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Optimizing Production Planning in Cement Manufacturing Using SVR

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Abstract

The devastating earthquake that caused significant destruction in 11 provinces on February 6, 2023, has accelerated the growth rate of the cement sector. This rapid growth, coupled with increasing stock market activity, marks a golden age for the sector while emphasizing the critical need for accurate future production forecasting. Leveraging the predictive capabilities of machine learning algorithms, experiments were conducted using five years of production data from a cement factory in the Southeastern Anatolia region. The Support Vector Regression (SVR) model, an application of the Support Vector Machine (SVM) algorithm, was tested with RBF, linear, sigmoid, and polynomial kernels. Among these, the SVR model with the RBF kernel yielded the best performance across four evaluation metrics: Mean Squared Error (MSE): 0.002926, Root Mean Squared Error (RMSE): 0.054094, Mean Absolute Error (MAE): 0.048611, and Mean Absolute Percentage Error (MAPE): 0.052697. This paper highlights the effectiveness of SVR-RBF in providing reliable production forecasts for the cement industry and supporting strategic planning to address dynamic market demands.

Keywords

Cement, Kernels, Prediction, SVM, SVR, Production planning

INTRODUCTION

Cement is an indispensable material in modern construction, obtained through the calcination and grinding of specific raw materials. It is the backbone for a wide range of structures, from residential buildings to large-scale infrastructure projects, and plays a critical role in urban development [1]. The production process involves heating raw materials like limestone and clay to high temperatures, which is both resource-intensive and energy-demanding. Consequently, accurate forecasting in production planning has become vital for optimizing operations, reducing costs, and meeting fluctuating market demands. As in all production processes, forecasts for use in future production planning are very important. In production planning processes, prediction studies using machine learning algorithms have become quite popular in recent years. Machine learning algorithms are increasingly being used in production planning processes to make predictions and optimize various aspects of production. These algorithms identify patterns, forecast future production needs, demand trends, inventory levels, and other key factors. By leveraging machine learning in production planning, companies can improve efficiency, reduce costs, and better meet customer demands [2]. One of these algorithms, SVR, which is specialized for regression of SVM, can be a valuable tool in optimizing production processes to predict cement production using machine learning algorithms. Predicting cement production using machine learning algorithms such as SVR can be a valuable tool in optimizing production processes. SVM works with labeled data, so it is suitable method to analyze data and find hidden patterns among the data [3]. SVM can perform well with small datasets compared to some other machine learning algorithms. This is because SVM focuses on finding the best separation or decision boundary between different classes in the data, and it does not rely on the entire dataset to do so. In contrast, other algorithms like deep learning models may require great number of data for training to learn and generalize patterns effectively. SVM's ability to handle small datasets is advantageous in situations where limited data is available for training [4].

The cement sector is generally associated with many economic activities, but as a result of the economic development and rapid population growth experienced between 2000 and 2020, production and consumption have doubled. In 2020, it was among the top 10 producers in the world, while it ranked 2nd in exports with a foreign exchange input of 1.2 billion dollars [5]. By utilizing an SVR-based prediction system in cement production planning processes, companies can gain insights into anticipated output levels, optimize resource allocation, manage inventory effectively, and ultimately enhance operational efficiency. Many data sets can be used for cement production estimation, such as laboratory experiments, industrial production data or simulation data. The data set used in this paper includes production data values of a cement factory in the Southeastern Anatolia region. To apply SVR to predict cement production, historical data related to factors influencing production such as Electricity consumption amount, Coal consumed waste and as raw material; Limestone, Marn, Ash, Iron Ore, Fluorite, Bauxite parameters can be used. This data can be used to train the SVM model to recognize patterns and relationships that affect cement production. Once the SVR model is trained with relevant features and historical output data, it can then be used to make predictions for future production levels based on input variables. The model's ability to identify complex patterns in the data makes it useful for forecasting variations in cement production under different scenarios.

Production Planning and Control (PPC) plays a critical role in optimizing manufacturing systems, especially in complex interdepartmental structures. The advent of Industry 4.0 has introduced vast data availability, advanced processing power, and extensive storage capacity, making Machine Learning (ML) an attractive solution for addressing production challenges. A systematic review of 93 recent studies highlights that ML-supported PPC (ML-PPC) methodologies can significantly enhance decision-making in production planning. These studies suggest that integrating machine learning into production planning not only optimizes operations but also offers valuable insights for addressing issues such as inventory management, demand fluctuations, and resource allocation. However, the research also reveals gaps, including limited integration of customer, environmental, and human aspects into ML-PPC models, as well as challenges in adapting ML models to dynamic production systems. These insights underscore the importance of PPC in cement production forecasting, where precise planning, driven by accurate machine learning models like SVR, can lead to improved efficiency and sustainability [6].

The remaining sections of the paper are organized as follows: The "Materials and Methods" section covers detailed information on cement production, different types and properties of cement, an overview of the SVM algorithm, and the error metrics employed to evaluate model performance. The "Literature Review" section provides an overview of related research on machine learning applications in cement production and forecasting. The "Data Preprocessing" section discusses the dataset in detail, including any preprocessing steps undertaken to prepare the data for modeling. The "SVR Model and Experimental Results" section describes the SVR model design and presents the findings from experiments conducted with various SVM kernel functions. Finally, the "Conclusion" section includes a comprehensive evaluation of the results, summarizing the paper's contributions and suggesting directions for future research.

MATERIALS AND METHODS

Cement Production

The raw materials used in cement production are limestone, marl, ash, iron ore, fluorite, bauxite, and other additives. The production process begins with the procurement of these raw materials. These raw materials arrive in larger pieces than necessary and are first crushed into large fragments. This allows the materials to be broken down into smaller pieces for easier processing in subsequent steps. The crushed raw materials are then ground into a powder during the grinding step. This process homogenizes the cement and increases efficiency [7]. The homogenized raw materials are mixed in specific proportions. This mixture is formulated to reflect the main characteristics of the cement. The degree of homogenization is very important as it directly affects the quality of the cement. The homogeneous mixture is heated in a preheating unit. The heating process helps conserve energy. The mixture heated in the preheater is then processed in the cement kiln. Cement kilns rotate continuously, and their internal temperatures reach around 1600°C. The limestone and clay used in the raw materials combine to form clinker, the main component of cement. The resulting clinker is subsequently cooled from the high temperature. This process preserves the physical properties of the clinker. Air and some cooling systems are used for the cooling process. The cooled clinker is then ground into a powder.

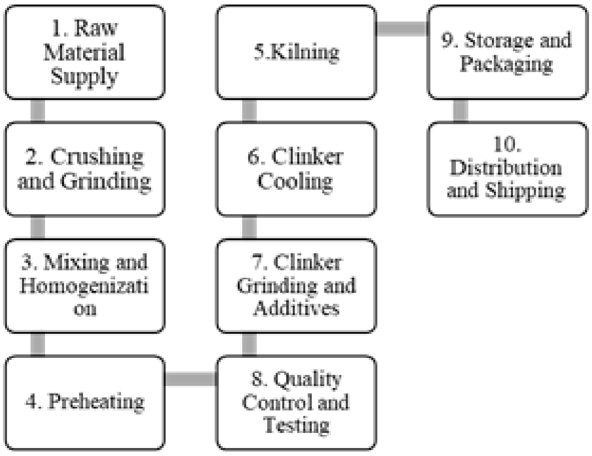

Figure 1. Cement Production Steps

The grinding of clinker determines the final form of the cement. Other raw materials are added during the grinding process as we can see Figure 1. The produced cement undergoes continuous laboratory testing. The purpose of these tests is to assess the quality of the cement. Various quality control tests are conducted at every stage of cement production. The aim of these tests is to ensure compliance with standards. Cement is stored in silos, which protect the produced cement from moisture. Cement can be packaged in two forms: bagged and bulk. Bulk cement is used for large projects, while bagged cement is used for smaller projects. The packaged cement is distributed to customers based on demand. All these processes are illustrated in the cement production scheme above.

Types and Properties of Cement

CEM I Portland Cement (Clinker Ratio 95-100%): The most preferred type of cement, suitable for all applications.

CEM II Portland Composite Cement (Clinker Ratio 65-94%): Suitable for marine structures, dams, piers, and similar constructions.

CEM III Blast Furnace Slag Cement (Clinker Ratio 5-64%): More environmentally friendly compared to CEM I and CEM II. Used in areas exposed to abrasive effects, such as breakwaters.

CEM IV Pozzolanic Cement (Clinker Ratio 45-89%): Used in projects requiring high durability. Applicable in plaster and wall mortar, road surfacing, and construction chemicals.

CEM V Composite Cement (Clinker Ratio 20-64%):

Frequently used in treatment systems and water channel projects [8].

Support Vector Machine (SVM)

SVM is one of the supervised learning algorithms used in data mining and machine learning. SVM is particularly effective in classification problems, but can also be applied in regression analysis. Its main purpose is to find the best boundary (hyperplane) that separates the data into two or more classes [16] as we can see in Figure 2. Initially used to solve classification problems, SVM has been used by most authors in linear and nonlinear classifications by developing SVM regression SVR methods [12].

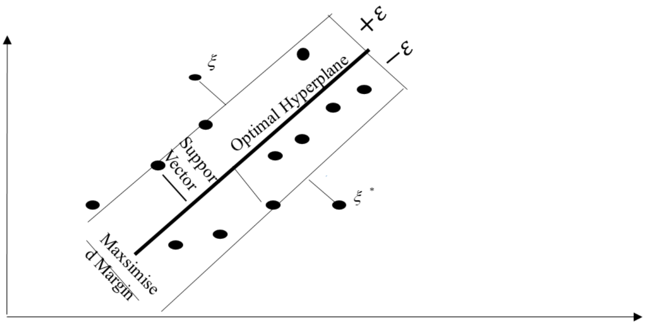

Figure 2. SVM

Training dataset $\{(X_1, Y_1)....(X_t, Y_t)\} \subset X \times R,$

X is input, Y is output. Our goal is to find a function f(x) for all training data input pairs with the least deviation ε for input Xi to Yi. As long as the errors are smaller than ε, we ignore them, and when they are larger, we review and recalculate the Wi(weights) and bi(bias).

$$f(x) = (w, x) + b \text{ with } w \in X, b \in R \tag{1}$$

$$\text{minimize} \frac{1}{2}||w||^2$$

$$\text{subject to } \begin{matrix} y_i - (w, x_i) - b \leq \varepsilon \\ (w, x_i) + b - y_i \leq \varepsilon \end{matrix} \tag{2}$$

In Eq. (1;), the function f can be applied to optimisation problems that approximate all pairs (Xi, Yi) with precision ε, convex optimisation problems. When the loose variables ς_i, ζ^*_i apply equation Eq. (1), it is desired to allow some errors, the optimisation problem equation becomes like Eq. (2) When SVM (equation 3.1) to nonlinear SVR, we get a hyper-parameter C that we can optimize (equation 3.2). We allow for an extra ς_i, ζ^*_ideviation from the margin of our data.

$$\text{minimize} \quad \frac{1}{2}w^T w + C\sum_{i=1}^{n}(\varsigma_i + \zeta^*_i)$$

$$\text{subject to} \quad \begin{matrix} y_i - (w, x_i) - b \leq \varepsilon + \varsigma_i \\ (w, x_i) + b - y_i \leq \varepsilon + \zeta^*_i \\ \varsigma_i, \zeta^*_i \geq 0 \end{matrix} \tag{3}$$

$$|\zeta|_\varepsilon := \begin{matrix} 0 & if \quad |\zeta| \leq \varepsilon \\ |\zeta| - \varepsilon & \text{otherwise} \end{matrix} \tag{4}$$

SVM algorithms use many mathematical functions defined as different types of kernel functions. For example Linear, Nonlinear, Polynomial, Gaussian, Radial Basis Function (RBF), the Gaussian Radial Basis Function, Hyperbolic Tangent and Sigmoid. In this paper we used the SVR of the sklearn.svm library with four different kernels.

Support Vector Regression (SVR)

The type of SVM method used for regression is called SVR. SVR is a powerful regression technique, especially when there are nonlinear relationships. Its success depends on the correct parameter settings and the selection of the appropriate kernel function.

Error Metrics

Error metrics are used to evaluate the success of the model in the work of the machine learning algorithm. Error metrics are used to measure the accuracy of the predictions as a result.

Mean Square Error (MSE): Measures how far the estimates are from the true values. It is the average of the squares of the errors.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_{Real} - Y_{Predicted})^2$$

Root Mean Square Error (RMSE): The square root of MSE, expressed in original error units. $\text{RMSE} = \sqrt{MSE}$. Mean Absolute Error (MAE): Measures how far the estimates are from the true values, the average of the absolute values of the errors.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_{Real} - Y_{Predicted}|$$

Mean Absolute Percentage Error (MAPE): is a commonly used metric in regression analysis to evaluate the accuracy of a predictive model. It measures the average magnitude of errors as a percentage, making it easy to interpret in terms of how large the errors are relative to the actual values.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_{Real} - Y_{Predicted}|}{Y_{Real}} * 100$$

LITERATURE REVIEW

In this section, we reviewed the articles that use machine learning algorithms in production forecasting in terms of the methods and their successes they have achieved. Indonesia is one of the largest palm oil producing regions, so [9] suggested SVR and ANN models to determine production development for the coming years. The forecasts made by SVR with RBF kernel achieved better results than ANN. Thus, they achieved 3%-6% better results in 3-year forecasting. They estimated cement production in Turkey between 2000 and 2016 for this they used Double Exponential Smoothing (DES), Simple Exponential Smoothing (SES), and 3-Period (2017-2018-2019) Double Moving Average (DMA) methods. The results obtained are parallel to each other in all three methods, and the 3-Period Double Moving Average showed a better performance, with MSE=8.39, MAD=2.39 and MAPE=0.04 values [10].

In the paper where they made energy consumption estimation in complex production processes of cement production, they compared the time-varying delay deep belief network (TVD-DBN), least squares SVM and deep belief network methods. In the study where they sought solutions to the problems of nonlinearity, time delay and uncertainty in energy consumption, they increased the generalization ability of the models by eliminating the varying delay [11].

They used SVR to predict the mechanical properties of cement mortar. They used the SVR parameters 'C' expressing the complexity of the model, 'γ' affecting the complexity of the model, and 'ε' expressing the distance from the true value, and they obtained the best results with RBF kernel as R2=0.9772, RMSE=2.564, MAPE=3.909 from the experiments [12].

Energy consumption plays a crucial role as an indicator of efficiency in cement production, particularly within raw material grinding systems. However, the complex nature of these systems—characterized by strong interdependencies, time lags, inherent nonlinearity, and uncertainty—poses significant challenges for accurate modeling. To tackle these issues, a novel LSTM model incorporating spatial attention is introduced. This approach leverages LSTM networks to effectively capture long-term temporal relationships, while the spatial attention mechanism enhances the model's sensitivity to critical information and strengthens spatial awareness. The proposed SA-LSTM model's performance was benchmarked against methods such as LSTM, Seq2Seq, ARIMA, SVM, and XGBoost, demonstrating its clear superiority over the alternatives [13].

Cement production is an energy-intensive process, significantly impacting the energy footprint of concrete systems. A predictive process model was developed to optimize clinker quality while reducing energy consumption, integrating kiln feed chemistry and critical process variables. Using two years of data from an operational cement plant, a new analytical model combining quality and operational data was created, independent of fuel type. A Feedforward Network trained on this data showed superior accuracy compared to the standard Bogue model, with lower mean square error (MSE). This approach enhances energy efficiency while maintaining or improving clinker quality [14].

A study focused on the clinker production process in cement manufacturing developed an optimization framework based on neural networks and genetic algorithms, utilizing one year of operational data. The raw material-to-coal feed mass ratio in the precalciner and the coal feed mass ratio in the rotary kiln were selected as the primary independent variables and control parameters. Specific standard coal consumption served as the key performance indicator and optimization objective. This approach demonstrated the capability of advanced algorithms to improve energy efficiency and reduce resource consumption in industrial cement production settings [15].

DATA PREPROCESSING

The dataset used in this paper includes daily production data from a five-year period, spanning from January 1, 2018, to December 31, 2023. Given that data preprocessing is a crucial step in machine learning and data mining, this stage aimed to prepare the data by correcting missing values and handling inconsistencies to ensure data quality. Due to various factors, including operational issues or maintenance, certain days lacked production data in the dataset. To address this, we used the mean imputation method, where missing production values were filled with the average values calculated from available production data. This approach was implemented using Scikit-Learn's SimpleImputer function. Non-production days (where no data was recorded due to planned shutdowns or other interruptions) were also carefully considered to ensure these values were represented accurately without skewing the data. The dataset comprises ten features: Electricity_Consumption, Coal_Consumption, Waste_Consumption, Limestone, Marn, Ash, Iron_Ore, Fluorite, Bauxite, and Clinker_Production. As all features are numerical, they were normalized using the MinMaxScaler() function in Scikit-Learn to scale the values between 0 and 1, facilitating consistent input for the SVR model. The nine features excluding Clinker_Production were used as independent variables to predict Clinker_Production, which serves as the dependent variable in this paper. By conducting thorough preprocessing, including missing data imputation and normalization, the dataset was standardized to improve model accuracy and ensure that the SVR model could reliably detect patterns in the clinker production process.

SVR MODEL AND EXPERIMENTAL RESULTS

In the experiments where we used the SVR function of SVM, three parameters were used. These parameters are kernel, C, and gamma, and fixed values were used for C=1e3 and gamma=0.00001, while 4 different values were used for Kernel (RBF, Linear, Sigmoid, Polynomial). As can be seen from Figure 3, where we show the relationship between sns.heatmap and each feature, each feature is related to cement production, but no correlation is observed between each other.

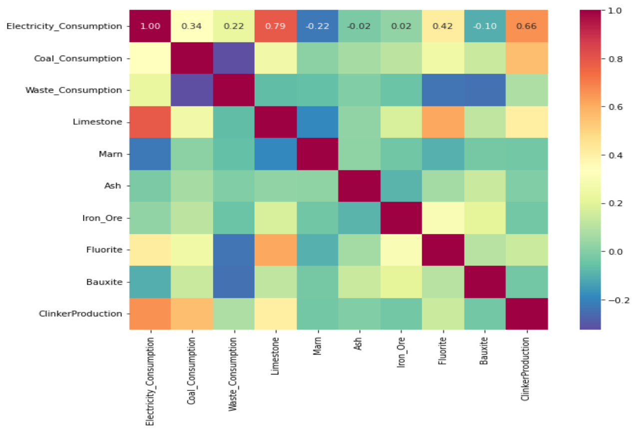

Figure 3. Attributes correlation matrix.

The results obtained with RBF, Linear, Sigmoid, Polynomial kernels for four different MAE, MAPE, MSE, AND RMSE are as in Table 1. In this paper, where we tested the applicability of SVMs to the cement sector, a very good result of MAPE = 0.052697 was obtained by using 80% of the data in the data set consisting of 5 years of data as train and 20% as test and making a next day prediction at each step.

Table 1. SVR Results with different kernels.

Kernal	MSE	RMSE	MAE	MAPE
RBF	**0.002926**	**0.054094**	**0.048611**	**0.052697**
Linear	0.012483	0.111729	0.078095	0.085754
Sigmoid	0.003544	0.059530	0.054906	0.059412
Polynomial	0.009608	0.098022	0.083199	0.089994

As can be seen from Figure 4, the cement production prediction including the last 200 days was visualized and the graph was visualized with 0.1 precision, preventing the overlapping of the graphs.RBF kernel is one of the SVM kernels that is easy to tune and preferred in many prediction problems [17].

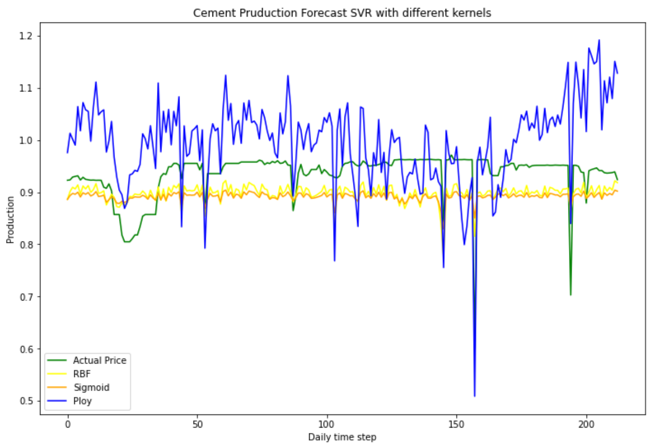

Figure 4. Cement Production forecast with different kernels.

CONCLUSION

Cement production is a cornerstone of the heavy industry sector, characterized by massive kilns operating at extremely high temperatures. The interruption of these kilns significantly disrupts production schedules and increases operational costs. Accurate forecasting and meticulous production planning are therefore crucial to maintain efficiency and sustainability in cement manufacturing processes. The MAPE value of 0.052697 achieved through our experiments indicates a high level of accuracy, offering a reliable foundation for future production planning and forecasting endeavors.

Beyond production forecasting, accurately predicting electricity consumption is integral to optimizing energy usage and reducing operational costs. Energy expenses constitute a substantial portion of overall costs in the cement industry, driven by high electricity and fuel demands during clinker production and kiln operations. By forecasting electricity consumption accurately, factories can better align their energy procurement and usage strategies, resulting in significant cost savings and minimized environmental impact. Despite its contributions, this study has certain limitations and areas for future improvement that warrant attention. While the study focuses solely on SVR, potentially limiting the exploration of other effective algorithms, the results obtained are promising. Additionally, the dataset is restricted to a single factory and specific variables, excluding external factors such as market trends or environmental impacts that could influence cement production. Furthermore, the model requires retraining of the weights obtained from the dataset to adapt to new conditions caused by changing circumstances. Future work will focus on further enhancing forecasting accuracy by leveraging updated datasets and optimizing the parameters of various deep learning algorithms. Additionally, integrating energy efficiency considerations into production planning models can unlock new opportunities for cost reduction and sustainability, ensuring that energy-intensive processes like cement production meet both economic and environmental objectives.

REFERENCES

[1]. Gao, T., Shen, L., Shen, M., Liu, L., and Chen, F., 2016, Analysis of material flow and consumption in cement production process. *Journal of Cleaner Production*, 112, 553-565.

[2]. Karahan, M., 2015, Forecasting Amount of Export Demand with Artificial Neural Networks Method: A Comparative Analysis of ARIMA and ANN. *Ege Academic Review*, 15(2), 165-172.

[3]. Cunningham, P., Cord, M., and Delany, S. J., 2008, Supervised learning. Machine learning techniques for multimedia: case studies on organization and retrieval. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 21-49.

[4]. Pasupa, K., and Sunhem, W. (2016, October). A comparison between shallow and deep architecture classifiers on small dataset. *2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE)*, IEEE, pp. 1-6.

[5]. Çağatay, B, 2021, Future Forecasts Regarding The Cement Sector In TURKEY; New Policies In The Light Of Global Trade and Macroeconomic Variables, *Dumlupınar Üniversitesi İİBF Dergisi*, 4(8), 95-115.

[6]. Usuga Cadavid, J. P., Lamouri, S., Grabot, B., Pellerin, R., and Fortin, A., 2020, Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing*, 31, 1531-1558.

[7]. Gao, T., Shen, L., Shen, M., Liu, L., and Chen, F., 2016, Analysis of material flow and consumption in cement production process. *Journal of Cleaner Production*, 112, 553-565

[8]. TURKCIMENTO, Date of access: 3/11/2024. https://www.turkcimento.org.tr/tr/cimento_nerelerde_kullanilir.

[9]. Martin, M. 2002, On-line support vector machine regression. *European Conference on Machine Learning*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 282-294.

[10]. Jueyendah, S., Lezgy-Nazargah, M., Eskandari-Naddaf, H. and Emamian, S., 2021, Predicting the mechanical properties

of cement mortar using the support vector machine approach. *Construction and Building Materials*, 291, 123396.

[11]. Mustakim,A.B. and Hermadi, I., 2016, Performance comparison between support vector regression and artificial neural network for prediction of oil palm production. *Journal of Computer Science and Information*, 1(8).

[12]. Tüzemen, A. and Yıldız, Ç., 2018, Prudential Forecasting Analysis: Türkiye Cement Production. *Journal of Management and* Economics Research, 16(3), 162-177.

[13]. Hao, X., Wang, Z., Shan, Z., and Zhao, Y., 2019, Prediction of electricity consumption in cement production: a time-varying delay deep belief network prediction method. *Neural Computing and Applications*, 31, 7165-7179.

[14]. Liu, G., Wang, K., Hao, X., Zhang, Z., Zhao, Y., and Xu, Q., 2022, SA-LSTMs: A new advance prediction method of energy consumption in cement raw materials grinding system. *Energy*, 241, 122768.

[15]. Ali, A. M., Tabares, J. D., and McGinley, M. W., 2022, A machine learning approach for clinker quality prediction and nonlinear model predictive control design for a rotary cement kiln. *Journal of Advanced Manufacturing and Processing*, 4(4), e10137.

[16]. Pan, L., Guo, Y., Mu, B., Shi, W., and Wei, X., 2024, Operation optimization of cement clinker production line based on neural network and genetic algorithm. Energy, 303, 132016.

[17]. Salcedo-Sanz, S., Rojo-Álvarez, J. L., Martínez-Ramón, M., and Camps-Valls, G., 2014, Support vector machines in engineering: an overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 4(3), 234-267.