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Scheduling and Dynamic Energy Optimization in Cement Mills

Abstract

Background/Aim: This study aims to address energy consumption challenges in cement milling operations by developing an integrated framework that incorporates production uncertainties and inventory management efficiency. The main objective is to minimize energy costs while improving production planning and environmental sustainability.

Methods: In this context, statistical and machine learning techniques, including Autoregressive Integrated Moving Average (ARIMA), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM), are employed for electricity price forecasting. Based on the forecasting results, a Mixed Integer Linear Programming (MILP) model is developed to optimize production scheduling and energy consumption. The proposed framework incorporates forecasted electricity-price fluctuations into production scheduling to generate cost-oriented production plans while satisfying operational constraints.

Results: Among the forecasting methods, the LSTM model demonstrates superior performance with the lowest error rates. Furthermore, the optimization model provides efficient production plans that satisfy operational constraints and improve resource utilization.

Conclusion: The results indicate that integrating forecasting techniques with optimization models significantly enhances energy efficiency and production management in cement plants, while also contributing to environmental sustainability and strengthening the competitive advantage of industrial operations.

Keywords: *Price Forecasting, Scheduling, Energy, Optimization, Mixed-Integer Linear Programming (MILP)*

Çimento Değirmenlerinde Çizelgeleme ve Dinamik Enerji Optimizasyonu

Öz

Bu çalışma, çimento öğütme operasyonlarında enerji tüketimiyle ilgili zorlukları ele almak amacıyla, üretim belirsizliklerini ve stok yönetimi etkinliğini bütüncül bir çerçevede ele alan bütünleşmiş bir yapı geliştirmeyi amaçlamaktadır. Temel amaç, üretim planlamasını ve çevresel sürdürülebilirliği iyileştirirken enerji maliyetlerini minimize etmektir. Bu kapsamda, elektrik fiyat tahmini için Otoregresif Entegre Hareketli Ortalama (ARIMA), Aşırı Gradyan Artırma (XGBoost) ve Uzun Kısa Süreli Bellek (LSTM) gibi istatistiksel ve makine öğrenmesi teknikleri kullanılmaktadır. Tahmin sonuçlarına dayanarak, üretim çizelgelemesini ve enerji tüketimini optimize etmek amacıyla Karma Tam Sayılı Doğrusal Programlama (MILP) modeli geliştirilmiştir. Önerilen yöntem, üretim faaliyetlerini dalgalanan elektrik fiyatlarına göre uyarlayarak enerji maliyetlerini başarıyla azaltmaktadır. Tahmin yöntemleri arasında, LSTM modeli en düşük hata oranları ile en üstün performansı göstermektedir. Ayrıca, optimizasyon modeli operasyonel kısıtları karşılayan ve kaynak kullanımını iyileştiren etkin üretim planları sunmaktadır. Elde edilen sonuçlar, tahmin tekniklerinin optimizasyon modelleriyle entegre

edilmesinin, çimento tesislerinde enerji verimliliğini ve üretim yönetimini önemli ölçüde artırdığını, aynı zamanda çevresel sürdürülebilirliğe katkıda bulunduğunu ve endüstriyel operasyonların rekabet avantajını güçlendirdiğini göstermektedir.

Anahtar kelimeler: *Fiyat Tahmini, Çizelgeleme, Enerji, Optimizasyon, Karma Tam Sayılı Doğrusal Programlama*

1.INTRODUCTION

Nowadays, energy optimization and environmental sustainability are of critical importance in the operational processes of industrial plants. In this context, cement production, which is one of the most energy-intensive sectors, has great potential in terms of both minimizing energy costs and reducing environmental impacts.

In the cement production process, energy costs account for 50% to 60% of the production costs and electricity costs account for 21% of the total cost of cement production [1, 2]. Therefore, improving energy efficiency and minimizing energy costs is a key element of a sustainable business strategy. Electricity prices vary hourly depending on the weather, the cost of the initial energy source (such as coal and natural gas), and the hourly supply and demand. Fluctuations in energy prices can have a significant impact on the cost structure of the mill. Therefore, forecasting energy prices and deciding which product to produce on which day and at what time when creating the production schedule is a critical factor in minimizing energy costs and increasing production efficiency. Forecasting energy costs in advance will also make the energy purchasing process more consistent and reduce purchasing costs for the company.

The main objective of this study is to increase the efficiency, economics, and environmental sustainability of the cement production process through strategic optimization of energy consumption in grinding operations. In this context, one of the study's unique contributions is the presentation of an approach that integrates predicted energy prices into a mathematical model-based solution methodology aimed at planning the production schedule and minimizing environmental impact. Furthermore, this study aims to contribute to the literature by including real-life applications in terms of energy management and environmental sustainability in the cement industry. This level of integration and its industrial application using real data has not been previously addressed in the literature within this sector.

1.1. Current System

The cement production process involves a series of simultaneous, energy-intensive operations, including raw material preparation, clinker production, cement grinding, and storage. Cement leaving the mill is transferred to silos and subsequently shipped by truck to different regions.

Production planning requires the coordination of cement mill operations and silo storage while considering variations in electricity prices throughout the day. In Türkiye's day-ahead electricity market, hourly electricity prices are determined one day in advance by EPİAŞ based on nationwide supply and demand. Therefore, the timing of energy-intensive grinding operations can have a direct effect on production costs. Operational planning must also account for practical restrictions such as silo capacities, mill downtime, energy requirements, and product demand.

1.2. Literature Review

1.2.1. Scheduling

In the pursuit of advancing energy efficiency and mitigating operational costs within electricity-intensive industrial processes, a series of pivotal studies has been undertaken. Hadera and Harjunkoski [3] address the intricacies of continuous-time batch scheduling, specifically focusing on optimizing electricity consumption costs in steel-making processes. Their research, based on a steel plant melt-shop model, formulates the scheduling challenge as a continuous-time MILP problem. By

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addressing the complexities of day-ahead electricity markets, such as price volatility and deviation penalties, the proposed model demonstrates a clear capacity for substantial cost savings. Its adaptability is particularly noteworthy for energy-intensive industries, offering a robust strategy for navigating liberalized electricity markets.

Castro et al. [4] contribute significantly by exploring a novel continuous-time scheduling formulation tailored for continuous plants navigating variable electricity costs. The study confronts challenges related to multiple due dates, utility availability, and the dynamic nature of energy pricing. Introducing a hybrid MILP scheduling model to efficiently represent storage units, the research underscores the importance of integrating variable electricity costs into scheduling decisions. Notably, their proposed model indicates potential cost savings of approximately 20% and advocates for the integration of mathematical formulations into industry decision-making tools.

Swanepoel et al. [5] offer valuable insights into integrated energy optimization within the cement industry. The research not only develops a comprehensive model encompassing time formulation, energy consumption, and raw material usage, but also delineates a strategic roadmap. The first stage involves model creation and optimization to strategically minimize costs and energy usage. The second stage includes establishing management structures, continuously monitoring implemented strategies, and maintaining an iterative process for setting and achieving energy-saving goals. The incorporation of the Process Toolbox (PTB) system for process control and monitoring adds a layer of sophistication, emphasizing the system's pivotal role in achieving optimization goals through continuous data collection and processing. This holistic approach further integrates strategic planning, operations control, and reporting into the fabric of energy optimization strategies.

In addressing electricity resource shortages, Zhao et al. [6] propose a model that integrates Smart Grid and Demand Response (DR) methods, with a specific focus on the industrial sector. Their paper outlines a model for optimizing cement production by incorporating Time-of-Use (TOU) options and utilizing the Particle Swarm Optimization (PSO) algorithm. The application of the PSO algorithm to adjust start probabilities is meticulously detailed to minimize electricity costs. The case study involving a 5,000 tpd cement plant showcases successful load shifting, particularly in grinding operations, resulting in tangible reductions in electricity bills.

In the intricate realm of mathematical modeling for production processes, key contributions from esteemed scholars provide a robust foundation for understanding and addressing complex challenges. The works of Kis and Kovács [7] and Petkov and Maranas [8] serve as pivotal landmarks in this domain. Kis and Kovács [7] intricately delve into timing problems within parallel machine environments, presenting both the mathematical program and the dual maneuver approach. Significantly, the dual maneuver approach emerges as a superior solution, showcasing its efficacy in addressing specific problem characteristics. Petkov and Maranas [8] address multi-period production planning, introducing a mathematical model coupled with Monte Carlo simulation to maintain balance in the production process. Their strategies, encompassing order sizing and inventory management, prove indispensable for industries engaged in multi-term planning, offering a holistic perspective on production optimization.

Expanding the purview to production programming challenges, Mahdieh et al. [9] contribute innovative solutions tailored for parallel machines and flexible flow lines. Their models, rigorously evaluated for accuracy and effectiveness, not only showcase theoretical prowess but also demonstrate practical potential to offer suitable solutions in diverse production environments.

Emir and Güler [2] discuss the intricacies of electricity consumption in cement production. The study, carried out for all processes and machines in a cement plant, shows promising results supported by a mixed-integer programming model that uses the previous day's electricity prices to optimize energy consumption. The observed cost reduction compared to the current pricing scheme not only increases competitiveness but also underlines the achievement of increased energy efficiency in cement plants.

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Hadera et al. [10] present a model specifically optimized for electricity purchases. Considering the dynamic interplay of changing electricity prices and production restrictions, their model recommends tracking electricity consumption at fixed intervals for an optimized purchasing strategy, showcasing a strategic approach to energy management in the steel production sector.

The comprehensive landscape of energy-efficient production systems, decision support tools, and mathematical models is encapsulated in the review by [11]. This holistic review provides profound insights into planning for power consumption, carbon footprint reduction, and energy consumption patterns within manufacturing industries. Its overview enriches our understanding of energy management in the broader production sector.

This literature review concerning energy-efficient planning and optimization strategies in electricity-intensive industries is essential for improving our understanding of operational dynamics in these sectors. The motivation for undertaking this research stems from a gap in both industry practice and academic literature, where integrated studies considering energy pricing, production, and inventory scheduling holistically remain scarce. This study seeks to fill this gap by optimizing energy use in cement mills, thereby enhancing overall process efficiency and sustainability.

1.2.2. Price Forecasting

In a study on hourly electricity price forecasting, Weron and Misiorek [12] compared the performance of twelve time-series methods for short-term spot price forecasting in auction-type electricity markets under various market conditions. They focused on traditional autoregressive (AR) models and AR models with non-parametric innovations (pre-processed spiking AR, threshold AR, and semi-parametric ARs). The models evaluated datasets incorporating (1) time series of hourly spot prices and system-wide loads, and (2) hourly spot prices alongside air temperatures. Their results indicated that models incorporating system load as an exogenous variable generally performed better than pure price models. However, because seasonal and annual variations affect this dependence, air temperature was found to be a less significant factor than load on electricity prices. Finally, semi-parametric models were noted to provide superior point and range estimates, with the authors highlighting their potential under differing market conditions.

In another study, Dooley and Lenihan [13] analyzed the ability of two time-series forecasting methods to predict lead and zinc prices: the lagged forward price model and the ARIMA model. The authors stated that both models demonstrated similar predictive capacity for zinc prices. However, for lead price forecasting, the ARIMA model produced more accurate results in five out of eight cases, outperforming the lagged forward price model. Although they did not reach a definitive conclusion regarding the single best overall method, they noted that the ARIMA model yielded superior results in 9 out of 16 overall test cases.

Another foundational study [14] compared the forecasting accuracy of different time-series models for oil prices, specifically exponential smoothing (ES), Holt-Winters (HW), and autoregressive integrated moving average (ARIMA) models. Six distinct performance metrics were used to evaluate predictions against actual historical data. The authors observed that the HW model outperformed the ES model at a 95% confidence interval. Ultimately, because the ARIMA (2,1,2) model yielded better results than ES, it was identified as providing the most accurate overall predictions.

In the realm of electricity price prediction, Windler et al. [15] conducted a comparative analysis between ARIMA and XGBoost models. Similarly, Zhang et al. [16] proposed a sophisticated two-stage stochastic programming framework for joint production planning and electricity supply, utilizing scenario generation via ARIMA and ARIMAX models. These approaches provide comprehensive frameworks that balance expected outcomes against critical risk factors, offering valuable insights into electricity price prediction and planning.

Zakeri [17] developed a time-series approach to produce short-term forecasts of hourly electricity prices in the Turkish market using multiple regression. Using price and demand data from EPİAŞ, the author applied specific pre-processing steps, including spike filtering and replacing outliers

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outside the 99.7% confidence interval with statistically calculated values. Although an ARX model was initially established, the presence of multiple seasonalities in the price series prompted a shift toward a broader regression model. For seasonality, the author incorporated demand as an exogenous variable and weekends as dummy variables, subsequently fitting the residuals into an ARMA(8,8)-GARCH(24,1) framework. Notably, this study distinguishes itself in the literature by providing a detailed theoretical foundation accompanied by complete R code implementations.

Overall, the literature demonstrates a rich body of research on statistical techniques for price forecasting, alongside growing interest in machine learning and hybrid approaches. Accurately modeling and forecasting electricity prices in competitive markets remains crucial for market participants seeking to optimize operational strategies [18]. Building on these insights, this study applies several price forecasting methods within the context of the Turkish electricity market.

To the best of our knowledge, the literature lacks an integrated approach that combines short-term energy forecasting with detailed mathematical optimization and evaluates it in a real-world industrial setting. While previous studies examine energy forecasting and production scheduling separately, a gap remains in combining energy price or demand forecasting, detailed production and inventory scheduling, and industrial evaluation within a single framework. This indicates a need for more integrated decision-support approaches that jointly consider forecasting and operational production planning in energy-intensive manufacturing environments.

2. MATERIALS AND METHODS

2.1. Price Forecasting

This section introduces the process of electricity price forecasting, focusing on its challenges and methodologies. Section 2.1.1 analyzes historical price data to identify patterns and trends, providing a foundation for forecasting. Section 2.1.2 includes building predictive models by integrating factors such as demand, production, and past prices, aiming to address the unique behaviors of different markets and enhance accuracy.

2.1.1. Price Data Analysis

Predicting electricity prices is a challenging process because electricity cannot be stored. Statistical models used to forecast electricity prices combine external factors such as production and demand by linking them to previous prices. However, it is not possible to find a single model because each market behaves differently. Statistical models have been frequently used in the literature to model these behaviors.

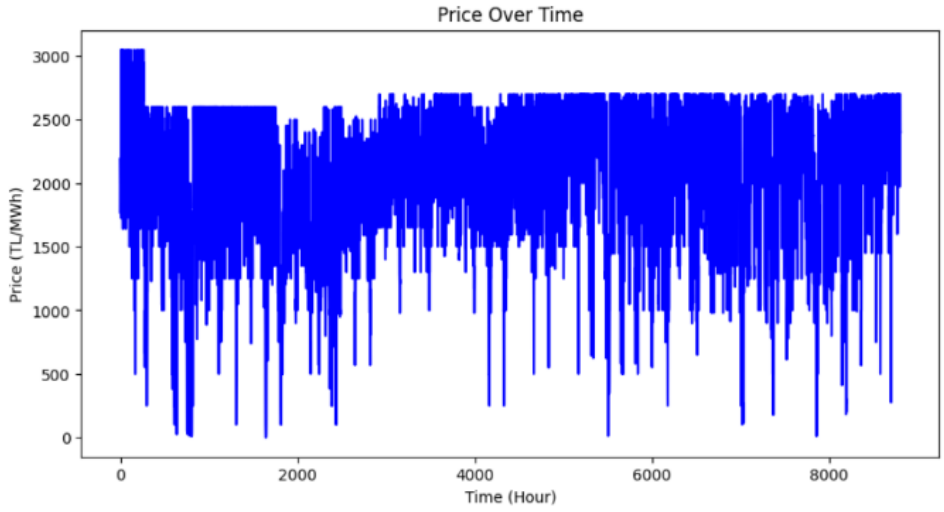

Figure 1. Hourly Price Data

In this study, as illustrated in Figure 1, we used the hourly electricity price provided by EPİAŞ. The dataset covers the period from 21.03.2023 to 21.03.2024 and includes electricity price, imbalance amount, transaction volume, offered sales amount, and offered purchase amount data used for the XGBoost model. We used 80% of the dataset as the training set and the remaining 20% as the test set. The test period starts on 08.01.2024 at 14:00. Electricity prices obtained from EPİAŞ are expressed in Turkish lira per megawatt-hour (TL/MWh), where TL denotes the Turkish lira. The summary statistics of PTF (Piyasa Takas Fiyatı, Market Clearing Price) are presented in Table 1.

Table 1. Summary Statistics of PTF TL/MWh

Min	Max	Median	Mean	Var	Std Dev
0.01	3050	2099.99	2007.91	303012.5	500.46

When the preprocessed statistical summary is examined, it is seen that the variance of the data is very high. This is normal for electricity price data and is known as volatility. Additionally, there are sharp ends called 'spikes' in the dataset, which may cause the variance to be high. We used the price's 99.7% confidence interval as the confidence interval and classified data points outside of it as outliers to identify outliers. Spike preprocessing was applied to the dataset after outlier detection. The summary statistics of the preprocessed PTF data are given in Table 2.

Table 2. Summary Statistics of Pre-Processed PTF TL/MWh

Min	Max	Median	Mean	Var	Std Dev
0.01	3050	2099.99	2011.91	290764.3	539.22

After the pre-processing step, as seen in Figure 2, the variance of the dataset partially decreased.

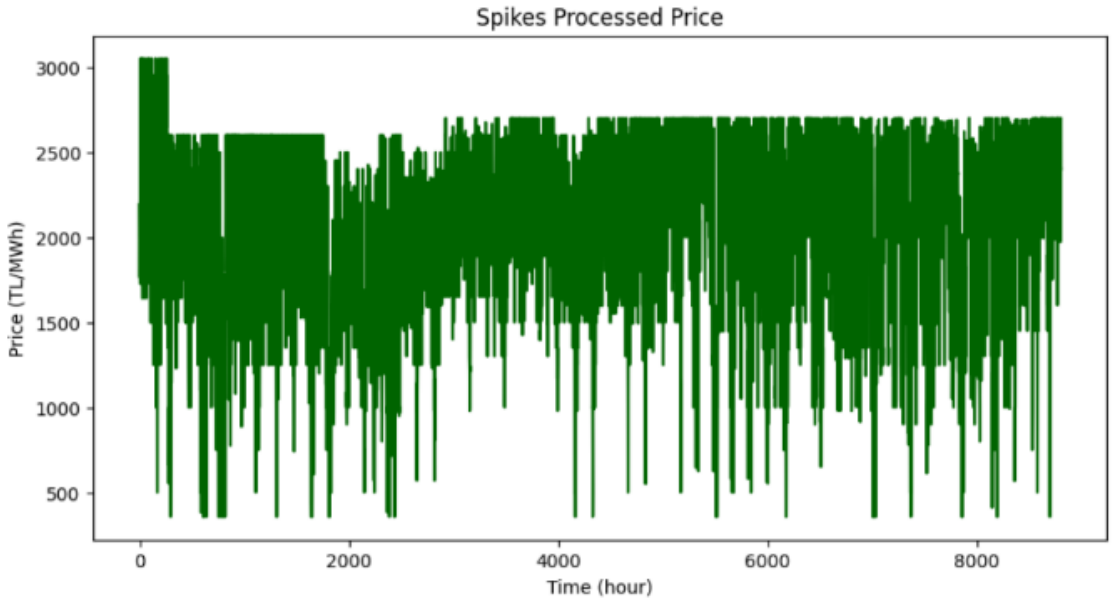

Figure 2. Pre-Processed Price Data

2.1.2. Building Forecast Models

"All models are wrong, but some are useful," says George Box. An ideal model for determining the behavior of data does not always exist. Keeping this in mind, we try to find the model closest to reality in the following frequently used methods, which are time series and ML forecasting methods. All methods used to predict future values based on past data are depicted in Table 3, and below are the best-fitting models explained. The performance of the models is given in detail in the Model Comparison section.

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2.1.2.1. ARIMA

ARIMA is a widely used forecasting technique for forecasting time series data. ARIMA describes the time series based on its previous values, that is, its lags and lagged forecast errors. The parameters of the ARIMA model are (p, d, q), and each of the terms is AR, the difference required to make the time series stationary (I) and the MA term, respectively [19]. Looking at Figure A1 in Appendix A, it can be said that the ARIMA (1,1,1) model has learned the behavior of the data well.

2.1.2.2. Long-Short Term Memory (LSTM)

LSTMs are effective artificial neural network models, especially for processing sequential data such as time-series forecasting. They are designed to capture long-term dependencies in time series and retain relevant short-term information through their memory-cell structure. LSTMs have been widely studied in the literature due to their ability to model complex datasets. The architecture used in this study consisted of two LSTM layers, two dropout layers, and one dense output layer. Each LSTM layer contained 60 neurons, and a dropout rate of 0.2 was applied. The hyperbolic tangent (tanh) activation function was used in the LSTM layers, the sigmoid function was used as the recurrent activation function, and a linear activation function was used in the dense output layer. The model was trained using the Adam optimizer with a learning rate of 0.001 and the mean squared error loss function. The batch size was set to 12, and the model was trained for a maximum of 200 epochs.

The observations were divided chronologically to preserve the temporal structure of the data. The final 20% of the dataset was reserved as an independent test set, while the final 20% of the remaining development data was used as the validation set. The observations were not shuffled during training. Early stopping was applied by monitoring the validation loss with a patience value of 15 epochs. If the validation loss did not improve for 15 consecutive epochs, training was terminated, and the model weights corresponding to the lowest validation loss were restored. According to the results presented in Figure B1 in Appendix B, the LSTM model captured the general behavior of the dataset and achieved a test RMSE of 255.3 and a test MAPE of 11.4%.

In the methods mentioned above, the time series forecasting method is univariate. In other words, the target variable was predicted using a past value. However, this is not the case in real life. There are other factors that power prices exhibit, including highly volatile times, seasonal trends, calendar impacts, and non-linearity [18]. In the XGBoost method, a prediction is made using four features that affect the electricity price in the Turkish market (imbalance amount, ask amount, bid amount and volume).

2.1.2.3. XGBoost algorithm

XGBoost is a tree-based machine learning algorithm. The fundamental goal of gradient boosting, like with other boosting techniques, is to improve output variable predictions by building and fitting new models sequentially rather than independently during the learning process. Adding weak trees to the collection repeatedly with varying weights is the fundamental principle of XGBoost [20]. Also, XGBoost makes use of sophisticated regularization to lessen overfitting and enhance model generalization [21]. Focusing on the four factors that determine PTF, we analyze the XGBoost model dataset and train the model to determine the impact of these factors on prices. For preprocessing, Robust scaling is applied for features.

Looking at the results in Figure C1 in Appendix C, it can be said that the XGBoost model has learned the behavior of the data well.

2.1.3. Model comparison

It may not be sufficient to evaluate the forecasting models solely through graphical comparisons. Therefore, the predictive accuracy of the forecasting methods was first evaluated using RMSE and MAPE. RMSE measures the square root of the mean squared forecast errors, whereas MAPE represents the average absolute forecast error as a percentage. These measures enable the forecasting performances of different models to be compared using the same criteria. The RMSE and MAPE results

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obtained from the forecasting models are presented in Table 3.

Table 3. RMSE and MAPE of All Methods

Method	**RMSE**	**MAPE %**
Linear Regression	559.9	32.7
Seasonal Regression	499.4	29
Moving Average (24)	485.9	25.5
Moving Average (168)	538.3	31.1
Moving Average (720)	545	32
Simple Exponential Smoothing	895	39.7
Holt's Linear	2600.1	113.5
Additive Holt - Winters	1060.2	45.1
Multiplicative Holt - Winters	1200.1	50
ARIMA (1,1,1)	298.3	11.7
ARIMA (24,1,24)	499.2	29.3
ARIMA (12,1,7)	596.9	33.6
SARIMA (5,0,15) (0,1,0)24	955.2	41.3
SARIMA (24,0,24) (0,1,0)24	498.8	27.6
Auto SARIMA (1,1,1) (1,1,1)24	511.4	27.9
LSTM	255.3	11.4
XGBoost	318.4	16.4

Table 3 presents the RMSE and MAPE values obtained from the hourly electricity price forecasting models. Among the evaluated models, the LSTM model achieved the lowest error rates, with an RMSE of 255.3 and a MAPE of 11.4%. The ARIMA (1,1,1) model achieved an RMSE of 298.3 and a MAPE of 11.7%, while XGBoost produced an RMSE of 318.4 and a MAPE of 16.4%. Therefore, the LSTM model was selected as the electricity price forecasting method used in the subsequent production scheduling model.

However, RMSE and MAPE provide point estimates of forecasting accuracy and do not indicate whether the observed differences between forecasting models are statistically significant. Therefore, an additional pairwise statistical comparison was performed. To ensure that the models were compared on the same observations, the analysis was conducted using the common set of 1,737 hourly observations for which aligned forecasts were available. Squared-error loss was used so that the statistical analysis was consistent with the RMSE criterion. The loss differential was calculated as the squared-error loss of LSTM minus the squared-error loss of the competing model. Accordingly, a negative mean loss differential indicates that LSTM has a lower average forecasting loss.

Because hourly forecast errors may exhibit serial dependence, the variance of the mean loss differential was estimated using heteroskedasticity- and autocorrelation-consistent Newey–West standard errors with 24 lags. The resulting statistic is reported as the DM/HAC statistic. The loss differential was calculated as the squared-error loss of LSTM minus the squared-error loss of the competing model; therefore, a negative value indicates lower forecasting loss for LSTM. Since LSTM was compared with 11 competing forecasting methods, the resulting p-values were adjusted using the Holm procedure to account for multiple comparisons. Statistical significance was evaluated at the 5% level. The results of these pairwise comparisons are presented in Table 4.

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Table 4. Comparison of LSTM with other methods

Comparison	Mean loss difference	DM/HAC statistic	Holm-adjusted p-value
LSTM vs Linear Regression	−249,928.24	−7.007	7.33×10^{-12}
LSTM vs Seasonal Regression	−186,078.94	−5.655	1.56×10^{-8}
LSTM vs Moving Average (24)	−165,987.42	−11.138	6.52×10^{-28}
LSTM vs Moving Average (168)	−224,532.07	−9.542	7.02×10^{-21}
LSTM vs Moving Average (720)	−232,926.58	−9.963	1.32×10^{-22}
LSTM vs Simple Exponential Smoothing	−733,034.13	−22.002	3.06×10^{-106}
LSTM vs Holt's Linear	−20,442,818.71	−10.187	1.58×10^{-23}
LSTM vs Additive Holt-Winters	−4,899,350.33	−9.428	1.67×10^{-20}
LSTM vs Multiplicative Holt-Winters	−1,882,182.28	−11.309	1.06×10^{-28}
LSTM vs ARIMA (1,1,1)	−304,744.76	−19.422	5.00×10^{-83}
LSTM vs XGBoost	−23,632.18	−6.963	7.33×10^{-12}

The statistical results support the selection of LSTM. The mean loss differential was negative in all 11 pairwise comparisons, indicating that LSTM produced a lower squared-error forecasting loss than each of the competing models included in the statistical analysis. Moreover, all differences remained statistically significant at the 5% level after the Holm adjustment. In particular, the comparison between LSTM and ARIMA (1,1,1) resulted in a mean loss differential of −304,744.76 and a DM/HAC statistic of −19.422, with a Holm-adjusted p-value of 5.00×10^{-83}. Similarly, the comparison between LSTM and XGBoost resulted in a mean loss differential of −23,632.18 and a DM/HAC statistic of −6.963, with a Holm-adjusted p-value of 7.33×10^{-12}. Thus, the lower forecasting loss of LSTM relative to the two principal alternative models was statistically significant.

The superior forecasting performance of the LSTM model can be associated with the characteristics of hourly electricity prices and the sequential learning capability of the model. Electricity prices exhibit high volatility, nonlinear fluctuations, and temporal dependencies over different time horizons. The memory-cell structure of LSTM enables the model to retain relevant information from previous observations and capture both short-term price fluctuations and longer-term temporal dependencies. In contrast, ARIMA primarily models linear relationships between past observations and forecast errors, which may limit its ability to represent complex nonlinear price movements.

Although XGBoost can capture nonlinear relationships between electricity prices and explanatory variables, it does not inherently preserve the sequential structure of time-series observations in the same way as LSTM. In this study, XGBoost used imbalance amount, offered sales amount, offered purchase amount, and transaction volume as explanatory variables. However, the LSTM model directly learned the temporal behavior of electricity prices from sequential observations.

ARIMA and some SARIMA configurations provided lower point forecast errors than several traditional methods such as Linear Regression, Simple Exponential Smoothing, Holt's Linear, and Holt–Winters models. Nevertheless, the statistical comparison further supported the selection of LSTM. Its squared-error forecasting loss was significantly lower than that of ARIMA (1,1,1), XGBoost, and the other benchmark models included in the pairwise analysis after adjustment for multiple comparisons.

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Therefore, both the point forecast accuracy measures and the statistical significance tests support the selection of LSTM for the subsequent production scheduling analysis.

Hybrid forecasting models combining statistical time-series and deep learning methods were not evaluated in this study. ARIMA, LSTM, and XGBoost were implemented and assessed as standalone models to compare their individual forecasting performance. The development and evaluation of hybrid approaches, such as ARIMA–LSTM, were beyond the scope of the present study and are suggested as a direction for future research.

2.2. Mathematical Model

The production and inventory system is based on a 14-day production plan, which is generated on an hourly basis by evaluating historical data and fluctuations in energy costs. A MILP model is developed to provide a 14-day production planning schedule for cement mills. The hourly production planning schedule is designed to ensure that production processes are managed according to certain parameters. A dynamic planning strategy has been implemented, aimed at mandatory maintenance planning and determining the most appropriate periods to increase the efficiency of cement plants.

2.2.1. Minimization Model

The main purpose of "Minimization Model" is to strategically optimize the production planning program in order to minimize energy costs effectively. The model aims to find the most efficient way to divide products into cement plants, days, and hours, taking into account various parameters and constraints. The objective function minimizes the energy consumed by the mill during production and the total energy cost of cement factories, which includes the heating process until the mill reaches the required operating state.

Sets and indices

I	*Set of products indexed by i, m ϵ I (1 to 6)*
J	*Set of cement mills indexed by j (1 to 4)*
K	*Set of silos indexed by k (1 to 10)*
D	*Set of days indexed by d (1 to 14)*
T	*Set of 30-minute time periods indexed by t (1 to 672)*

Parameters

V_{id}	*The demand quantity of product i on day d (tons)*
A_k	*The capacity of SILO k*
EC_{ij}	*The energy consumed in a time period t while producing product i in mill j (kWh)*
PC_{ij}	*The amount of product i produced by mill j in 30 mins (tons/30 mins)*
IE_j	*The amount of energy consumed by mill j when it is idle (kWh)*
EP_t	*The energy price forecast on time range t (TL/kWh)*
U_{ij}	*Manufacturability of product i on mill j (binary)*
P_{ik}	*Storability of product i in SILO k (binary)*
IC_{ik}	*The initial inventory amount of product i in SILO k*

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T_{mi} *Transition from more additive product to less additive product when switching from product m to product i (binary)*

Decision variables

X_{ijt} *1, if product i is produced in cement mill j in time range t, 0, ow.*

Y_{ijtk} *Quantity of product i assigned to SILO k at time t from mill j (tons)*

SC_{itk} *The inventory amount of product i in SILO k at the end of time range t (tons)*

O_{itk} *The quantity of product i released (output) from SILO k in time range t (tons)*

B_{jd} *1, if there is maintenance in cement mill j on day d, 0, ow*

Q_{jt} *1, if there is warm-up period in cement mill j in time range t, 0, ow*

S_{ijt} *1, if the output classified as product i is transferred from cement mill j to a silo in time range t, 0, ow.*

Model formulation

$$Minimize\ \sum_i \sum_j \sum_t EC_{ij}\, X_{ijt}\, EP_t PC_{ij} + \sum_j \sum_t IE_j\ Q_{jt}\, EP_t \quad (1)$$

Constraints

$$\sum_i X_{ijt} \leq 1 \qquad \forall j \epsilon J, t \neq 1 \quad (2)$$

$$\sum_i X_{ijt} = 0 \qquad \forall j \epsilon J, t = 1 \quad (3)$$

$$IC_{ik} + \sum_j Y_{ijtk} - O_{itk} = SC_{itk} \qquad \forall i \epsilon I, k \epsilon K, \mathrm{t} = 1 \quad (4)$$

$$SC_{i,t-1,k} + \sum_j Y_{ijtk} - O_{itk} = SC_{itk} \qquad \forall i \epsilon I, k \epsilon K, t \neq 1 \quad (5)$$

$$S_{ijt} \cdot PC_{ij} = \sum_k Y_{ijtk} \qquad \forall i, j, t \quad (6)$$

$$\sum_i SC_{itk} \leq A_k \cdot 0.9 \qquad \forall k, t \quad (7)$$

$$\sum_i SC_{itk} \geq A_k \cdot 0.25 \qquad \forall k, t \quad (8)$$

$$\sum_{t=((d-1)\cdot 48)+1}^{t=48\cdot d} \sum_k O_{itk} \geq V_{id} \qquad \forall i, d \quad (9)$$

$$O_{itk} \leq SC_{itk} \qquad \forall i, k, t \quad (10)$$

$$\sum_i X_{ijt} + Q_{jt} \leq 1 \qquad \forall j, t \quad (11)$$

$$\sum_i X_{ijt} + Q_{jt} \geq \sum_i X_{ij(t+1)} \qquad \forall j \epsilon J, t \neq 672 \quad (12)$$

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$$\sum_i X_{ij(t+1)} \geq Q_{jt} \qquad \forall j \epsilon J, t \neq 672 \qquad (13)$$

$$\sum_i X_{ijt} \leq \sum_i S_{ijt} \qquad \forall j, t \qquad (14)$$

$$X_{ijt} - \sum_m \left(X_{mj(t-2)} . T_{mi}\right) \leq \sum_i S_{ijt} \qquad \forall m \epsilon I, i \epsilon I, j \epsilon J, t = 3, \dots, 672 \qquad (15)$$

$$X_{mj(t-2)} . T_{mi} + X_{ijt} \leq S_{mjt} + 1 \qquad \forall m \epsilon I\ , i \epsilon I, j \epsilon J\ , t = 3, \dots, 672 \qquad (16)$$

$$\sum_{m \neq i} X_{mj(t-1)} + X_{ijt} \leq X_{ij(t+1)} + 1 \qquad \forall m \epsilon I, i \epsilon I, j \epsilon J\ , t = 2, \dots, 670 \qquad (17)$$

$$B_{jd} = 0 \qquad \forall j \epsilon J, d = 6{,}7{,}13{,}14 \qquad (18)$$

$$\sum_j B_{jd} \leq 1 \qquad \forall d \qquad (19)$$

$$\sum_{d=1}^{d=5} B_{jd} = 1 \qquad \forall j \qquad (20)$$

$$\sum_{d=8}^{d=12} B_{jd} = 1 \qquad \forall j \qquad (21)$$

$$\sum_i \sum_{t=((d-1)\cdot 48)+17}^{t=((d-1)\cdot 48)+17+15} X_{ijt} \leq (1 - B_{jd}) \cdot 16 \qquad \forall j, d \qquad (22)$$

$$\sum_{t=((d-1)\cdot 48)+17}^{t=((d-1)\cdot 48)+17+15} Q_{jt} \leq (1 - B_{jd}) \cdot 16 \qquad \forall j, d \qquad (23)$$

$$X_{ij(t+1)} \leq X_{ijt} + X_{ij(t+2)} \qquad \forall i \epsilon I, j \epsilon J, t < 670 \qquad (24)$$

$$X_{ij(t+1)} \leq X_{ijt} + X_{ij(t+3)} \qquad \forall i \epsilon I, j \epsilon J, t < 669 \qquad (25)$$

$$X_{ij(t+1)} \leq X_{ijt} + X_{ij(t+4)} \qquad \forall i \epsilon I, j \epsilon J, t < 668 \qquad (26)$$

$$Y_{ijtk} \leq P_{ik} \cdot A_k \cdot U_{ij} \qquad \forall i, j, t, k \qquad (27)$$

$$SC_{itk} \leq P_{ik} \cdot A_k \qquad \forall i, t, k \qquad (28)$$

$$X_{ijt} \leq U_{ij} \qquad \forall i, j, t \qquad (29)$$

$$O_{itk} \leq P_{ik} \cdot A_k \qquad \forall i, t, k \qquad (30)$$

$$X_{ijt} \in \{0{,}1\} \qquad \forall i, j, t \qquad (31)$$

$$S_{\boldsymbol{ijt}} \in \{0{,}1\} \qquad \forall i, j, t \qquad (32)$$

$$B_{jd} \in \{0{,}1\} \qquad \forall j, d \qquad (33)$$

$$Q_{jt} \in \{0{,}1\} \qquad \forall j, t \qquad (34)$$

$$Y_{ijtk} \geq 0 \qquad \forall i, j, t, k \qquad (35)$$

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$$SC_{itk} \geq 0 \qquad \forall i, t, k \qquad (36)$$

$$O_{itk} \geq 0 \qquad \forall i, t, k \qquad (37)$$

The primary goal of this mathematical model is to strategically optimize the production planning schedule to minimize energy costs effectively. By considering various parameters and constraints, the model aims to find the most efficient way to allocate products to cement mills, days, and hours. According to the Equation (1) of the mathematical model, the objective function minimizes the total energy cost of the cement mills, which includes the cost of energy consumed by the mill during production, the heating process until the mill reaches the required operating condition, and during product changeovers.

Constraints (2) and (3) ensure that there is no production during the startup period and prevent multiple products from being produced at any given time in the production process of the same cement mill. That is, they ensure efficient and effective production by preventing duplication or overlap during the production process. Constraints (4) and (5) indicate the occupancy rates of the silos. In the first period, the initial inventory amount in the silos was taken into account, and it balances the product quantities in the silo by collecting the amount of product in the previous time in the Silos and the amount of product produced at this time.

Constraint (6) ensures that all cement produced in the mills, including material produced during product changeovers, is transferred to the appropriate silos.

Constraint (7) refers to the fact that the quantity in each silo at t time cannot exceed 90% of the SILO capacity. This restriction prevents overloading and protects against possible storage problems, ensuring the system operates within safe limits. Constraint (8) prevents the quantity of products stored in silos from falling below 25% of the SILO capacity at any time.

Constraint (9) ensures that the products removed from the Silos for delivery at t hours of the d day meet the total demand on the d day. This restriction allows the storage and distribution system to effectively meet the daily demand requirements for each product. By applying this restriction, the system ensures that the storage and distribution processes are compatible with demand, ensuring that products are delivered to customers efficiently and on time. Constraint (10) expresses that the amount of product delivered on time t cannot exceed the amount available in the silo.

Cement mills are large machines that must reach a certain speed to start production. They require a half-hour warming-up period to reach this speed. During this period, there is no production, but energy consumption occurs. Constraints (11)–(13) ensure that a warm-up period is assigned before a cement mill starts production.

If it is necessary to start the production of product i while there is product m production in the mill, there is a product transition in that mill and there may be a change in the silo of the changed product. Constraints (14) - (17) allow the product transition event to be assigned between two products produced in the mill.

In order to ensure the uninterrupted operation of the facility, regular maintenance of the cement mills is required. The maintenance requirements incorporated into the mathematical model reflect the plant's existing maintenance policy rather than an assumed scheduling rule. Each cement mill is scheduled for maintenance once per week, and each maintenance operation lasts eight consecutive hours. Therefore, two maintenance operations are required for each mill over the 14-day planning horizon. According to the plant's operational practice, maintenance is not performed on weekends, and the maintenance days of different cement mills cannot coincide. Constraint (18) prevents mill maintenance from being assigned to weekends. Constraint (19) allows assigning a maximum of one mill maintenance time on the same day when assigning a maintenance time to the mills. Constraints (20) and (21) guarantee that the mills are assigned maintenance time during the week for a 2-week scheduling. Constraints (22) and (23) ensure that neither production nor warm-up takes place during

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the maintenance period. Constraints (24) - (26) force that when the product i is assigned, three consecutive periods force the assignment of the same product i. Because when a product starts to be produced, it must be produced for a certain period of time, short-term product production is not an applied procedure due to the fact that cements have high purity degrees and consume too much energy. Constraints (27) - (30) establish the relation between the binary parameters and decision variables. Constraints (27) and (28) show that the transferred quantity cannot exceed the capacity of the silo by looking at the storage condition of the i-product coming from the mill. Constraint (29) looks at the producibility of the product to be produced in the mill. Constraint (30) controls the storability of the product in the silo shown as "P_{ik}" and ensures that the amount of product to be withdrawn does not exceed the amount of product in the silo. This equation prevents excessive withdrawals that could overwhelm the storage system and maintains the integrity and stability of the overall process. Constraints (31) – (34) represent binary variables, and Constraints (35) – (37) express the non-negativity of the other decision variables.

2.2.2. Maximization Model

The purpose of the "maximization model" is to strategically optimize the production planning program in order to maximize product profit effectively. The objective function is to maximize product profit by reducing the cost of energy consumed by cement mills during production from the sales of the requested products, and the cost of heating the mills until they reach the required operating conditions. Unlike the minimization model, information about the prices of products per ton is needed, and there has been a change in the demand satisfaction process equation in the model.

Parameters

F_i The price of product i per ton **(**TL)

Objective function

$$Maximize\ \sum_i \sum_t \sum_k O_{itk} F_i\ -(\sum_i \sum_j \sum_t EC_{ij}\ X_{ijt}\ EP_t PC_{ij}\ +\ \sum_j \sum_t IE_j\ Q_{jt}\ EP_t) \quad (38)$$

Constraints

$$\sum_{t=((d-1)\cdot 48)+1}^{t=48\cdot d} \sum_k O_{itk}\ \leq V_{id}\ .\ 1.3 \qquad \forall i, d \quad (39)$$

Considering various parameters and constraints, the model aims to find the most efficient way to allocate products to cement mills, days, and hours. The objective function maximizes profit by subtracting production and warm-up energy costs from sales revenue. Constraint (39) ensures that the products removed from the Silos for delivery at t hours of the d day meet the total demand on the d day. This constraint is that the storage and distribution system must effectively meet the daily demand requirements for each product, the demand cannot be fully met because the data used is not an integer. For this reason, product output up to 30% more than the demand has been allowed by applying relaxation to the restriction.

2.3. Case Study

In manufacturing companies, optimizing production and waiting times, silo usage, and delivery delays through careful planning reduces costs. As shown in Table 5, not all products are manufactured

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at each cement mill. Products are allocated to silos according to their capacities, with initial inventories detailed in Table 6 and 7.

Table 5. Product-Based Specific Energy Consumption & Mill Capacity & Power

Cement Mill	Product Type	Specific Energy of Mill	Capacity	Mill Total Power Consumption
1	1	21.4	19.8	750
	2	22.4	17.4	
	6	24.7	15.6	
	4	24.1	16.9	
2	1	21.4	19.8	750
	2	22.4	17.4	
	6	24.7	15.6	
	4	24.1	16.9	
3	1	15.7	76.1	2417
	3	16.6	71.9	
	2	18.4	64.2	
	6	20.4	56.3	
	4	21.1	55.4	
4	1	27.3	26.5	1400
	5	35.1	19.7	

Table 6. Silos and capacities according to product types

SILO	Capacity
1	2800
2	2800
3	2800
4	2800
5	11000
6	2200
7	2200
8	2100
9	2100
10	21000

According to the plant's existing inventory management policy, silo inventory levels are required to remain between 25% and 90% of their capacities. These limits therefore represent actual operational requirements of the case-study plant rather than assumed parameter values. The product types and quantities initially found in the silos are also shown in Table 7.

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Table 7. Initial Amount and Product Storability in SILOs

SILO	Product	Initial Inventory
1	1	812
2	2	700
3	3	700
4	4	700
5	4	2750
6	1	550
7	5	550
8	1	525
9	6	525
10	1	11789

Product-transition requirements were defined according to the plant's actual production practice. In particular, when production switches from a product with a higher additive ratio to a product with a lower additive ratio, a one-hour transition process is required. Since each period in the mathematical model represents 30 minutes, this operational requirement corresponds to two consecutive periods. During the transition, production continues according to the capacity of the product with the lower additive ratio, while the produced material is transferred to the silo associated with the product having the higher additive ratio. Therefore, the two-period transition duration represents an actual production rule currently applied at the plant rather than an assumed modeling parameter. The corresponding product-transition relationships are presented in Table 8.

Table 8. Transition from additive to non-additive

Transition from m to i	1	2	3	4	5	6
1	0	0	0	0	0	0
2	1	0	1	0	0	1
3	1	0	0	0	0	0
4	1	1	1	0	1	1
5	1	1	1	0	0	1
6	1	0	1	0	0	0

In the production planning schedule, the additive ratios of products are of high importance in the transition between products. The additive ratios of the cement products are given in Table 9. If the product in the mill has a higher additive ratio than the previous product, the transition between products occurs quickly. However, if the product to be produced in the mill has a lower additive ratio than the previous product, while product production continues for an hour during the product transition in the mill, the product is produced according to the capacity of the product with a lower additive ratio. However, the product is conveyed to the silo assigned to the product with the higher additive ratio.

Table 9. Cements Additive Ratios

Product	Additive Ratio
1	1%
2	20%
3	5%
4	50%
5	40%
6	12%

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2.4. Ethical Approval

Ethical approval is not required for this study.

3. RESULTS AND DISCUSSION

In this study, schedules have been created for four cement mills for a two-week period. These schedules take the production requirements into account to meet the demands at the mills. Certain conditions need to be met for the production of products. When the mill is not operational, it requires a certain amount of time to reach a state where production can begin, represented as "W" in the schedule. The mills also require maintenance intervals lasting 8 hours at regular intervals, represented as "M" in the schedule. The variables assigned in these schedules have direct relationships with the electricity price. The model, coded in Python and solved using GUROBI, obtained optimal solutions within 6–48 hours for the complete 14-day planning horizon. Therefore, the current implementation is more appropriate for tactical production planning than for real-time or same-day re-optimization.

3.1. Energy cost minimization

Production activities in the cement sector were intense in July 2023. Therefore, the cement mills operated more intensively during this month. Since there was no demand for Product 3, this product was not produced. Below is the production schedule prepared according to demand quantities, which is not published per company requests.

As seen in Figure 3, in Cement Mill 1, it was observed that it produced the first, second, fourth and sixth products. Since there is a cost associated with starting up the mill, production of the products occurred without shutting down the mill after it was started. Cement Mill 2 and Cement Mill 1 are identical mills. Cement Mill 2 produced the same products as Cement Mill 1 and did not produce for 6 days, and it was observed that it did not produce products on the fifth, sixth, ninth and tenth days. The detailed schedule is given in Figure D1 in Appendix D. Cement Mill 3 is the most heavily utilized mill among the mills, producing a large number of products with minimal energy. Therefore, it is observed that the most intensively used mill is Cement Mill 3. Cement Mill 3 produced the first, second, fourth and sixth products. Cement Mill 4 produced the fifth product and the first product. Cement Mill 4 is the least efficient mill among the mills, producing fewer products with excessive energy consumption, and moreover, the fifth product can only be produced in Cement Mill 4.

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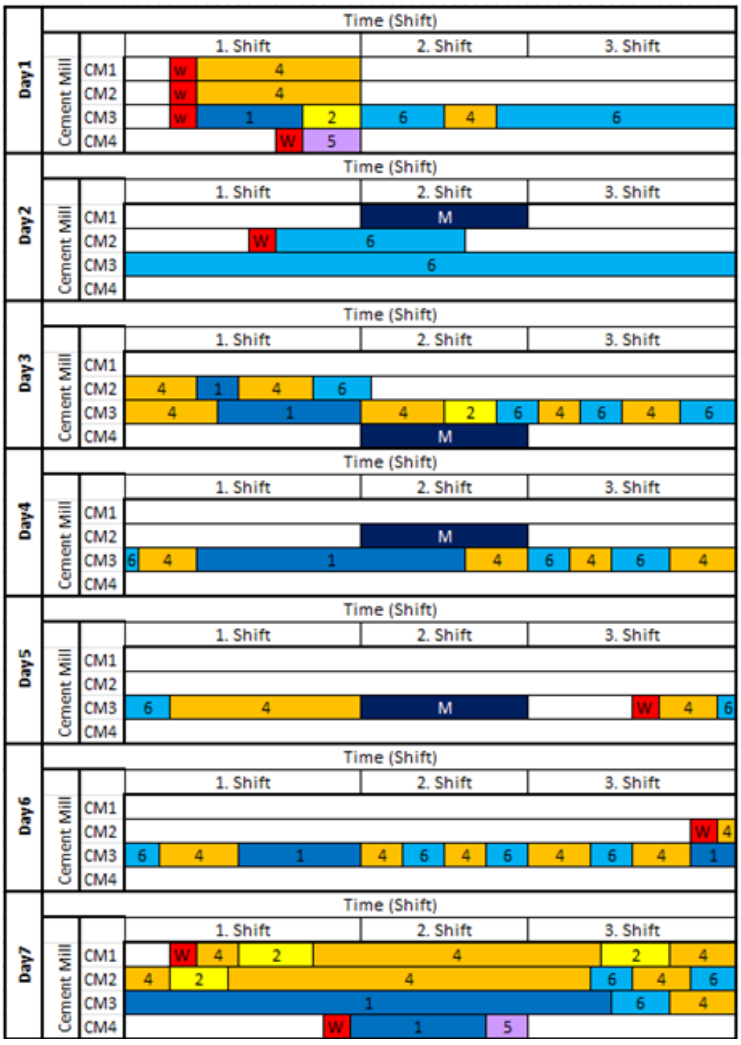

Figure 3. 7-Day Minimization Model Schedule

3.2. Profit Maximization

Since the current packaging of the requested quantities cannot be fully filled, the company has allowed more product output up to 30% of the requested quantity. Therefore, product output is permitted up to 130% of demand.

Figure 4 shows the results of the maximization model. According to the schedule results of Cement Mill 1, it is observed that it produces the fourth, second, and sixth products in a different order. Since there is a cost associated with bringing the mill into operation, production of products is carried out after the mill is opened without shutting it down. Cement Mill 2 has produced the same products as Cement Mill 1. Cement Mill 3 is the most intensively used mill among the mills and produces a large number of products with minimum energy. Therefore, it is seen that Cement Mill 3 is the most intensively used mill. According to the program results, it has produced the first, second, fourth, and sixth products. Since the mills are not operational during maintenance, there is a need for a warm-up period for post-maintenance production, and this applies to Cement Mill 3 as well. Cement Mill 4 produced the first product followed by the fifth product. Cement Mill 4 is the least efficient mill among the mills, producing fewer products with excessive energy consumption. Additionally, the fifth product can only be produced in Cement Mill 4.

In this model, the restriction of transferring the one-hour test production amount from the additive to the pure product to the additive product silo has been successfully implemented. Detailed representation graphics of this transition are presented in Figure 4.

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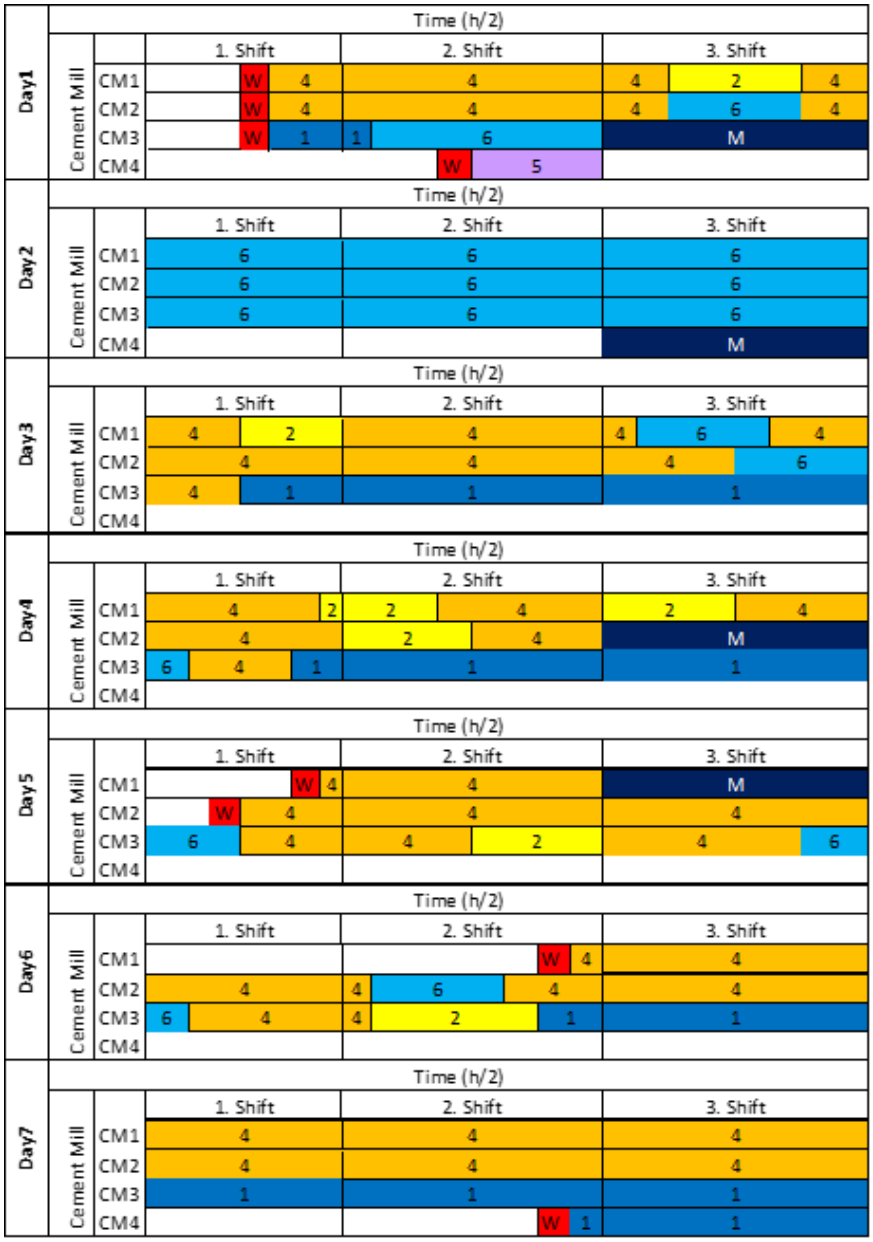

Figure 4. 7-Day Maximization Model Schedule

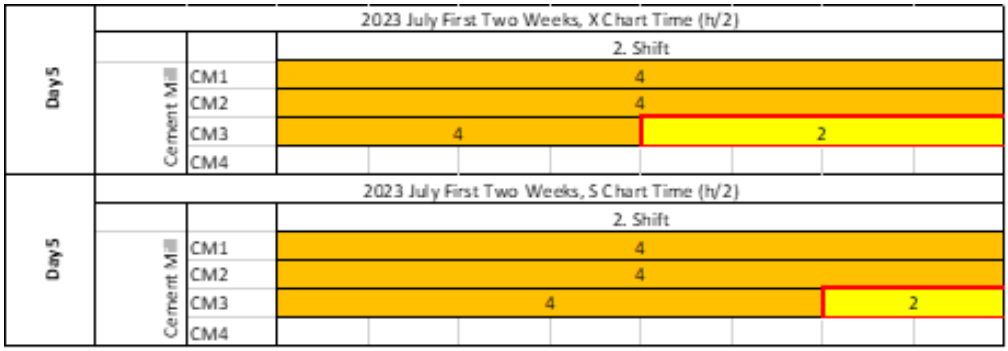

Figure 5. X and S Charts for the Maximization Model

Figure 5 shows the decision variables X_{ijt} and S_{ijt} for the 5th day of the first two weeks of July 2023. Upon examining the graphs, it is observed that in period 44, Cement Mill 3 transitions from the

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4th product to the 2nd product. Since the 4th product is more blended compared to the 2nd product, a direct transition was not possible, and therefore, the one-hour test production quantity was transferred to the 4th product silo.

This study presented comprehensive production schedules for four cement mills over a two-week period, addressing the need to meet factory demands while considering production requirements. The schedules factored in necessary maintenance periods ("M") and warm-up times ("W") for optimal operational efficiency.

4. CONCLUSION

The proposed model allowed transitions from additive to less additive cements and introduced two distinct objectives: profit maximization and energy cost minimization. The study's findings underscore the efficacy of the mathematical model in optimizing production schedules, reducing energy costs, and managing transitions between different cement types. The implementation of this model provides a systematic approach for incorporating time-varying electricity prices into production scheduling decisions and may contribute to improved energy-cost management and operational efficiency in the cement industry. The primary scientific contributions of this work are threefold:

1. Integrated Framework: To the best of our knowledge, this work is among the first to bridge short-term price/demand forecasting with continuous/discrete production and inventory scheduling in a unified optimization model tailored for the cement sector.

2. Methodological Novelty: The study demonstrates how predictive machine learning/time-series models can be embedded into a mixed-integer linear programming (MILP) formulation.

3. Empirical Industrial Validation: Beyond theoretical formulation, the proposed approach was evaluated using real-world operational data from the Turkish electricity market (EPİAŞ) and an active cement manufacturing facility, supporting the practical applicability of the proposed framework under realistic industrial conditions.

4.1. Limitations

Despite its contribution, the current study operates under a few boundary conditions. First, the accuracy of the optimization model is inherently dependent on the quality of the short-term price forecasts; unexpected market anomalies may impact overall schedule optimality. Second, the formulation assumes stable operational conditions without major unforeseen equipment breakdowns over the planning horizon. Finally, while the model is built for cement mills, adapting it to other electricity-intensive sectors (such as steel or paper) requires structural re-parameterization.

The silo inventory bounds, product-transition duration, and maintenance frequency used in the model were obtained from the operating rules of the case-study plant rather than introduced as discretionary modeling assumptions. Consequently, sensitivity analysis was not performed on these requirements because varying them would represent operating policies different from those currently implemented at the plant. Nevertheless, these parameters can be modified if the framework is applied to facilities with different inventory, transition, or maintenance policies.

4.2. Future Studies

Future studies should address hybrid models that combine machine learning techniques like time series analysis and deep learning to enhance accuracy. Integrating external factors such as weather and demand changes into these models can better capture market dynamics, offering more reliable forecasts.

Future work could also incorporate local renewable energy integration into the current model, addressing the joint uncertainty of both market electricity prices and self-generated renewable supply.

Furthermore, while the proposed model solves a 14-day planning problem within a reasonable

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execution time suitable for industrial acceptance, scaling the problem to larger instances or tighter decision horizons may increase computational complexity. To address this, future research could explore decomposition techniques (e.g., Bender's decomposition) as well as heuristic or metaheuristic approaches to further accelerate solution times while maintaining solution quality.

Peer-review: External, Independent.

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Declarations:

1. Statement of Originality:

The authors declare that this manuscript presents original research, has not been published previously, and is not under consideration for publication elsewhere. All sources used in the study have been appropriately acknowledged and cited.

2. Author Contributions:

Concept: MG,İN,AK,İK,BÇY; ***Conceptualization:*** MG,İN,AK,İK,BÇY; ***Literature Search:*** MG,İN,AK,İK,BÇY; ***Data Collection:*** MG,İN,AK,İK,BÇY; ***Data Processing:*** MG,İN,AK,İK,BÇY; ***Analysis:*** MG,İN,AK,İK,BÇY; ***Writing – original draft:*** MG,İN,AK,İK,BÇY; ***Writing – review & editing:*** MG,İN,AK,İK,BÇY.

3. Ethics approval:

Ethical approval is not required for this study, as it does not involve human participants or animal subjects. The study uses electricity market data and industrial operational data.

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The authors declare no competing interests.

6. GenAI Usage Statement:

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7. Sustainable Development Goals:

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APPENDIXES

Appendix A. ARIMA Result

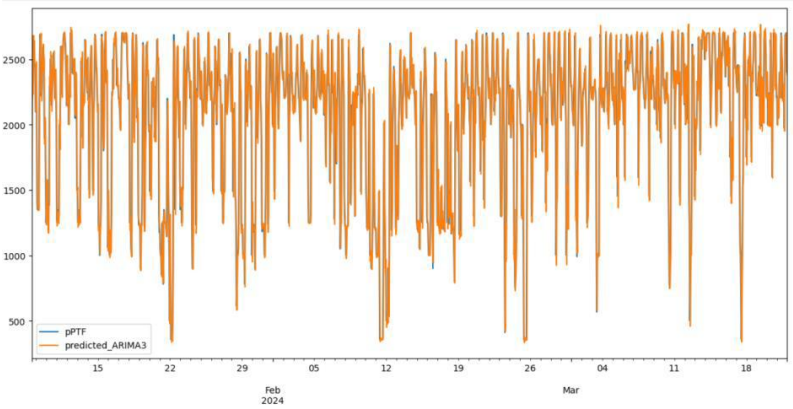

Figure A1. ARIMA (1,1,1) Results on Test Dataset

Appendix B. LSTM Result

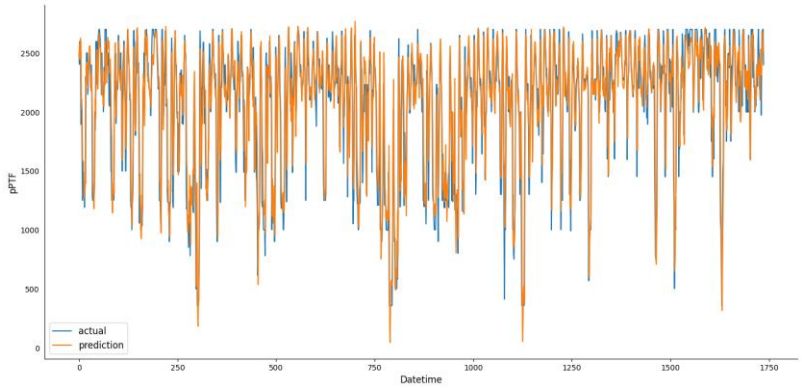

Figure B1. LSTM Results on Test Dataset

Appendix C. XGBoost Result

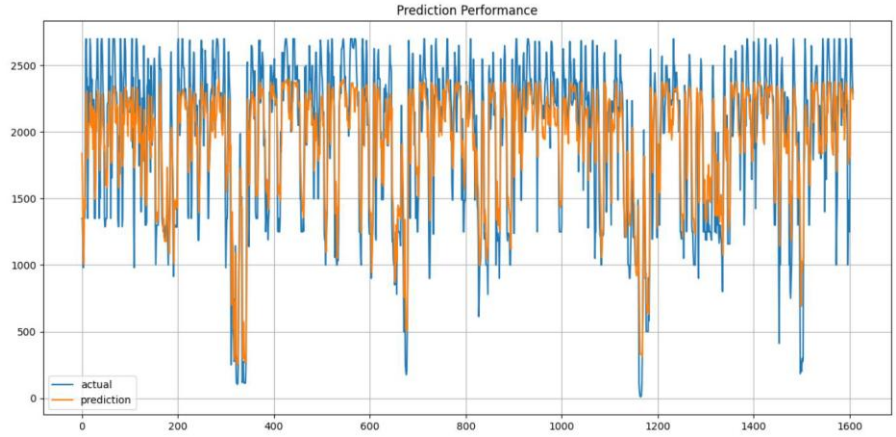

Figure C1. XGBoost Results on Test Dataset

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Appendix D. Schedule of First Two Weeks of July

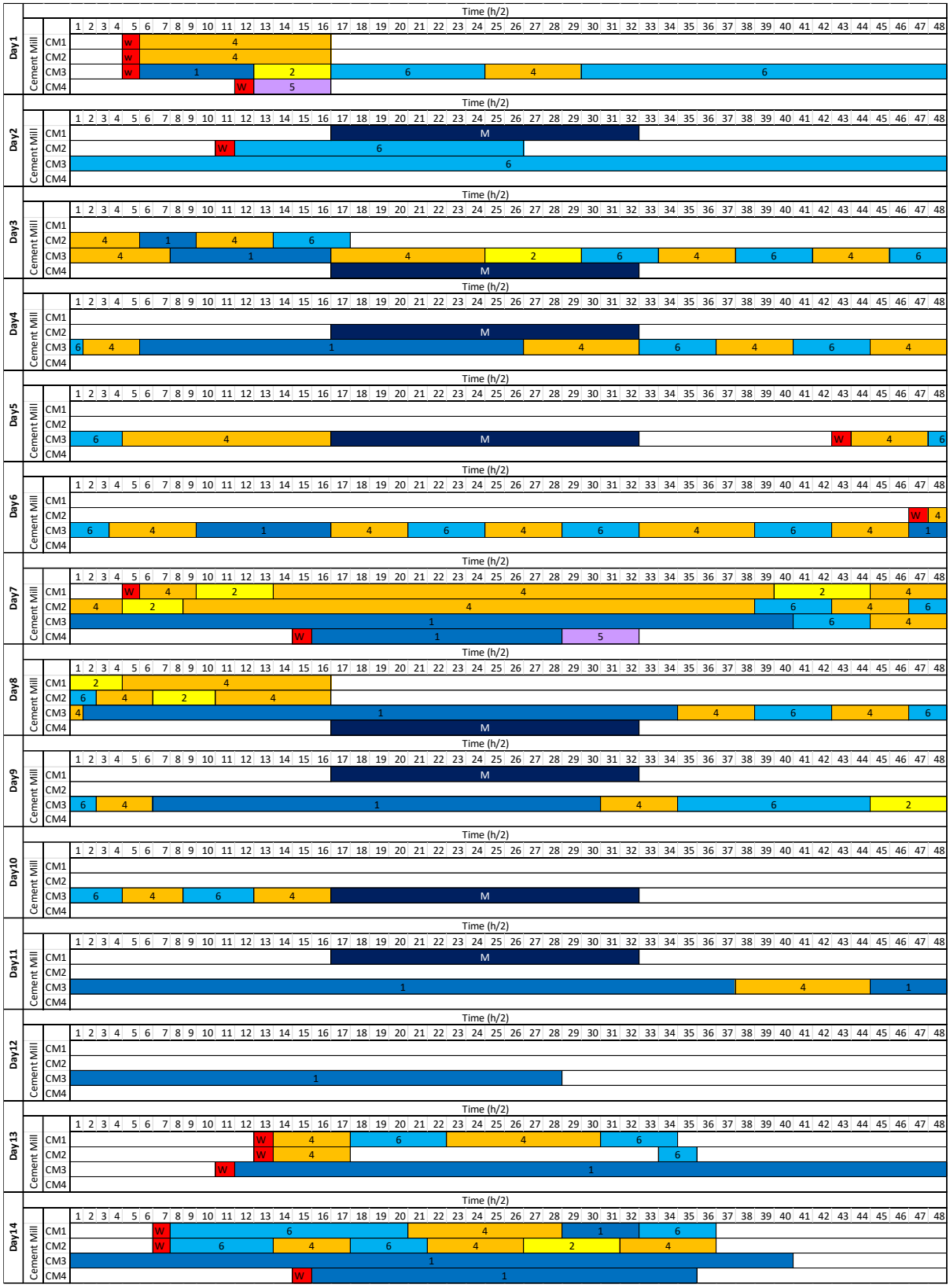

Figure D1. Schedule of First Two Weeks of July