Impact of Modeling on Production Capacity Planning

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Production capacity planning is a key factor in improving the efficiency of industrial processes, enhancing resource utilization, and reducing operating costs. However, the multitude of operational variables and the difficulty in predicting the success of production processes necessitate integrated modeling frameworks to support decision-making. Therefore, this study aimed to demonstrate the impact of an integrated modeling framework on improving production capacity planning, evaluate its effectiveness in predicting the success of production tasks, identify the most influential operational variables, and demonstrate its role in supporting operational decisions and improving resource utilization. The study adopted a hybrid modeling framework that combines Multi-Agent Systems (MAS) for coordinating production units, Binary Logistic Regression for estimating the probability of success of production tasks, and Internet of Things (IoT) technologies to provide real-time operational data. The proposed framework was applied to 200 operational observations representing production process data at Lafarge Iraq Cement Plant – Bazian Plant. The results showed that the binary logistic regression model is statistically significant, and that operational variables significantly contribute to explaining the probability of success of production tasks. The model's quality indicators demonstrated high explanatory power, and it achieved a classification accuracy of 94%, confirming its effectiveness in predicting the success or failure of production tasks. Maintenance delays, raw material availability, and production rate were identified as the most influential variables in production capacity planning. The study's scientific value lies in providing an integrated modeling framework that combines multi-agent systems, binary logistic regression, and Internet of Things (IoT) technologies to support production capacity planning in the cement industry. This framework contributes to improved resource utilization, increased efficiency in production processes, and enhanced data-driven operational decisions.

Keywords: Production capacity planning, multi-agent systems, dual logistic regression, Internet of Things, cement industry.

أثر النمذجة على تخطيط الطاقة الإنتاجية

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يعد تخطيط الطاقة الإنتاجية من العوامل الأساسية في تحسين كفاءة العمليات الصناعية، وتعزيز استغلال الموارد، وخفض تكاليف التشغيل، إلا أن تعدد المتغيرات التشغيلية، وصعوبة التنبؤ بنجاح العمليات الإنتاجية، يفرضان الحاجة إلى أطر نمذجة متكاملة، تدعم اتخاذ القرار، لذا، هدفت هذه الدراسة إلى بيان أثر إطار نمذجي متكامل في تحسين تخطيط الطاقة الإنتاجية، وتقييم كفاءته في التنبؤ بنجاح المهام الإنتاجية، وتحديد أهم المتغيرات التشغيلية المؤثرة فيها، فضلًا عن بيان دوره في دعم القرارات التشغيلية، وتحسين استغلال الموارد، واعتمدت الدراسة إطارًا نمذجيًا هجينًا يجمع بين أنظمة الوكلاء المتعددين (MAS) لتنسيق الوحدات الإنتاجية، والانحدار اللوجستي الثنائي (Binary Logistic Regression) لتقدير احتمالية نجاح المهام الإنتاجية، وتقنيات إنترنت الأشياء (IoT) لتوفير البيانات التشغيلية الآنية، وتم تطبيق الإطار المقترح على (200) ملاحظة تشغيلية، تمثل بيانات عملية الإنتاج في مصنع لافارج العراق للإسمنت – مصنع بازيان، وأظهرت النتائج أن انموذج الانحدار اللوجستي الثنائي يتمتع بدلالة إحصائية، وأن المتغيرات التشغيلية تسهم بصورة معنوية في تفسير احتمالية نجاح المهام الإنتاجية، كما أظهرت مؤشرات جودة الانموذج قدرة تفسيرية مرتفعة، وحقق الانموذج دقة تصنيف بلغت (94%)، مما يؤكد كفاءته في التنبؤ بنجاح، أو فشل المهام الإنتاجية، كما تبين أن تأخر الصيانة، وتوافر المواد الخام، ومعدل الإنتاج تمثل أكثر المتغيرات تأثيرًا في تخطيط الطاقة الإنتاجية، وتتمثل القيمة العلمية للدراسة في تقديم إطار نمذجي متكامل يجمع بين أنظمة الوكلاء المتعددين، والانحدار اللوجستي الثنائي، وتقنيات إنترنت الأشياء، لدعم تخطيط الطاقة الإنتاجية في صناعة الإسمنت، بما يسهم في تحسين استغلال الموارد، ورفع كفاءة العمليات الإنتاجية، وتعزيز القرارات التشغيلية المعتمدة على البيانات.

الكلمات المفتاحية: تخطيط الطاقة الإنتاجية، أنظمة الوكلاء المتعددين، الانحدار اللوجستي المزدوج، إنترنت الأشياء، صناعة الإسمنت.

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1. Framework

1.1. Introduction

Capacity planning is one of the most important activities in industrial operations management, as it aims to balance production capacity and demand, thereby contributing to improved resource utilization, increased performance efficiency, and reduced operating costs. With the continuous development of manufacturing technologies, modern modeling methods have become an effective tool for supporting operational decisions and improving planning efficiency.

Multi-agent systems, binary logistic regression, and Internet of Things (IoT) technologies are among the most prominent technologies used to improve capacity planning. They provide an intelligent environment for coordinating production processes, predicting their probability of success, and leveraging real-time operational data.

Therefore, this study aims to analyze the impact of modeling on capacity planning by building an integrated model that combines these technologies, applying it to the Lafarge Iraq Cement Plant – Bazian Plant as a case study.

1.2. Research Problem

Industrial organizations face challenges in production capacity planning due to the multitude of operational variables and the difficulty in predicting the success of production processes. This necessitates the use of intelligent models that support decision-making and improve resource utilization efficiency. The main research question is: What is the impact of an integrated modeling framework on improving production capacity planning? The sub-questions are:

1. How efficient is the integrated modeling framework in predicting the success of production tasks?
2. Which operational variables have the greatest impact on the success of production tasks and production capacity planning?
3. To what extent does the proposed modeling framework contribute to supporting operational decisions and improving resource utilization?

1.3. Research Significance

The significance of this research stems from presenting an integrated modeling framework to support production capacity planning. This framework combines artificial intelligence and modern modeling techniques, contributing to improved prediction accuracy, increased resource utilization efficiency, and enhanced operational decision-making in industrial organizations.

1.4. Research Objectives

1. To demonstrate the impact of an integrated modeling framework on improving production capacity planning.
2. To evaluate the efficiency of the proposed modeling framework in predicting the success of production tasks.
3. Identifying the operational variables that most significantly influence the success of production tasks and production capacity planning.
4. Demonstrating the role of the proposed model framework in supporting operational decisions and improving resource utilization.

1.5. Research Methodology

This research adopted an applied approach using a case study at the Lafarge Iraq Cement Plant/Bazian Plant. A comprehensive model framework was developed and evaluated based on 200 operational observations using binary logistic regression to identify the factors influencing the success of production tasks and supporting production capacity planning.

2. Literature Review

Modeling methods are widely used in various industries, including aircraft, automotive, and metallurgy, providing optimization of production processes and increased efficiency. For example, a multi-agent system is used at a Russian aircraft engine manufacturing plant located in Perm Russia(1). The system took into account a complex nomenclature, including more than 10,000 unique parts and 20-100 technological operations for each part. The model automated the selection of equipment, optimized the operation sequence, and distributed resources between production lines. Its implementation resulted in equipment downtime reduction by 15%, which allowed for an 8% increase in the output without additional investments in equipment. The financial effect consisted in operating cost reduction by 12 million rubles per year by minimizing downtime and optimizing machine loading.

Discrete event simulation has been used by a German-based European automotive components manufacturer to improve small-scale production of automotive parts(2). The model, developed with the Arena software, enabled the balancing of production lines, considering the variability of demand and equipment constraints. In the course of the project, bottlenecks at the assembly stage were detected, which enabled the redistribution of workstations and a 25% reduction in the cycle time. This led to a 20% increase in production and an increase in annual profit of 1.5 million euros due to increased performance without capital costs.

At the metallurgical plant in Chelyabinsk, a linear programming model was used to increase the capacity of the steelmaking shop(3). The model was built using the MATLAB program, and considered the constraints on the availability of raw materials (ore, coal), furnaces and human resources. The objective was to increase the steel production with the least energy and raw material costs. The optimization led to a 10% increase in the load of the furnaces and an 8% reduction in energy costs (5 million rubles annually). The model also decreased the planning time from two weeks to three days, thus improving production management.

Such examples show how different modeling methods – multi-agent systems, simulation modeling, and linear programming – can be adjusted to specific tasks and industries, providing improved operational efficiency and financial results.

However, traditional approaches such as linear programming cannot cope with dynamic processes, including equipment failures and changes in demand(4). Multi-agent systems (MAS) simulate production as the interaction of autonomous components representing equipment, personnel, or stages(5).

Binary logistic regression allows predicting operational results, and IoT technologies provide real-time monitoring(6). These methods are especially relevant for industries with high energy intensity, such as cement and oil refining.

This study is aimed to examine the simulation impact on capacity planning using MAS, regression and IoT as evidenced by Lafarge Iraq (Bazian Cement Plant) and Basra Refinery (South Refineries Company), optimizing resources and reducing environmental risks.

3. Materials and Methods

3.1. Multi-Agent Model

Multi-agent systems (MAS) are baseي on the concept of distributed artificial intelligence, where a group of independent agents interact to achieve common goals by making local decisions that contribute to improving the overall system performance[7]. Wooldridge indicates that intelligent agent is characterized by three main attributes: reactivity, proactivity, & the ability to interact with other agents[8]. In industrial environments, MAS represent network of interacting operational element that mimic equipment, production lines, and various stages industrial processes[9].

The study used the Lafarge Iraq Bazian Cement Plant as a case study. The main production units within plant were represented by independence agents, each representing a component of the production system, such as rotary kiln, cement mills, & material handling units. This allowed for simulation of operational interactions between these units & supported production capacity planning decisions.

The model is built based on set of key operational variables relate to production processes: batch volume, kiln operating hours, power consumption, resource utilization, maintenance delay, material availability, production rate, and kiln utilization. Production success was use as a binary variable to evaluate efficiency of production process execution.

To implement the model, the following steps were taken:

1. **Inputting** Operational Data of production processes, including batch sizes, furnace operating hours, power consumption, resource utilization rate, maintenance delays, raw material availability, production rate, & furnace utilization rate.
2. **Defining** Agents, where each agent represents an independent production unit with its own local decision making logic, tailor to the nature of the unit's work[10].
3. **Coordinating** Agent Operations using mechanisms that foster cooperation between production units and minimize conflicting resource utilization, thereby improving operational efficiency[11].
4. **Improving** Task Distribution by applying modeling techniques to distribute operational loads, reduce downtime, & optimize production capacity[12].
5. **Producing** optimal operating schedule that determines the distribution of production processes across different units, taking into account the actual operational constraints of the plant[13].
6. **Integrating** Internet of Things (IoT) technologies by leveraging sensor data relate to temperature, energy consumption, and

equipment status. This enables continuous updating of operational information & supports decision-making(14).

This model is based on the concept of decentralized management, where each agent relies on set of local decision-making rules. Optimal system performance is achieved through interaction and coordination among all agents. This allows the model to handle uncertainties, such as equipment failures or changes in demand levels, while maintaining efficient resource utilization and improving production capacity planning(15)(16).

Figure (1) illustrates the general structure of the multi-agent model and how its components are integrated with IoT technologies to support production capacity planning.

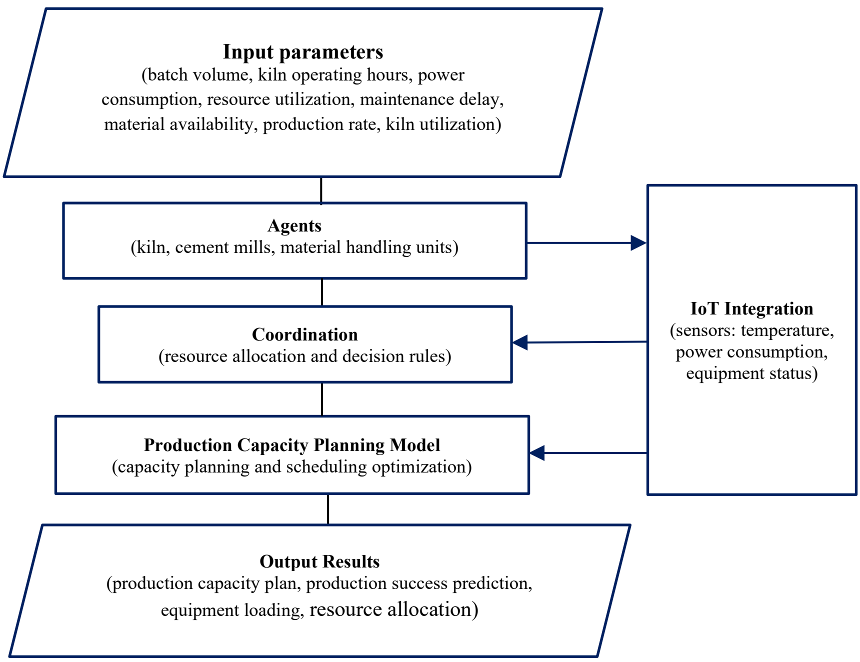

Figure 1. Conceptual framework of a proposed multi-agent production capacity planning model integrated with the Internet of Things. Source: Author.

3.2. Binary Regression

Binary logistic regression is used to estimate the probability of a production task succeeding (Production Success = 1) or failing (Production Success = 0) by using the logit function, which relates a set of independent variables to the probability of the dependent variable occurring[17]. The model is theoretically based, according to Hosmer and Lemeshow, on the assumption that the logarithm of the probability ratio (logit) is linearly related to the explanatory variables included in the model[18].

Model Formulas[19]:

$$P(y = 1|x) = \frac{e^{\beta_0 + \sum \beta_j x_{ij}}}{1 + e^{\beta_0 + \sum \beta_j x_{ij}}} \qquad (1)$$

The regression coefficients (β) are estimated using the Maximum Likelihood Estimation (MLE) method, which aims to find the best values for the coefficients that achieve the highest probability of matching the model to the data.

Logit Conversion[20]:

$$\ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \sum \beta_j x_{ij} \qquad (2)$$

The study used the following independent variables in constructing the logistic regression model:

(x_1: Batch Volume (tons), x_2: Kiln Operating Hours, x_3: Power Consumption (MW), x_4: Resource Utilization (%), x_5: Maintenance Delay (hours), x_6: Material Availability (%), x_7: Production Rate (tons/hour), x_8: Kiln Utilization (%))

The dependent variable is:

Y: Production Success (Binary), where the value (1) indicates the success of the production task, while the value (0) indicates its failure.

The model's parameters were estimated using the Maximum Likelihood Estimation (MLE) method, which is one of the most widely used methods in logistic regression models due to its efficiency in estimating the model's parameters[21].

To verify the model's quality, a set of statistical indicators was used, including the Nagelkerke coefficient of determination (R^2), the chi-square test to measure the model's significance, and the Akaike Information Criterion (AIC) to compare the models(22).

The multicollinearity problem between independent variables was also tested using the Variance Inflation Factor (VIF) and tolerance values to ensure the independence of the variables and the stability of the regression coefficient estimates(23).

The study also employed the Hosmer Lemeshow test to verify the model's suitability to the data. Furthermore, the model's ability to classify correctly was assessed using the Classification Table and Receiver Operating Characteristic (ROC) curve analysis to measure its efficiency in distinguishing between successful and unsuccessful production tasks.

3.3. Data Collection

Data collection in this study was based on the principles of sampling analysis to ensure data representativeness and minimize systematic errors(24). The study relied on operational production data collected during 2025 from the selected case study, Lafarge Iraq-Bazian Cement Plant, using commonly used capacity planning indicators in cement manufacturing processes. The dataset included 200 production observations, providing sufficient information to estimate and evaluate the proposed binary logistic regression model.

The study addressed a range of operational variables that directly affect capacity planning, including batch size (tons), kiln operating hours, energy consumption (MW), resource utilization (%), maintenance delay (hours), material availability (%), production rate (tons/hour), and kiln utilization (%). The dependent variable was represented by production success (binary), where 1 indicates successful completion of the production task, while 0 indicates failure.

Prior to statistical analysis, the dataset was screened for suitability for model estimation. Data screening procedures included checking for missing values, identifying potential outliers, and reviewing the consistency of recorded observations. Additionally, the distribution of variables was assessed using appropriate statistical procedures, including the Shapiro-Wilk test, to evaluate data quality before model estimation(25).

The collected data were subsequently analyzed using binary logistic regression to examine the impact of selected operational variables on the probability of production task success and to identify the factors that most significantly contribute to optimizing production capacity planning.

3.4. Proposed Production Capacity Planning Model

Capacity planning in manufacturing environments is often affected by numerous operational challenges, including inefficient resource utilization, production interruptions, equipment downtime, fluctuations in production demand, and changes in material availability. These factors can lead to decreased production efficiency, increased operating costs, and a negative impact on the overall performance of manufacturing systems(26)(27). While traditional planning methods offer useful scheduling solutions, they are typically limited in their ability to represent the dynamic interactions between production resources and constantly changing operating conditions(28)(29).

Accordingly, the proposed model for improving capacity planning was developed by integrating intelligent decision support with statistical forecasting techniques. The model focuses on improving operational decision-making, increasing resource utilization, reducing production delays, and supporting more efficient allocation of production resources. These improvements are crucial in energy-intensive industries, such as cement manufacturing(30)(31).

The proposed framework integrates three complementary components:

Multi-Agent System (MAS): This represents the distributed management of key production units, including kilns, cement mills, and material handling units, enabling production resources to work collaboratively and respond to changing operating conditions(32).

Binary Logistic Regression: This estimates the probability of success for a production task based on selected operating variables and supports production planning decisions under operational uncertainty(33).

Internet of Things (IoT): This utilizes sensor data related to equipment status, operating conditions, and energy consumption to provide up-to-date operational information that supports production planning and decision-making(34).

Integrating these components provides a unified framework that combines operational monitoring, intelligent coordination, and statistical forecasting within a single production capacity-planning model. The proposed framework is designed to enhance production-planning flexibility, support optimal resource utilization, and improve decision-making under changing manufacturing conditions. Furthermore, the integration of IoT technologies aligns with the principles of the Fourth Industrial Revolution, as real-time operational information contributes to improved planning accuracy and production system responsiveness[35] (Xu et al., 2018).

4. Results

4.1. Descriptive Statistics of the Study Variables

Before conducting the binary logistic regression analysis, descriptive statistics for the study variables were calculated in order to provide a preliminary description of the data characteristics, and to identify the extent of the dispersion of values and their limits, which helps in forming a general idea of the nature of the variables used in the production capacity planning analysis.

Table 1. Descriptive Statistics of the Study Variables

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Batch Volume (tons)	200	3555	5000	4422.18	325.95
Kiln Operating Hours	200	24	48	35.6	5.1
Power Consumption (MW)	200	95.4	130	114.38	6.79
Resource Utilization (%)	200	65.6	98	83.01	7.21
Maintenance Delay (hours)	200	0	6	3.12	1.42
Material Availability (%)	200	78.3	99	90.52	4.55
Production Rate (tons/hour)	200	77.92	207.42	127.99	27.54
Kiln Utilization (%)	200	66.8	98	84.32	7
Production Success (Binary)	200	0	1	0.46	0.5

4.2. Correlation Analysis

To obtain a preliminary understanding of the relationships between operational variables included in the study, Pearson correlation coefficients were calculated. Correlation analysis provides an initial indication of the strength and direction of relationships between independent variables before estimating a binary logistic regression model. It also helps in identifying potential correlations that may affect production capacity planning.

Table (2) Pearson Correlation Matrix of the Study Variables

Variables	BV	KOH	PC	RU	MD	MA	PR	KU
Batch Volume (BV)	1							
Kiln Operating Hours (KOH)	-0.71	1						
Power Consumption (PC)	0.68	-0.55	1					
Resource Utilization (RU)	0.63	-0.76	0.57	1				
Maintenance Delay (MD)	-0.54	0.69	-0.46	-0.72	1			
Material Availability (MA)	0.52	-0.61	0.43	0.66	-0.64	1		
Production Rate (PR)	0.79	-0.83	0.58	0.74	-0.67	0.6	1	
Kiln Utilization (KU)	0.61	-0.7	0.49	0.87	-0.63	0.69	0.73	1

Note: All coefficients are significant at $p < 0.01$.

4.3. Multicollinearity Test

Before applying the two-way logistic regression model, the multicollinearity problem between the independent variables was tested using the Tolerance and Variance Inflation Factor (VIF) indices, to ensure that there were no high correlations between the variables that might affect the stability of the regression coefficient estimates or reduce the reliability of the statistical model.

Table 3. Multicollinearity Diagnostics

Independe nt Variables	Batch Volume	Kiln Operating	Power Consumpti	Resource Utilization	Maintenan ce Delay	Material Availabilit	Production Rate	Kiln Utilization
Tolerance	0.491	0.428	0.612	0.356	0.477	0.542	0.395	0.371
VIF	2.037	2.336	1.634	2.809	2.097	1.845	2.532	2.695

4.4. Binary Logistic Regression Model

After confirming the absence of linear interference between the independent variables, a two-way logistic regression model was applied to estimate the probability of success of the production task based on the operational variables used in the study. Before interpreting the model coefficients, the overall significance of the model was tested using Omnibus Tests of Model Coefficients to determine the extent to which the independent variables contributed to improving the predictive power of the model compared to a model based solely on the constant.

Table 4. Omnibus Tests of Model Coefficients

Test	Chi-square	df	Sig.
Step	220.888	8	0
Block	220.888	8	0
Model	220.888	8	0

4.5. Model Summary

After confirming the significance of the logistic regression model using the Omnibus Tests of Model Coefficients, the model's quality was assessed using a set of statistical indicators that demonstrate the extent to which the independent variables explain the change in the dependent variable (production success). These indicators include the −2 log likeness value, the Cox & Snell R^2 coefficient, and the Nagelkerke R^2 coefficient.

Table 5. Model Summary

-2 Log Likelihood	Cox & Snell R Square	Nagelkerke R Square
50.937	0.675	0.902

4.6. Hosmer–Lemeshow Goodness-of-Fit Test

Before interpreting the regression coefficients, the fit of the logistic regression model to the data was tested using the Hosmer-Lemeshow test, one of the most widely used tests for assessing model fit. This test compares the predicted values with the actual values of the dependent variable; a non-significant value (Sig. > 0.05) indicates good agreement between the model and the data.

Table 6. Hosmer–Lemeshow Test

Chi-square	df	Sig.
5.327	8	0.723

4.7. Classification Table

After confirming the significance of the logistic regression model and its goodness of fit to the data, its ability to classify production tasks as successful or unsuccessful was evaluated using a classification table. This table shows the model's ability to correctly distinguish between successes and failures, as well as its overall classification accuracy.

Table 7. Classification Table

Observed	Predicted: Failure (0)	Predicted: Success (1)	Percentage Correct
Failure (0)	103	5	0.9537
Success (1)	7	85	0.9239
Overall Percentage			0.94

4.8. Variables in the Equation

After confirming the significance of the logistic regression model and its good fit to the data, the regression coefficients for the independent variables were analyzed to determine the extent to which each variable influenced the probability of success of the production task. This table shows the regression coefficients (B), standard error (S.E.), Wald's test, significance level (Sig.), and odds ratio (Exp(B)).

Table 8. Variables in the Equation

Variables	B	S.E.	Wald	Sig.	Exp(B)
Batch Volume (tons)	-0.02	0.009	4.892	0.027	0.98
Kiln Operating Hours	2.878	1.142	6.345	0.012	17.775
Power Consumption (MW)	0.023	0.089	0.067	0.796	1.023
Resource Utilization (%)	-0.067	0.171	0.152	0.696	0.936
Maintenance Delay (hours)	-3.365	0.831	16.404	0	0.035
Material Availability (%)	0.512	0.165	9.658	0.002	1.668
Production Rate (tons/hour)	0.921	0.337	7.473	0.006	2.511
Kiln Utilization (%)	0.116	0.17	0.465	0.495	1.123
Constant	-172.264	53.524	10.359	0.001	—

4.9. Importance Ranking of Operational Variables

After identify the variables affecting the logistic regression model, the operational variables are ranked according their relative importance based to the results of the Wald test and the level of statistical significance, with the aim of identifying the factors that contribute most to improving the probability of success of production tasks and supporting production capacity planning decisions.

Table 9. Importance Ranking of Operational Variables

Rank	Operational Variable	Wald Statistic	Sig.	Importance Level
1	Maintenance Delay	16.404	0	Very High
2	Material Availability	9.658	0.002	High
3	Production Rate	7.473	0.006	High
4	Kiln Operating Hours	6.345	0.012	Moderate
5	Batch Volume	4.892	0.027	Moderate
6	Kiln Utilization	0.465	0.495	Low
7	Resource Utilization	0.152	0.696	Low
8	Power Consumption	0.067	0.796	Very Low

5. Discussion

The study results showed that the proposed model, which combines Multi-Agent Systems (MAS), Binary Logistic Regression, and Internet of Things (IoT) technologies, has a high capacity to support production capacity planning at the Lafarge Iraq – Bazian Cement Plant. The Omnibus test proved the statistical significance of the model, while the Nagelkerke R^2 indices and classification results showed that the model has high explanatory and predictive power, confirming its suitability for analyzing the factors affecting the success of production processes. This result is consistent with what[36] [37] indicated, namely that the significance of the logistic regression model reflects the ability of the independent variables to explain and predict the dependent variable to an acceptable degree.

The results also showed that maintenance delay is the most influential factor in the success of production tasks, followed by material availability and then production rate. These results indicate that improving preventive maintenance programs and ensuring a continuous supply of raw materials directly contribute to increasing the efficiency of production capacity planning and reducing the likelihood of process disruptions. This finding is consistent with a study conducted at a Russian aircraft engine plant, which demonstrated that using multi-agent systems contributed to reducing equipment downtime and improving the utilization of production resources(38).

The results also align with a study by a European automotive component manufacturer, which showed that employing modeling in production line balancing contributed to reducing cycle time and increasing production capacity by improving resource allocation and identifying operational bottlenecks(39). This reinforces the current study's finding that improving the production rate and the availability of raw materials are among the most important factors influencing the success of production capacity planning.

Conversely, some variables, such as electrical power consumption, resource utilization, and kiln utilization, did not show a significant impact within the model. This can be explained by the fact that the effect of these variables becomes indirect when analyzed in the presence of more influential operational variables, such as maintenance, production rate, and raw material availability. This aligns with what(40) indicated regarding the differing relative importance of variables when analyzed within a multiple regression model.

Overall, the study's results confirm that integrating multi-agent systems with binary logistic regression and Internet of Things (IoT) technologies provides a comprehensive framework to support production capacity planning in the cement industry. This contributes to improving the quality of operational decisions and prioritizing improvements based on actual data. The results also highlight the importance of focusing on preventative maintenance, ensuring a continuous flow of raw materials, and improving production rates as the most influential factors in the success of production processes. This, in turn, enhances resource utilization efficiency and raises the level of operational performance of the organization.

6. Conclusions

The results of this study demonstrate that integrating Multi-Agent Systems (MAS), Binary Logistic Regression, and Internet of Things (IoT) provides an effective framework for supporting production capacity planning in the cement industry. The proposed model successfully identified the operational factors influencing the success of production tasks and provided a reliable basis for production planning and operational decision-making.

The Binary Logistic Regression model proved statistically significant, while the model evaluation indicators confirmed its high explanatory and predictive power. The achieved classification accuracy indicates that the proposed model can effectively distinguish between successful and unsuccessful production tasks, supporting its practical applicability in industrial environments.

Among the operational variables, maintenance delays were identified as the most influential factor on the success of production tasks, followed by material availability and production rate. These results indicate that optimizing maintenance scheduling, ensuring a continuous supply of raw materials, and enhancing production performance play a crucial role in improving production capacity planning.

Overall, the proposed framework demonstrates that combining intelligent production coordination across multiple agent systems, statistical forecasting using binary logistic regression, and real-time operational information provided by the Internet of Things (IoT) can support more efficient use of production resources and improve operational planning in the cement industry. Furthermore, the proposed model can serve as a practical decision support framework that can be adapted to similar industrial production systems.

7. Recommendations

Adopting the proposed integrated modeling framework represents a significant step towards improving production capacity planning and enhancing the efficiency of operational decisions in industrial enterprises. Strengthening preventive maintenance programs, ensuring the continuous availability of raw materials, and improving production rate management will contribute to increased production efficiency and reduced downtime. Expanding the use of Internet of Things (IoT) technologies will provide real-time operational data, enhancing the accuracy of planning and response to operational variables. Furthermore, employing binary logistic regression models to predict the success of production tasks supports proactive planning and improves the quality of operational decisions. Applying the proposed modeling framework to other industrial sectors and integrating artificial intelligence and machine learning technologies into future studies can contribute to increasing the efficiency and accuracy of production capacity planning.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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