated with D-Optimal design is used to optimize the operating conditions of the CPU process. Five parameters at three different levels are considered for each at different points in the processes to propose optimal operating conditions. The criteria for selecting the appropriate model included the model p-value (P value < 0.05), the p-value of disproportion (>0.05), and the coefficient of determination R^2 (> 0.9). The p-value of the model (<0.05) indicates that the probability of the model being incorrect is less than 5%. In the following sections of the paper, each response level (Y) is represented using a quadratic equation as given in Eq. (1):

$$Y = \alpha_0 + \sum_{i=1} 6\alpha_i X_i + \sum_{i=1} 6\alpha_{ii} X_i^2 + \sum i \sum j \alpha_{ij} X_i X_j \quad (1)$$

where Y represents the predicted response associated with each factor level combination, X_i the levels of the independent variables, and α the regression coefficients of the independent variables. Also, i represents the linear effect, ij the interaction effect, and ii the squared effect. In this study, after validating the simulation results by comparing them with data available in the literature [29-30] and achieving good agreement, different operating

conditions were tested under the RSM D-Optimal design. Finally, the results were analyzed using statistical software and the optimal operating conditions for the process were proposed. The independent variables and the interactions are statistically considered significant if the p-value is lower than 0.05. According to Table 2, statistical analysis results show that B, and C independently, fail to have an effect on R1. Nevertheless, their interaction, such as A, E, AD, DE, A^2 and, D^2 affect the process as seen in Eq. (2). Therefore, according to hierarchical principle, their effects must be considered in the mathematical model.

$$Y = 2.569E+09 + 5.122E+07A + 6.823E+07\ E - 8.192E+07\ AD + 4.286E+07DE + 7.077E+07\ A^2 + 4.627E+07\ D^2 \quad (2)$$

3. Results and discussion

3.1. Evaluation of the prediction potential of the developed model

By determining R, R^2 mean square, R^2 adjusted error and predictions that are not significant in a regression model Adjusted R^2 were evaluated in the developed RSM model. In this Article, before analyzing the variables, the correlation between the independent variables and the responses has been examined. For analysis of variance (ANOVA), various equations including linear, two-factor interaction, quadratic, and cubic were used, in Table 2 provides summary statistics of the responses for these equations. Table 2 provides an overview of the performance evaluation, and application of the predictive model to the response. Quadratic is the best answer prediction model. According to the data in the table, the best values for optimizing energy consumption based on all parameters are as follows. The predicted R^2 of 0.6372 is in reasonable agreement with the adjusted R^2 of 0.7569. That is, the difference is less than 0.2 and can be used for interpolation. Also, random error values less than 0.0500 also show that the conditions of the model are acceptable. In this model, the parameters A, E, AD, DE, A^2 and, D^2 have the most influence on fuel consumption, and values greater than 0.1000 indicate that the conditions of the model are not significant (Appendix-Table A1). Table 2 shows the values determined for the proven models and the performance evaluation. The value of R^2 shows that the model can explain more than ninety percent of the variance of the operational data and the expected values and proves the correctness of the model. In Table 3, the statistical models for evaluation are given by mentioning the equation.

Table 2. Models' summary statistics and evaluation of their performance

Source	Sequential p-value	Adjusted R^2	Predicted R^2	R^2	
Linear	< 0.0001	0.7009	0.6826	0.7139	Suggested
2FI	0.0374	0.7266	0.6364	0.7623	
Quadratic	0.0061	0.7569	0.6372	0.7992	**Suggested**
Cubic	0.1488	0.7850	-0.4682	0.8878	

Table 3. Equations of statistical models for evaluation

Equation	Number
$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{i,pre} - Y_{i,exp}\right)2}{\sum_{i=1}^{n}\left(Y_{i,exp} - Y_{m}\right)2}$	(3)
$\text{Adjusted } R^2 = 1-(1-R^2) \times \frac{n-1}{n-k-1}$	(4)

The results of the analysis of the difference between the observed and expected values are shown in Fig. 1. Given that the difference between the simulated points in the prediction model is small, the unpredictable values are also minimized and the models used in this study are known as reliable models. The kcal of the kiln fuel consumed is a key issue. The chemical parameters of the kiln feed analysis are also of particular importance. These parameters have been selected based on experience and a high probability of affecting the amount of energy consumed, directly affecting fuel consumption, product cost price and energy share.

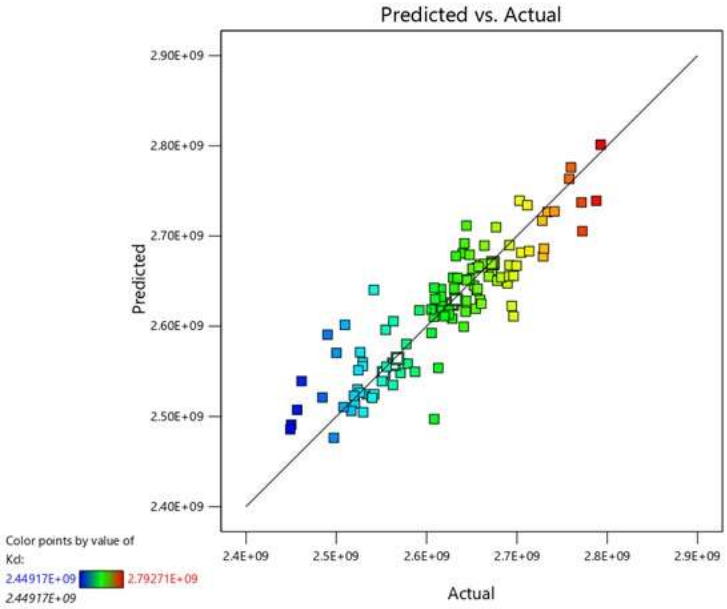


Fig. 1. Predicted versus actual plots of response: fuel consumption

For ease of reading, we used A to represent the LSF agent, B to represent the Residual on the sieve 90-micron agent, C to represent the SM agent, D to represent the AM agent and, E to LP. Table A1 in the appendix shows that the main influencing factors were A, E, AD, DE, A^2 and, D^2. Although factor C was not significant, it is considered significant due to its interaction effect. A model F-value of 18.90 indicates that the model is significant, and P-values less than 0.05 indicate that the model conditions are significant.

As shown in Fig. 2, fuel consumption were significantly affected by the individual factors LSF, SM, and AM, with each factor having a subsequent "increasing" trend. As shown in Fig. 2, fuel consumption were significantly affected by the individual factors LSF, SM, and AM, with each factor having a subsequent "increasing" trend. For the 90-micron sieve residue, as can be seen in the figure, the trend was essentially constant and almost unaffected.

The response surface plots for the interactive conditions are shown in Figure 3. The contour plots for the AC factor in Fig. 3(A) are completely elliptical, indicating a significant interaction between them. In this factor, at first, the trend was decreasing, but it gradually increased during the operating conditions. Fig. 3(D) is the contour diagram of response levels in an ellipse. This shows that there is a significant interaction between the component elements in this statement. First, the trend decreased and then increased with the increase of SM, and with the increase of AM, the trend was significantly increasing. Fig. 3(C-E-F) shows that the contours of AE, CE, and DE were irregularly circular and highly interactive. In Fig. 3€, with the gradual increase of LP, the number of fuel consumption has decreased, but it has started to increase with the increase of SM. In Fig. 3(F), the same behavior as in the previous

figure was observed, with the increase in the amount of LP kilocalories consumed, there is a decreasing trend, and with the increase in AM, we have seen an increasing trend. In Figure C, fuel consumption increased with the increase of LSF and the trend was decreasing with the increase of LP.

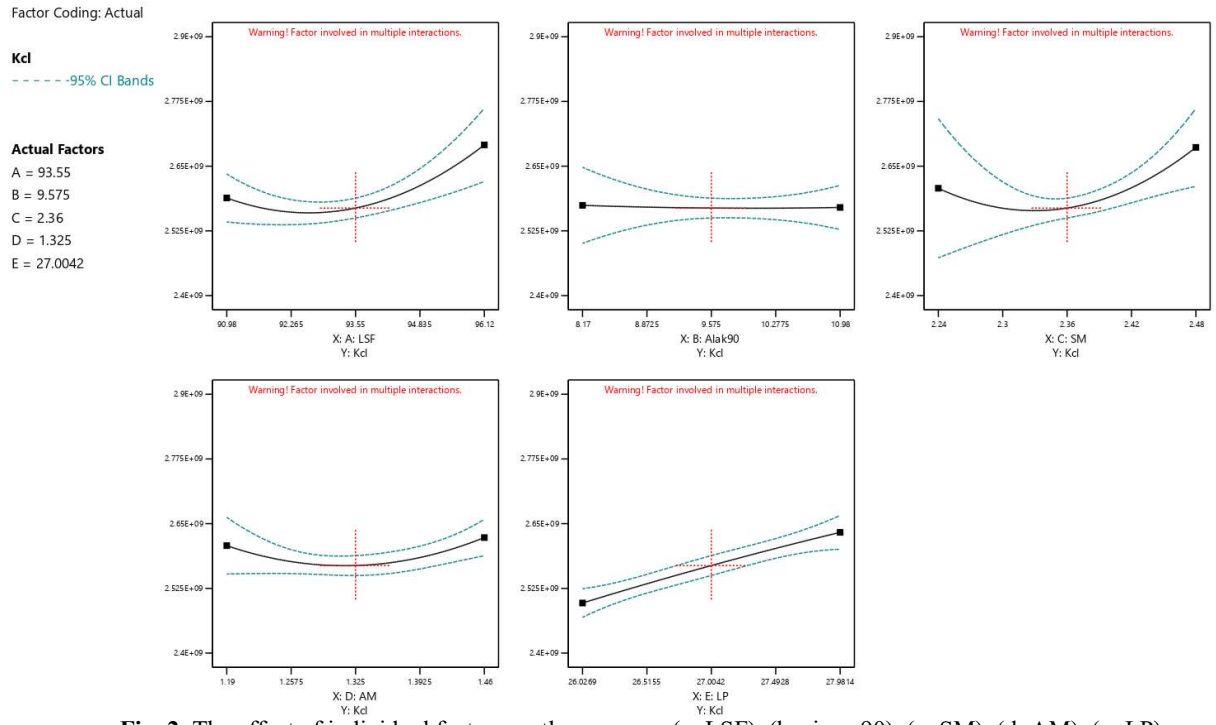


Fig. 2. The effect of individual factors on the response (a: LSF), (b: sieve 90), (c: SM), (d: AM), (e: LP)

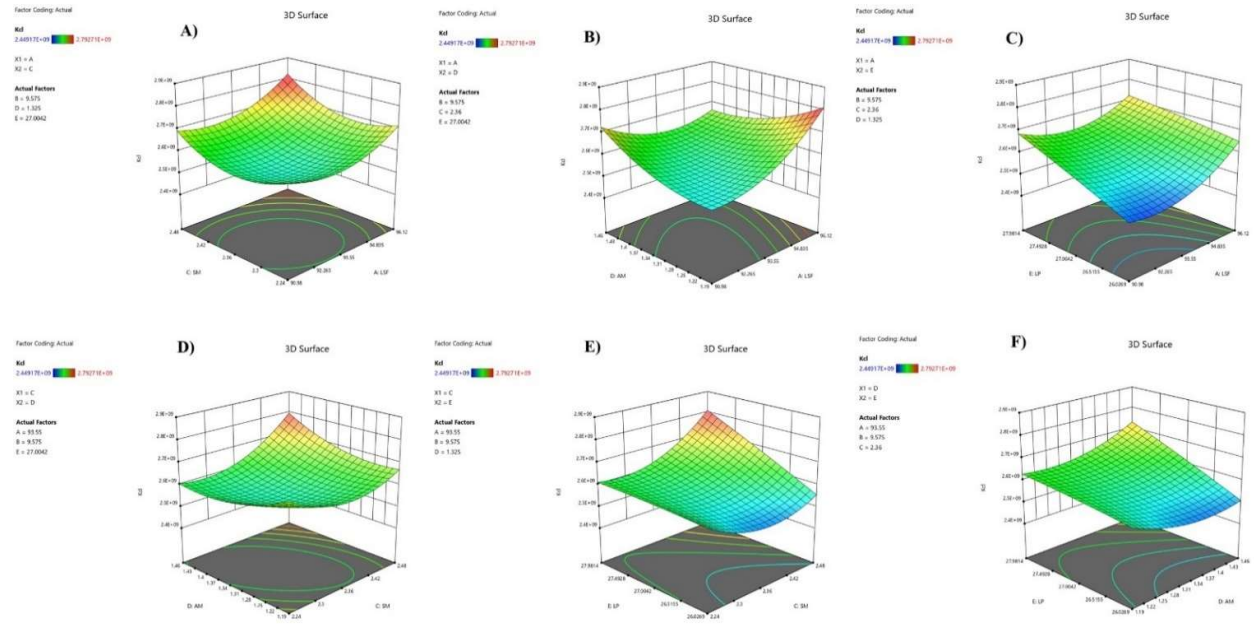


Fig. 3. Response surface & contour plots of different interaction conditions in the three-dimensional mode for response: (A) LSF and SM on fuel consumption, (B) LSF and AM on fuel consumption, (C) LSF and LP on fuel consumption, (D) SM and AM on fuel consumption, (E) SM and LP on fuel consumption, (F) AM and LP on fuel consumption

3.2. Model optimization and validation

Predictive modeling is a statistical technique used to predict future behavior. It analyzes empirical data to create a model that helps predict future outcomes. As you can see in Table 4, the response optimization results are suitable and reliable because they are in the 95% prediction interval.

Table 4. Confirmed data for the predicted model (fuel consumption)

Predicted mean	standard deviation	Standard error of the mean	with 95% confidence in the true range (lowest)	with 95% confidence in the true range (highest)
2.56911E+09	3.83551E+07	9.66782E+06	2.54992E+09	2.5883E+09

4. Conclusion

In this study, to overcome the time-consuming and difficult mechanical constraints on the influence of parameters on each other in the cement production process, a numerical response surface model was investigated using operational and experimental data. Using real production data, Design Expert software was used to obtain the relationship between fuel consumption and chemical modules and optimize them to determine the best efficiency. Although the model works well in practice, in general, predictive models do not always provide correct data for optimization and more accurate values should be obtained in reality and operation. In Zabol Cement Industries Company, we concluded that the number of chemical modules for kiln feed analysis, LSF and AM had the greatest impact on fuel consumption (since the number of these two parameters has an upward and increasing trend, we have seen an increase in the number of kilocalories consumed compared to the LP parameter. By reducing the amount of LSF by one unit, we will see a ten-unit reduction in the amount of kilocalories consumed in the oven, which will result in better cooking. It has an inverse relationship and its increase reduces fuel consumption and the residual on the 90-micron sieve was not visible in the model due to the low range of changes. Finally, the proposed solution was operationally evaluated in the relevant unit and the accuracy of the above optimizations was evaluated. In this research, the lowest value of the range of each factor is considered to be the low level and the highest value is considered to be the high level and the midpoint between the low and high levels is considered to be the medium level. Finally, the optimal number of analyzed parameters in which the fuel consumption is at its best is given in Table A3 of Appendix A.

Nomenclature

Symbols

Y	Predicted response	LP	Liquid Phase
T	Temperature	LSF	Limestone Saturation Factor
Abbreviations		MS	Mean Squares (Anova Test)
AM	Alumina modulus	P-Value	Probability in Statistical Significance Testing
DF	Degree of freedom	RSM	Response Surface Methodology
F- Value	Ratio of Variance (Anova Test)	SM	Silica Modulus

References

[1] Rasul, M.G., Widianto, W., Mohanty. B., 2005. Assessment of the thermal performance and energy conservation opportunities of a cement industry in Indonesia, Applied Thermal Engineering, 25 (17-18), 2950-2965. DOI: 10.1016/j.applthermaleng.2005.03.003.

[2]. Fergani, Z., Touil, D., Morosuk. T., 2016. Multi-criteria exergy-based optimization of an Organic Rankine Cycle for waste heat recovery in the cement industry, Energy Convers. Manag, 112, 81-90. DOI: 10.1016/j.enconman.2015.12.083.

[3]. Ahamed. Ju., Madlool, N.A., Saidur, R., Shahinuddin, M.I., Kamyar, A., Masjuki. H.H., 2012. Assessment of energy and exergy efficiencies of a grate clinker cooling system through the optimization of its operational parameters, Energy, 46, 664-674, http://dx.doi.org/10.1016/j.energy.2012.06.074.

[4]. Fellaou, S., Bounahmidi, T., 2017. Evaluation of energy efficiency opportunities of a typical Moroccan cement plant: Part I. Energy analysis. Applied Thermal Engineering, 115, 1161–1172. https://doi.org/10.1016/j.applthermaleng.2017.01.010.
[5]. Taweel, T., Sokolova, E., Sergeev, V., & Solovev, D., 2018. Energy and exergy analysis of clinker cooler in the cement industry. Paper presented at the IOP conference series: Materials Science and Engineering. DOI:10.1088/1757-899X/463/3/032101
[6]. Shao, W., Cui, Z., & Ma, X.-T., 2020. Experimental research on cement grate cooler system and numerical simulation of its clinker cooling process. Applied Thermal Engineering, 181, 115904. https://doi.org/10.1016/j.applthermaleng.2020.115904.
[7]. Shao, W., Cui, Z., Wang, N., & Cheng, L., 2016. Numerical simulation of heat transfer process in cement grate cooler based on dynamic mesh technique. Science China Technological Sciences, 59 (7), 1065–1070. https://doi.org/10.1007/s11431-016-6074-6.
[8]. Utlu, Z., Sogut, Z., Hepbasli, A., & Oktay, Z., 2006. Energy and exergy analyses of a raw mill in a cement production. Applied Thermal Engineering, 26 (17–18), 2479–2489. https://doi.org/10.1016/j.applthermaleng.2005.11.016.
[9]. Atmaca, A., & Atmaca, N., 2016. Determination of correlation between specific energy consumption and vibration of a raw mill in cement industry. Anadolu Üniversitesi Bilim Ve Teknoloji Dergisi A-Uygulamali Bilimler Ve Mühendislik, 17 (1), 209–219. DOI:10.18038/btda.11251.
[10] Benhelal, E., Zahedi, G.H., Shamsaei, E., Bahadori, A., 2013. Global Strategies and Potentials to Curb CO_2 Emissions in Cement Industry, Journal of Cleaner Production, 51, 142-161. https://doi.org/10.1016/j.jclepro.2012.10.049.
[11] Andrew R.M., 2018. Global CO_2 Emissions from Cement Production, Ear. Sys. Sci. Data, 10 (1), 195-217.
[12] Andrew R.M., 2019. Global CO2 Emissions from Cement Production, Earth System Science Data, 11 (4), 1675-1710.
[13] Koohestanian, E., Shahraki, F., 2021. Review on Principles, Recent Progress, and Future Challenges for Oxy-Fuel Combustion CO2 Capture Using Compression and Purification Unit, Journal of Environmental Chemical Engineering, 9 (4), 105777. https://doi.org/10.1016/j.jece.2021.105777.
[14] Koohestanian, E., Samimi, A., Mohebbi-Kalhori, D., Sadeghi, J., 2017. Sensitivity Analysis and Multi-Objective Optimization of CO_2CPU Process Using Response Surface Methodology, Energy, 122, 570-578. https://doi.org/10.1016/j.energy.2017.01.129.
[15] Ströhle, J., Hofmann, C., Greco-Coppi, M., Bernd, E., 2021. CO_2 Capture from Lime and Cement Plants Using an Indirectly Heated Carbonate Looping Process-the Anica Project, in TCCS-11. CO_2 Capture, Transport, and Storage, 11th International Trondheim CCS Conference.
[16] Koohestanian, E., Sadeghi, J., Mohebbi-Kalhori, D., Shahraki, F., Samimi A., 2021. New Process Flowsheet for CO_2 Compression and Purification Unit; Dynamic Investigation and Control, Iranian Journal of Chemistry and Chemical Engineering (IJCCE), 40 (2), 593-604. https://doi:10.30492/ijcce.2020.37779.
[17] Nie, S., Zhou, J., Yang, F., Lan, M., Li, J., Zhang, Z., Chen, Z., Xu, M., Li, H., Sanjayan, J.G. 2022. Analysis of Theoretical Carbon Dioxide Emissions from Cement Production: Methodology and Application, Journal of Cleaner Production, 334, 130270. https://doi.org/10.1016/j.jclepro.2021.130270.
[18] Mansouri, S., Shahraki, F., Sadeghi, J., Koohestanian, E., Sardashti Birjandi, M.R., 2024. Experimental Investigation of Energy Consumption and CO_2 Emission in Cement Kiln in Effect of Replacement Natural Pozzolan by Method of Grinding Clinker and Pozzolan Separately, Iran. J. Chem. Chem. Eng. (IJCCE), 43, 1, 382-394. 10.30492/ijcce.2023.1999807.5956
[19] Mansouri, S., Shahraki. F., Sadeghi. J., Koohestanian. E., Sardashti Birjandi. M.R., 2024. Using Response Surface Methodology Approach to Modeling and Optimization of the Combustion Process in Cement Kiln, Chem. Eng. Technol, 47, 6, 875–886. DOI**:** 10.1002/ceat.202300224.
[20]. Xray Laboratory, Zabol Cement Industries Company, Hamgaman Tose'e S&B Holding.
[21]. Myers, R.H., Montgomery, D.C., Anderson-Cook, C.M., 2016. Response Surface Methodology: Process and Product Optimization Using Designed Experiments, 4th Edition, John Wiley & Sons, ISBN: 978-1-118-91601,856 pages.
[22]. Derringer, G., Suich, R., 1980. Simultaneous optimization of several response variables. J. Qual. Technol. 12, 214–219. doi: 10.1080/00224065.1980.11980968.
[23] Karichappan. T., Venkatachalam. S., Jeganathan. P.M., 2014. Optimization of electrocoagulation process to treat grey wastewater in batch mode using response surface methodology, Journal of Environmental Health Science and Engineering, 12, 29. doi: 10.1186/2052-336X-12-29.
[24] Valipour. M, 2016. Optimization of neural networks for precipitation analysis in a humid region to detect drought and wet year alarms, Meteorological Applications, 23, 91-100. https://doi.org/10.1002/met.1533.
[25] Montgomery. D.C., Design and analysis of experiments, 2008, John Wiley & Sons.
[26] Valipour. M., Sefidkouhi. M.A.G., Eslamian. S., 2015. Surface irrigation simulation models: a review, International Journal of Hydrology Science and Technology, 5, 51-70. https://doi.org/10.1504/IJHST.2015.069279.
[27] Chou. W.L., Wang. C.T., Chang. W.C., Chang.S.Y., 2010. Adsorption treatment of oxide chemical mechanical polishing wastewater from a semiconductor manufacturing plant by electrocoagulation, Journal of hazardous materials, 180, 217-224. https://doi.org/10.1016/j.jhazmat.2010.04.017.
[28] Parkash Maran. J., Sivakumar. V., Thirugnanasambandham. K., Sridhar. R., 2013. Artificial neural network and response surface methodology modeling in mass transfer parameters predictions during osmotic dehydration of Carica papaya L, Alexandria Engineering Journal, 52, 507-516. https://doi.org/10.1016/j.aej.2013.06.007.
[29] Posch. S., Haider. M., 2012. Optimization of CO_2 compression and purification units (CO_2CPU) for CCS power plants, Fuel, 101, 254-263. https://doi.org/10.1016/j.fuel.2011.07.039.
[30] Jin, B., Zhao, H., Zheng. C., 2015. Optimization and control for CO_2 compression and purification unit in oxy-combustion power plants, Energy, 83, 416-430. https://doi.org/10.1016/j.energy.2015.02.039.

Appendix A

Table A1. ANOVA results for simplified model for response variable (quadratic model)

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
Model	5.561E+17	20	2.781E+16	18.90	< 0.0001	significant
A-LSF	7.881E+15	1	7.881E+15	5.36	0.0228	
B-Residual on the sieve 90-micron	1.270E+13	1	1.270E+13	0.0086	0.9262	
C-SM	2.749E+15	1	2.749E+15	1.87	0.1748	
D-AM	4.066E+14	1	4.066E+14	0.2764	0.6003	
E-LP	7.138E+16	1	7.138E+16	48.52	< 0.0001	
AB	2.748E+15	1	2.748E+15	1.87	0.1749	
AC	9.586E+13	1	9.586E+13	0.0652	0.7991	
AD	7.604E+15	1	7.604E+15	5.17	0.0252	
AE	3.620E+15	1	3.620E+15	2.46	0.1200	
BC	1.366E+13	1	1.366E+13	0.0093	0.9234	
BD	1.418E+13	1	1.418E+13	0.0096	0.9220	
BE	7.832E+14	1	7.832E+14	0.5324	0.4674	
CD	3.888E+15	1	3.888E+15	2.64	0.1073	
CE	4.309E+15	1	4.309E+15	2.93	0.0902	
DE	7.944E+15	1	7.944E+15	5.40	0.0223	
A^2	1.611E+16	1	1.611E+16	10.95	0.0013	
B^2	3.439E+13	1	3.439E+13	0.0234	0.8788	
C^2	4.313E+15	1	4.313E+15	2.93	0.0901	
D^2	7.860E+15	1	7.860E+15	5.34	0.0230	
E^2	1.172E+14	1	1.172E+14	0.0797	0.7784	

Table A2. Data runs received from the X-ray laboratory of Zabol cement Industries Company for experiment design [31]

Number	LSF	Residual on the sieve 90-micron	SM	AM	LP
1	90.98	9.62	2.35	1.36	27.29
2	93.65	10.31	2.38	1.43	27.78
3	94.65	9.38	2.38	1.23	27.59
4	92.14	9.87	2.34	1.3	26.57
5	95.36	9.55	2.36	1.43	27.79
6	94.4	8.47	2.48	1.41	26.10
7	92.65	10.8	2.39	1.43	27.95
8	93.22	9.93	2.32	1.3	26.29
9	93.27	10.97	2.32	1.35	27.05
10	93.88	9.45	2.4	1.19	27.58

Table A3. The optimal number of data after modeling

Parameter	fuel consumption	LSF	SM	AM	LP	Residual on the sieve 90-micron
The optimal number	2.569×10^{9}	93.55	2.36	1.33	27.1	9.3