

# AI-Powered Assessment of Lean Manufacturing Instruments to Boost Production and Energy Efficiency in A Cement Plant

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**Abstract**—Organizations currently encounter significant difficulties in meeting customer demands. Lean production represents a philosophy and a methodical approach focused on providing the highest value to customers by consistently identifying and removing waste throughout the entire organization. Lean manufacturing focuses on maximizing customer value while minimizing resource use, which subsequently lowers total manufacturing expenses. This is done by effectively coordinating people, machines, and materials to guarantee efficient use while avoiding unnecessary costs.

This research focuses on a cement plant where different lean manufacturing methods have been implemented to enhance two key production metrics: production output and energy consumption. Both traditional and AI modeling have been applied to the industrial indicators. A system has been improved through the use of evolutionary algorithms.

**Index Terms**—TPM, 5S, Kaizen, Genetic Algorithm, ANN, RSM, Optimization

## I. INTRODUCTION

Lean production is a philosophy and systematic method focused on providing maximum value to customers by continuously identifying and eliminating waste throughout the entire organization. Lean manufacturing focuses on generating greater customer value while utilizing fewer resources, which leads to a decrease in overall manufacturing expenses. This is accomplished by effectively balancing individuals, equipment, and resources to guarantee efficient use without excessive costs.

The idea of "minimum manufacturing expense" in lean thinking presupposes the methodical elimination of every type of waste from processes. An essential

criterion for effective lean implementation is that every person in the organization should be able to recognize waste, comprehend process flow, and aid in enhancing shop-floor efficiency. Lean is frequently misinterpreted as a tactic for cutting down employee numbers or pushing workers to accelerate without proper breaks. In fact, lean emphasizes working more efficiently via standardized procedures, enhanced problem-solving, and ongoing value creation instead of intensifying workload stress on workers.

Sugimori et al. [1] made one of the first scientific contributions to this area by systematically recording the essential concepts that support TPS. Lean philosophy focuses on removing waste, enhancing continuous improvement, and increasing process efficiency, supported by guiding principles that ensure quality is achieved at the source. The widely recognized concept of "doing it right the first time" emphasizes employee responsibility and accountability for both product quality and process results.

Post-World War II, Toyota Motor Corporation, under the guidance of Yang et al. [2], created the Toyota Production System, which eventually transformed into JIT, TQC, and World-Class Manufacturing, changing manufacturing by combining flexibility, quality, and efficiency. As stated by Berliner et al. [3], conventional cost accounting systems focus on financial metrics that frequently clash with strategic manufacturing objectives and overlook non-financial indicators like quality, throughput, and flexibility. As a result of old infrastructures and unpredictable returns on new systems, companies are increasingly aware of these constraints, prompting the use of kaizen costing

as a more effective method for ongoing enhancement in contemporary manufacturing.

Krafcik and Liker [4] emphasized the increasing interest from both academia and industry in lean product development, which is based on lean production and shown to improve manufacturing efficiency.

Womack et al. [5] outlined the progression of the automotive sector from traditional craftsmanship to mass production and finally to lean production, highlighting the enhanced effectiveness of lean methodologies.

Research on kitting systems indicates major advancements in picking efficiency, precision, ergonomics, and waste minimization.

Johansson and Johansson [6] illustrated that kitting assembly streamlines processes and speeds up assembly, whereas Tamaki and Nof [7] indicated that robotic-assisted kitting can cut costs and enhance productivity, flexibility, and control of material flow in automotive assembly lines.

Bozer and McGinnis [8] created a mathematical model to measure the relative advantages of kitting and line stocking regarding material handling efficiency, space utilization, and work-in-progress (WIP) levels. Their research, focused on the assembly of a stationary exercise bike, offered analytical proof of the benefits of kitting systems.

Barker [9] presented a value-adding framework based on time to assist in directing organizational growth and ongoing enhancement efforts. The research claimed that numerous manufacturing companies, especially in the United Kingdom, display intrinsic inefficiencies due to complicated production systems that are not aligned with essential value-adding processes. These inefficiencies reflect unexploited opportunities across the entire value chain. Through examining the conversion process from acquiring raw materials to final assembly, and citing instances from the electrical switchgear sector functioning within a post-MRP II setting with kanban-driven pull systems, the author illustrated the framework's efficiency in minimizing waste and enhancing performance.

Dilanthi [10] explored the historical development of lean manufacturing theory, highlighting its roots in the Toyota Production System as well as Ford's production ideology. The research examined the evolution of lean manufacturing concepts, definitions, principles, tools, and techniques, offering a contemporary view on lean theory and its theoretical foundations.

Tamiloli et al. [11] explored the difficulties linked to lean implementation in various manufacturing settings, such as job shops, batch production systems, and assembly lines. Through an empirical examination of 189 survey responses, the research revealed that the applicability of lean tools differs greatly among manufacturing environments, with Just-in-Time (JIT) and Kaizen playing a major role in inter-group variations. The research additionally suggested future investigation paths that include discriminant analysis and comparative studies among different types of manufacturing systems.

Chrismansson 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.

## II. METHODOLOGY:

### 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. Because 5S, Kaizen, and TPM are appropriate for continuous-process cement plants,

they were used in this study. Through the methodical elimination of superfluous things, appropriate labeling, and planned cleaning of crucial areas, the 5S model enhanced workplace organization. Through cooperative problem-solving between operators and engineers, kaizen enabled ongoing incremental gains in operational efficiency. By incorporating operators in normal maintenance and using predictive approaches on vital gear, TPM improved equipment reliability.

### 1.2. Modeling and optimization Techniques

Response Surface Methodology (RSM) is a statistical approach employed to model and enhance processes affected by various factors. It depicts the response through a second-order polynomial, with regression coefficients representing linear, quadratic, and interaction influences. RSM allows for the determination of ideal operating conditions and examination of factor interactions using contour and surface plots. An Artificial Neural Network (ANN) is a nonlinear modeling technique that connects inputs and outputs through linked neurons. The output of the neuron is calculated as a weighted sum of inputs along with a bias and an activation function. ANNs optimize by reducing prediction errors, which makes them proficient in handling complex nonlinear systems. A Genetic Algorithm (GA) is an evolutionary optimization technique that progressively enhances a population of solutions through selection, crossover, and mutation. Driven by a fitness function, GA effectively explores nonlinear and multimodal landscapes in search of optimal solutions

## III. APPLICATION OF LMS IN CEMENT PLANT

The study analyzed and evaluated the effectiveness of key Lean Manufacturing Tools (LMTs) applied in cement manufacturing, specifically Total Productive Maintenance (TPM), 5S, and Kaizen, to improve plant productivity in terms of production output (POTPD) and specific electrical energy consumption (EC). The existing levels of TPM, 5S, and Kaizen implementation were assessed and quantified as baseline indicators. The analysis revealed baseline implementation levels of 70% for TPM, 63.33% for 5S, and 6.69% for Kaizen, which corresponded to an average production output of 4748 TPD and an electrical energy consumption 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.

Furthermore, the implementation of TPM was expanded and operationalized to shift maintenance practices from reactive to proactive approaches. Through autonomous maintenance programs, operators were trained and empowered to perform routine activities such as cleaning, lubrication, and visual inspection of mills, conveyors, and packing machines. This initiative improved equipment reliability and reduced maintenance delays during setups. In the packing section, the introduction of pre-shift inspections of bag chutes and air pressure systems prevented last-minute adjustments, leading to a setup time reduction of approximately 8–10 minutes. Simultaneously, employee-driven Kaizen initiatives were encouraged and evaluated to address recurring process inefficiencies. Continuous improvement actions, such as preset pressure gauges for different bag sizes, automated lubrication systems, and optimized raw mill feed control, enhanced process stability and operational throughput.

As a result of the integrated application of TPM, 5S, and Kaizen, the plant achieved measurable performance improvements. Production output increased from 4748 TPD to 5315 TPD, representing an improvement of approximately 11.7%, while specific electrical energy consumption decreased from 67.8 kWh/Ton to 60.6 kWh/Ton, demonstrating the effectiveness of lean tool implementation in improving both productivity and energy efficiency.

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

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

IV. OUTCOMES AND DISCUSSIONS

4.1. Outcomes and Discussion for Production output (POTDP)

4.1.1. Regression model for POTDP

Equation (3) presents the second-order regression model for PO developed using data from all 27 experimental runs listed in Table 2.5. The

corresponding ANOVA results (Table 3) show an F-value of 77.11, confirming the statistical significance of the quadratic model and indicating a very low probability that this result is due to random error. The high values of R<sup>2</sup> (97.61%) and adjusted R<sup>2</sup> (96.51%) demonstrate that the model explains most of the variation in PO, with only a small fraction attributed to unexplained factors. The low standard error (S =

0.44) further reflects good model accuracy. In addition, p-values below 0.05 for the overall model as well as the linear and quadratic terms (at a 95% confidence level) validate the statistical significance of the model.

The final regression model for POTDP is expressed as follows:

$$\begin{aligned}
 \text{POTDP} = & 3628 + 4.36X_1 + 14.38X_2 + 72.9X_3 + \\
 & 0.9982X_1^2 - 0.0233X_2^2 - 1.977X_3^2 - \\
 & 0.0198X_1X_2 - 0.0228X_1X_3 - \\
 & 0.00502X_2X_3 \quad (1)
 \end{aligned}$$

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			

4.1.2. 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:

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

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:

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

Where,

$$\begin{aligned}
 y_1 &= \frac{1}{[1 + e^{-(3.3374 * x_1 - 0.9448 * x_2 - 2.5277 * x_3 + 0.1234 * x_4 - 2.333)}]} \\
 y_2 &= \frac{1}{[1 + e^{-(0.52686 * x_1 - 0.0275 * x_2 + 0.037796 * x_3 - 0.0023613 * x_4 + 0.47112)}]} \\
 y_3 &= \frac{1}{[1 + e^{-(2.368 * x_1 + 5.3996 * x_2 + 3.9879 * x_3 - 0.59143 * x_4 - 63.4828)}]}
 \end{aligned}$$

4.1.3. Maximization of POTDP

The optimization of manufacturing performance measures often involves highly nonlinear relationships with multiple interaction effects among process parameters. In the present work, the PO is represented by a ANN model derived from experimental data. Due to the nonlinear, non-convex nature of the objective function and the presence of quadratic and interaction terms, conventional gradient-based optimization techniques are prone to local optima and are therefore

unsuitable. Consequently, a Genetic Algorithm (GA) is employed to obtain the global optimum of PO.

The optimization problem is formulated as:

Objective function:

Maximize POTPD

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

Subject to constraints:

$$60 \leq X_1 \leq 95$$

$$50 \leq X_2 \leq 90$$

$$4 \leq X_3 \leq 15$$

An initial population of 50 chromosomes is randomly generated within the predefined variable bounds. This random initialization ensures diverse search space coverage at the beginning of the optimization process. Each chromosome is evaluated using the objective function, and the resulting PO value is treated as the fitness value. Tournament selection with a tournament size of two is employed to select parent chromosomes. This selection strategy balances exploration and exploitation by favoring fitter individuals while maintaining genetic diversity. A real-coded crossover operator with a crossover probability of 0.8 is used to generate offspring. This high crossover rate facilitates effective exchange of genetic information between parent solutions and enhances global search capability. 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

#### 4.2. Outcomes and Discussions for Energy Consumption (EC)

##### 4.2.1. Regression Model for EC

Equation (3) presents the second-order regression model for EC developed using data from all 27 experimental runs listed in Table 2.5. The corresponding ANOVA results (Table 3) show an F-value of 18.44, confirming the statistical significance of the quadratic model and indicating a very low probability that this result is due to random error. The high values of  $R^2$  (90.71%) and adjusted  $R^2$  (87.71%) demonstrate that the model explains most of the variation in EC, with only a small fraction attributed to unexplained factors. The low standard error ( $S = 2.35$ ) further reflects good model accuracy. In addition, p-values below 0.05 for the overall model as well as the linear and quadratic terms (at a 95% confidence level) validate the statistical significance of the model.

The final regression model for EC is expressed as follows:

$$EC = 9.5 + 1.628 X_1 + 0.486X_2 - 1.236X_3 - 0.01279X_1^2 - 0.00466X_2^2 + 0.03030X_3^2 + 0.00039X_1 X_2 + 0.00104X_1X_3 + 0.00027X_2X_3 \quad (3)$$

Table 5 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			

4.2.2. 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,

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

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

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

4.2.3. 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:

$$60 \leq X_1 \leq 95$$

$$50 \leq X_2 \leq 90$$

$$4 \leq X_3 \leq 15$$

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 POTDP obtained is 42.1.

Comparison between Models

Fig.1 and Fig. 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.

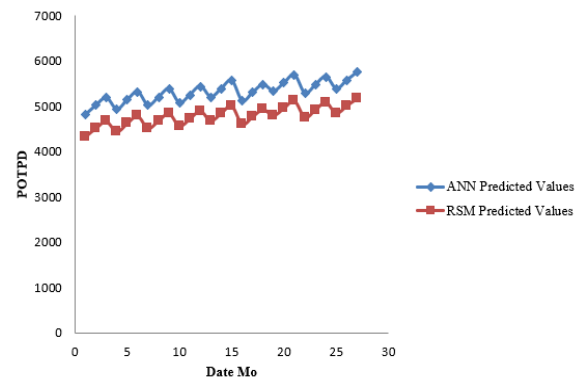


Fig. 1 Model Comparison for POTDP

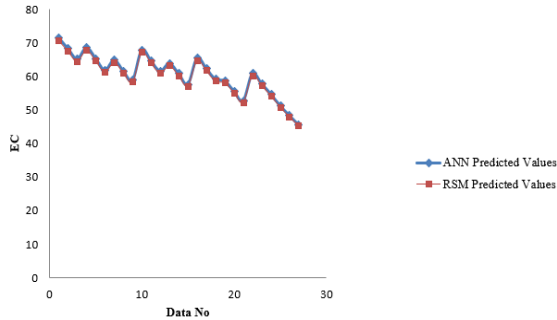


Fig. 2 Model Comparison for EC

## V. CONCLUSIONS:

The present research analyzed and evaluated key productivity indicators in cement manufacturing, namely production output tons per day (POTDP) and specific energy consumption (EC) in kWh/Ton, through the application of various Lean Manufacturing Techniques (LMTs). Based on the analysis, the following conclusions were derived:

- 1) The implementation of Lean Manufacturing Techniques significantly enhanced production performance, as the production output (POTDP) increased by approximately 21%, demonstrating the positive impact of lean practices on operational efficiency.
- 2) The second productivity indicator, specific electrical energy consumption (EC) in cement production, also showed measurable improvement. The average EC decreased from 67.8 kWh/Ton to 60.6 kWh/Ton, indicating improved energy efficiency as a result of lean tool implementation.
- 3) Based on the evaluation using the F-statistic as a performance indicator, Total Productive Maintenance (TPM) was identified as the most influential Lean Manufacturing Tool, contributing significantly to improvements in both production output and energy consumption.
- 4) Furthermore, the integrated application of Artificial Neural Networks (ANN) and Genetic Algorithm (GA) optimized process parameters, resulting in notable improvements in both POTDP and EC, thereby demonstrating the effectiveness of advanced optimization techniques in enhancing plant productivity.

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