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AI-Powered Evaluation of Lean Manufacturing Tools to Increase Cement Plant Productivity and Energy Efficiency

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Abstract

Meeting client demands is becoming a major challenge for organizations. Lean production is a rigorous methodology and mindset that aims to continually detect and eliminate waste across the entire business in order to provide the greatest value to consumers. The goal of lean manufacturing is to maximize customer value while limiting resource consumption, which reduces overall manufacturing costs. This is accomplished by efficiently managing personnel, equipment, and supplies to ensure effective utilization while preventing needless expenses. This study focuses on a cement factory where several lean manufacturing techniques have been applied to improve two important production metrics: energy consumption and production output. The industrial indicators have been subjected to both conventional and AI modeling. Evolutionary algorithms have been used to improve a system.

Keywords: *TPM, 5S, Kaizen, Genetic Algorithm, ANN, RSM, Optimization.*

1. Introduction

Lean manufacturing is a methodical approach and mindset that aims to maximize customer value by consistently finding and removing waste across the whole company. Lean manufacturing aims to reduce overall production costs by producing more value for customers while using fewer resources. This is achieved by skillfully balancing people, tools, and resources to ensure effective utilization without going over budget. Lean thinking's concept of "minimum manufacturing expense" requires the systematic removal of all waste from operations. Every employee in the company must be able to identify waste, understand process flow, and contribute to improving shop-floor efficiency in order for lean adoption to be successful. Lean is sometimes misunderstood as a strategy for reducing the number of employees or encouraging staff to work faster without taking adequate breaks. Instead than making employees' workloads more stressful, lean actually places an emphasis on increasing productivity through standardized processes, improved problem-solving, and continuous value creation. By methodically documenting the key ideas that underpin TPS, Sugimori et al. [1] made one of the earliest scholarly contributions to this field. The lean ideology, which is backed by guiding principles that guarantee quality is attained at the source, focuses on eliminating waste, improving continuous improvement, and boosting process efficiency. The well-known idea of "doing it right the first time" places a strong emphasis on employee accountability and responsibility for both process outcomes and product quality. Under the direction of Yang et al. [2], Toyota Motor Corporation developed the Toyota Production System after World War II. This system later evolved into JIT, TQC, and World-Class production, revolutionizing production by fusing efficiency, flexibility, and quality. According to Berliner et al. [3], traditional cost accounting systems ignore non-financial characteristics like quality, throughput, and adaptability in favor of financial measurements that often conflict with strategic manufacturing goals [4-5]. Companies are becoming more conscious of these limitations due to outdated infrastructures and uncertain returns on new systems, which has led to the adoption of kaizen costing as a more efficient approach for continuous improvement in modern production. Significant improvements in picking accuracy, efficiency, ergonomics, and waste reduction are indicated by research on kitting systems. While Tamaki and Nof [7] showed that robotic-assisted kitting can reduce costs and improve productivity, flexibility, and control of material flow in automobile assembly lines, Johansson and Johansson [6] demonstrated how kitting assembly simplifies procedures and expedites assembly. A mathematical model was developed by Bozer and McGinnis [8] to compare the benefits of kitting versus line stocking in terms of work-in-progress (WIP) levels, material handling efficiency, and space usage. Their study provided analytical evidence of the advantages of kitting methods and concentrated on the assembling of a stationary exercise bike. A time-based value-adding paradigm was introduced by Barker [9] to help guide organizational development and continuous improvement initiatives. According to the study, many manufacturing firms, particularly in the UK, exhibit inherent inefficiencies as a result of complex production systems that are out of step with crucial value-adding procedures. Untapped opportunities throughout the whole value chain are reflected in these inefficiencies. The author demonstrated the framework's effectiveness in reducing waste and improving performance by looking at the conversion process from obtaining raw materials to final assembly and providing examples from the electrical switchgear industry operating within a post-MRP II setting with kanban-driven pull systems. Dilanthi [10] examined the evolution of lean manufacturing theory over time, emphasizing its origins in Ford's production philosophy and the Toyota Production System. The study offered a modern perspective on lean theory and its theoretical underpinnings by examining the development of lean manufacturing concepts, definitions, principles, and tools. The challenges associated with implementing lean in several manufacturing environments, including assembly lines, job shops, and batch production systems, were examined by Tamiloli et al. [11]. Through an empirical analysis of 189 survey responses, the study found that there are significant differences in the applicability of lean techniques across manufacturing environments, with Just-in-Time and Kaizen contributing significantly to these differences. The study also recommended future research directions, such as comparison studies between various production system types and discriminant analysis. Chrisrmansson et al. [12] characterized lean manufacturing as a performance-oriented strategy focused on boosting organizational competitiveness via ongoing improvement and the removal of waste. They highlighted that ongoing lean success necessitates a nurturing organizational culture and enduring dedication from upper management. Lean manufacturing was likewise defined as an organized set of effective tools and best practices aimed at removing activities that do not add value. Two of the most crucial industrial performance metrics in this study are energy consumption (EC) in KWh/ton and production output per tons per day (POTPD). To increase the plant's productivity in terms of production output per tons per day (POTPD) and energy consumption (EC) in KWh/ton, particular LMTs such TPM, 5S, and Kaizen were implemented.

1.1. Lean Manufacturing Techniques (LMTs)

The literature has documented a number of Lean Manufacturing Tools (LMTs), such as 5S, Kaizen, Value Stream Mapping, Just-In-Time, Kanban, Poka-Yoke, Total Productive Maintenance (TPM), and Heijunka. This study employed 5S, Kaizen, and TPM since they are suitable for continuous-process cement facilities. The 5S model improved workplace organization by the systematic removal of unnecessary items, proper labeling, and scheduled cleaning of important areas. Kaizen allowed for continuous incremental improvements in operational efficiency through collaborative problem-solving between engineers and operators. TPM increased equipment reliability by employing predictive techniques on critical equipment and integrating operators into routine maintenance.

1.2. Modeling and optimization Techniques

Response Surface Methodology (RSM) is a statistical technique used to model and enhance systems affected by several inputs. The response is represented by a second-order polynomial with regression coefficients for linear, quadratic, and interaction impacts. RSM makes it possible to analyze factor interactions and determine ideal operating conditions through the use of contour and surface plots. An Artificial Neural Network (ANN) is a nonlinear modeling technique that connects inputs and outputs using linked neurons. The neuron's output is determined by a bias, an activation function, and a weighted sum of the inputs. A weighted total of the inputs, a bias, and an activation function are used to calculate the neuron's output. ANNs are adept at managing complicated nonlinear systems because they optimize by lowering prediction errors. A Genetic Algorithm (GA) is an evolutionary optimization method that uses crossover, mutation, and selection to gradually improve a population of solutions. GA efficiently investigates nonlinear and multimodal landscapes in search of ideal solutions, driven by a fitness function.

2. Application of LMS in cement plant

In order to increase plant productivity in terms of production output (POTPD) and specific electrical energy consumption (EC), the study examined and assessed the efficacy of key Lean Manufacturing Tools (LMTs) used in cement manufacturing, specifically Total Productive Maintenance (TPM), 5S, and Kaizen. As baseline indicators, the current TPM, 5S, and Kaizen implementation levels were evaluated and measured. According to the analysis, the baseline implementation levels for TPM, 5S, and Kaizen were 70%, 63.33%, and 6.69%, respectively. This translated into an average production output of 4748 TPD and an electrical energy usage of 67.8 kWh/Ton. Based on this assessment, structured improvement initiatives were designed and implemented to strengthen the application of these lean tools. The 5S methodology was applied and optimized through systematic Red Tag campaigns conducted in workshops, control rooms, and storage areas to eliminate unnecessary items and improve workplace organization. This intervention enhanced operational efficiency by minimizing non-value-added activities such as searching for tools and materials during equipment setup. For example, the installation of labeled tool racks near equipment significantly reduced setup preparation time, enabling technicians to save approximately 15–20 minutes per setup. Additionally, TPM was operationalized and broadened to change maintenance procedures from reactive to proactive. Operators were trained and given the authority to carry out standard tasks including cleaning, lubricating, and visually inspecting mills, conveyors, and packing machines through autonomous maintenance programs. This program decreased setup maintenance delays and increased equipment dependability. Pre-shift inspections of bag chutes and air pressure systems were implemented in the packing sector to avoid last-minute changes, which resulted in an 8–10-minute reduction in setup time. In order to solve persistent process inefficiencies, employee-driven Kaizen initiatives were simultaneously promoted and assessed. Process stability and operational throughput were improved by continuous improvement measures such automated lubrication systems, preset pressure gauges for various bag sizes, and optimized raw mill feed control. The plant saw quantifiable performance gains as a result of the integrated implementation of TPM, 5S, and Kaizen. Table 1 below shows the effect on POTPD and EC before and after LMTs

Table 1 Productivity evaluation using Lean Manufacturing Tools

Performance	Production Output (POTPD)	Energy KWh/ton
Before	4748	67.8
After	5315	60.6

While specific electrical energy consumption dropped from 67.8 kWh/Ton to 60.6 kWh/Ton, production output increased from 4748 TPD to 5315 TPD, indicating an improvement of roughly 11.7%. This shows how well lean tool implementation can improve both productivity and energy efficiency. Following productivity enhancement initiatives, representative sample data were obtained and summarized in Table 2 to support modeling and optimization analyses.

Table 2 **Sample data for various parameters**

SN	**TPM % (X1)**	**5S % (X2)**	**Kaizen events (X3)**	**Production Output (POTPD)**	**Energy KWh/ton**
1	60	50	4	4815.4	71.5
2	60	50	8	5021.2	68.3
3	60	50	15	5186.5	65.2
4	60	75	4	4935.7	68.6
5	60	75	8	5140.8	65.4
6	60	75	15	5315.6	61.9
7	60	90	4	5021.3	64.9
8	60	90	8	5203.7	61.7
9	60	90	15	5380.5	58.9
10	80	50	4	5075.8	67.9
11	80	50	8	5253.6	64.7
12	80	50	15	5440.2	61.6
13	80	75	4	5203.7	63.9
14	80	75	8	5389.5	60.9
15	80	75	15	5562.7	57.7
16	80	90	4	5121.4	65.5
17	80	90	8	5303.7	62.4
18	80	90	15	5476.9	59.2
19	95	50	4	5332.4	58.7
20	95	50	8	5513.9	55.7
21	95	50	15	5685.2	52.8
22	95	75	4	5287.1	60.9
23	95	75	8	5470.6	57.9
24	95	75	15	5652.4	54.8
25	95	90	4	5387.1	51.4
26	95	90	8	5569.6	48.5
27	95	90	15	5748.3	45.7

3. Outcomes and Discussions

3.1.Outcomes and Discussion for Production output (POTDP)

3.1.1.Regression model for POTDP

The second-order regression model for PO, which was created using information from each of the 27 experimental runs indicated in Table 2.5, is shown in equation (3). The F-value of 77.11 in the matching ANOVA findings (Table 3) confirms the quadratic model's statistical significance and shows a very low likelihood that this result is the product of random error. Only a small portion of the variance in PO can be attributed to unexplained causes, as shown by the high values of R^2 (97.61%) and modified R^2 (96.51%). Good model accuracy is also demonstrated by the low standard error (S = 0.44). Furthermore, the statistical significance of the model is confirmed by p-values < 0.05 for both the linear and quadratic terms (at a 95% confidence level) and the entire model. The final regression model for POTDP is expressed as follows:

$$\mathbf{POTDP} = 3628 + 4.36X_1 + 14.38X_2 + 72.9X_3 + 0.9982\mathrm{X}_1^2 - 0.0233{X_2}^2 - 1.977{X_3}^2 - 0.0198X_1\,X_2 - 0.0228X_1X_3 - 0.00502X_2X_3 \quad (3)$$

Table 3 **Statistical analysis of PO using ANOVA**

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	1388842	154316	77.11	0
Linear	3	1378711	459570	229.64	0
X1	1	736057	736057	367.8	0
X2	1	46355	46355	23.16	0
X3	1	586658	586658	293.15	0
Square	3	23562	7854	3.92	0.027
X1*X1	1	5172	5172	2.58	0.126
X2*X2	1	450	450	0.22	0.642
X3*X3	1	17940	17940	8.96	0.008
2-Way Interaction	3	18265	6088	3.04	0.057
X1*X2	1	18204	18204	9.1	0.008
X1*X3	1	57	57	0.03	0.868
X2*X3	1	4	4	0	0.966
Error	17	34021	2001		
Total	26	1422863			

3.1.2.ANN for POTDP

After the training phase, the optimized network parameters were extracted and employed to develop a mathematical formulation for POTDP prediction. The ANN architecture with three neurons in the hidden layer was identified as providing the most accurate and stable predictive performance. Accordingly, the ANN model can be expressed as:

$$\boldsymbol{POTDP = f\left(\sum_{j=1}^{3} w_{2j} f\left(\sum_{i=1}^{n} w_{1ji}x_i + b_{1j}\right) + b_2\right)} \quad \mathbf{(4)}$$

where x_i denotes the input variables; w_{1ji} and w_{2j} represent the connection weights between the input–hidden and hidden–output layers, respectively; and, b_{1j} and b_2 are the corresponding bias terms. Using optimized data for POTDP, the ANN model is represented below:

$$\boldsymbol{POTDP = 1234.4 * y_1 - 223 * y_2 - 12.2 * y_3 + 441}$$

Where,

$$y_1 = \frac{1}{[1 + e^{-(3.3374*x_1 - 0.9448*x_2 - 2.5277*x_3 + 0.1234*x_4 - 2.333)}]}$$

$$y_2 = \frac{1}{[1 + e^{-(-0.52686*x_1 - 0.0275*x_2 + 0.037796*x_3 - 0.0023613*x_4 + 0.47112)}]}$$

$$y_3 = \frac{1}{[1 + e^{-(-2.368*x_1 + 5.3996*x_2 + 3.9879*x_3 - 0.59143*x_4 - 63.4828)]}]}$$

3.1.3.Maximization of POTDP

Highly nonlinear relationships with numerous interaction effects among process parameters are frequently involved in the optimization of manufacturing performance metrics. In this work, an artificial neural network (ANN) model based on experimental data is used to describe the PO. Conventional gradient-based optimization approaches are inappropriate because of the nonlinear, nonconvex character of the objective function and the existence of quadratic and interaction elements, which might lead to local optima. In order to find the global optimum of PO, a Genetic Algorithm (GA) is used. The optimization problem is formulated as:

Objective function:

Maximize POTPD

$$POTDP = 1234.4 * y_1 - 223 * y_2 - 12.2 * y_3 + 441.22$$

Subject to constraints:

$$60 \leq X_1 \leq 95$$
$$50 \leq X_2 \leq 90$$
$$4 \leq X_3 \leq 15$$

Within the predetermined variable bounds, a starting population of fifty chromosomes is produced at random. Diverse search space coverage is ensured at the start of the optimization process by this random initialization. The PO value that results from evaluating each chromosome using the objective function is regarded as the fitness value. Parent chromosomes are chosen using tournament selection with a tournament size of two. By selecting fitter individuals while preserving genetic diversity, this selection approach strikes a balance between exploration and exploitation. Offspring are produced using a real-coded crossover operator with a crossover probability of 0.8. This high crossover rate improves global search capabilities and enables efficient genetic information sharing across parent solutions. Mutation is performed using a uniform/Gaussian mutation operator with a mutation probability of 0.05. Mutation introduces controlled randomness into the population, preventing premature convergence and enabling the algorithm to escape local optima. To preserve high-quality solutions, elitism is applied by retaining the best two individuals from each generation. This guarantees monotonic improvement in the best fitness value across generations. The GA is terminated after 50 generations, or earlier if no significant improvement in the best objective value is observed over successive generations. The GA converged to the following optimal set of decision variables:

$X_1 = 95$, $X_2 = 90$, $X_3 = 14.8$. Corresponding to above input, the maximum value of PO obtained is 14,589

3.2. Outcomes and Discussions for Energy Consumption (EC)

3.2.1. Regression Model for EC

The second-order regression model for EC, which was created using information from each of the 27 experimental runs indicated in Table 2.5, is shown in equation (3). With an F-value of 18.44, the accompanying ANOVA results (Table 3) support the quadratic model's statistical significance and suggest a very low likelihood that this result is the product of random error. Only a small portion of the variation in EC can be attributed to unexplained causes, as shown by the high values of R² (90.71%) and adjusted R² (87.71%). Good model accuracy is also demonstrated by the low standard error (S = 2.35) Table 4. Furthermore, the statistical significance of the model is confirmed by p-values < 0.05 for both the linear and quadratic terms (at a 95% confidence level) and the entire model. The final regression model for EC is expressed as follows:

$$\begin{aligned} EC = {} & 9.5 + 1.628\,X_1 + 0.486X_2 - 1.236X_3 - 0.01279X_1^2 - 0.00466{X_2}^2 + \\ & 0.03030{X_3}^2 + 0.00039X_1\,X_2 + 0.00104X_1X_3 + 0.00027X_2X_3 \end{aligned} \tag{5}$$

Table 4 Statistical analysis of EC using ANOVA

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	918.69	102.077	18.44	0
Linear	3	845.1	281.699	50.88	0

X1	1	543.93	543.933	98.24	0
X2	1	127.5	127.499	23.03	0
X3	1	169.68	169.681	30.65	0
Square	3	109.93	36.642	6.62	0.004
X1*X1	1	87.79	87.789	15.86	0.001
X2*X2	1	17.94	17.943	3.24	0.09
X3*X3	1	4.2	4.195	0.76	0.396
2-Way Interaction	3	0.36	0.121	0.02	0.995
X1*X2	1	0.23	0.226	0.04	0.842
X1*X3	1	0.13	0.125	0.02	0.882
X2*X3	1	0.01	0.011	0	0.965
Error	17	94.12	5.537		
Total	26	1012.81			

3.2.2.ANN for EC

Using optimized data for EC, the ANN model is represented below:

$$EC = 60.233 * y_1 - 0.523 * y_2 - 2.9 * y_3 + 7.888$$

Where,

$$y_1 = \frac{1}{[1 + e^{-(7.723*x_1 - 0.7634*x_2 - 2.5277*x_3 + 0.1294*x_4 - 2.344)}]}$$

$$y_2 = \frac{1}{[1 + e^{-(-0.6869*x_1 - 0.03428*x_2 + 0.04666*x_3 - 0.27463*x_4 + 0.58332)}]}$$

$$y_3 = \frac{1}{[1 + e^{-(-1.476*x_1 + 6.2334*x_2 + 4.3334*x_3 - 0.6793*x_4 - 7.344)]}]}$$

3.2.3.Minimization of EC

Energy consumption (EC) is a critical sustainability and cost-related metric in manufacturing systems. In this study, EC is expressed as an ANN model incorporating all key process parameters. The inherent nonlinearity and interaction terms limit the applicability of conventional gradient-based optimization methods. Consequently, a Genetic Algorithm (GA) is adopted to determine the global minimum of EC within the feasible operating domain.The optimization problem is formulated as:

Minimize EC

$$EC = 60.233 * y_1 - 0.523 * y_2 - 2.9 * y_3 + 7.888$$

Subjected to:

$60 \le X_1 \le 95$

$50 \le X_2 \le 90$

$4 \le X_3 \le 15$

The GA is implemented using real-coded chromosomes to represent continuous decision variables. Based on extensive use in nonlinear manufacturing optimization problems, the GA parameters are selected as follows:

- **Population size:** 50
- **Selection method:** Tournament selection (tournament size = 2)
- **Crossover probability:** 0.8 (real-coded crossover)
- **Mutation probability:** 0.05 (Gaussian/uniform mutation)
- **Elitism:** Best two individuals preserved per generation
- **Number of generations:** 50

This configuration ensures an effective balance between global exploration and local exploitation while avoiding premature convergence. The GA converged to the following optimal set of decision variables: X_1 = 64, X_2 = 52, X_3 = 15. Corresponding to above input, the maximum value of PO obtained is 42.1.

Comparison between Models

Figure 1 and Figure 2 illustrate a comparison between the actual and predicted values of the POTDP and EC. It is evident from the results that the ANN model demonstrates enhanced accuracy and a strong capability to model the nonlinear interactions between process variables.

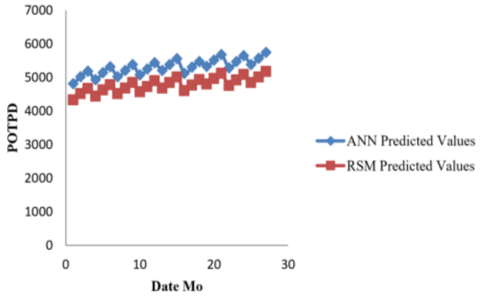

Figure 1 **Model Comparison for POTDP**

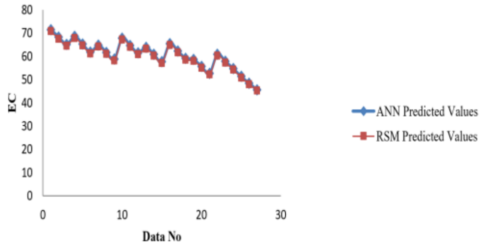

Figure 2 **Model Comparison for EC**

Conclusions

Using Lean Manufacturing Techniques (LMTs), this study assessed two important productivity metrics in the cement industry: production output (tons per day, POTDP) and specific energy consumption (kWh/ton, EC). The results demonstrate that operational performance was greatly enhanced by lean adoption. A 21% increase in production output demonstrated improved efficiency. The average EC decreased from 67.8 to 60.6 kWh/ton at the same time that energy performance improved. Among the lean tools, Total Productive Maintenance (TPM) emerged as the most impactful, as confirmed by F-statistic analysis, contributing substantially to both higher output and lower energy consumption. Additionally, the combined use of Artificial Neural Networks (ANN) and Genetic Algorithms (GA) further optimized process parameters, leading to additional gains in productivity and efficiency. Overall, the study demonstrates that integrating lean practices with advanced optimization techniques can significantly enhance cement plant performance by increasing output and reducing energy use.

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