SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V13I2P102
Volume 13 Issue 2, 12-21, February 2026

Original Article

Implementation of Lean Manufacturing System in Cement Plant by using an AI Approach

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Received: 16 November 2025 Revised: 17 December 2025 Accepted: 18 January 2026 Published: 20 February 2026

Abstract *- Organizations today face intense domestic and global competition driven by liberalization and rapid technological advancements. To sustain a competitive edge, managers adopt proven management philosophies such as Just-In-Time (JIT), Total Quality Management (TQM), Total Productive Maintenance (TPM), Six Sigma, and Lean Manufacturing Systems (LMS). However, selecting between people-oriented systems like LMS and technology-driven systems such as Flexible Manufacturing Systems (FMS) or Computer-Integrated Manufacturing Systems (CIMS) remains a challenge, as such initiatives demand significant investments and long-term commitment. This study focuses on implementing Lean Manufacturing Techniques such as TPM, 5S, and Kaizen in the cement plant. The three major performance parameters, such as Overall Equipment Effectiveness (OEE), Average Setup Time (ST), and Defect Rate Percentage (DP), have been evaluated. The AI tool, such as Artificial Neural Networks (ANN) and Genetic Algorithms(GA), has been applied for process optimization. It has been found that there is an improvement of 41%, 70% and 90% in OEE, ST, and DP, respectively, after applying LMTs in the cement plant.*

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

1. Introduction

Lean Manufacturing (LM) is a management ideology focused on optimizing customer needs by continuously eliminating waste across all processes. It emphasizes the efficient and balanced use of people, machines, and materials to achieve the lowest manufacturing cost without overburdening workers. Contrary to the misconception that lean means fewer employees or faster work, it actually promotes smarter, standardized, and value-driven operations. Unlike traditional manufacturing, which has long lead times dominated by Non-Value-Added (NVA) activities, lean manufacturing minimizes these wastes, reduces process lead time, and enhances efficiency by focusing on improving non-value-added areas rather than the limited value-added ones.

In this competitive world, LM is most widely used in all the manufacturing sectors, such as cement plants, steel plants, cable industries, etc. Nowadays, people are using it to improve different manufacturing aspects to make product cost competitive, and hence they can survive in today's hardcore market.

Several studies have examined the impact of LM. Landsbergis et al. [1] analyzed the effects of LM and total quality management on workers' health. Their findings indicated that implementing lean production increased work intensity and demands, while workers' decision-making autonomy remained limited. Consequently, this resulted in a higher incidence of Musculoskeletal Disorders among employees.

Donatelli and Harris [2] explained that Value Stream Mapping (VSM) provides a steady snapshot of a system, whereas imitation offers a dynamic animation that enables detailed examination and assessment of both the existing and proposed states of the process.

Cochran et al. [3] formulated a structured approach by adopting Value Stream Mapping (VSM) to redesign existing manufacturing systems. They recommended integrating physical simulation along with effective communication and support for all personnel to help them understand the value streams and contribute to the efficient redesign of the system.

Tapping et al. [4] described VSM as a schematic illustration of the overall system on a solo street using symbols and emblems. It encapsulates essential data alongside the progression of issues and information within the interface element via a current state map, assisting analysts in recognizing opportunities for enhancement. Based on this, a future state VSM is created, supported by continuous improvement or Kaizen plans, to guide the implementation of lean manufacturing initiatives.

Levinson and Rerick [5] emphasized that, among several lean measures, Manufacturing Cycle Efficiency (MCE) is a crucial indicator for the decrease of cycle time. It computes the ratio of VAT to TCT, offering a definitive evaluation of the efficiency with which a production process transforms time into customer value. Consequently, MCE accurately represents the extent of leanness in a system as determined by its temporal performance. Soriano-Meier and Forrester [6] assessed organizational leanness by examining critical characteristics like lean supply, manufacturing cost, and quality. Their study employed these parameters to evaluate the total level of leanness inside a business, offering a systematic method to gauge the efficiency of lean adoption.

Irfan et al. [7] examined that cement is integral to economic growth and infrastructural development, necessitating increased productivity. Lean manufacturing emphasizes efficiency by minimizing waste and process inefficiencies. This study examined a cement mill and investigated the deployment of LMs to improve production. The plant's present OEE stands at 65.0%, much beneath the world-class standard of 85.0%.

Hamdoon et al. [8] concluded that contemporary entities face significant competition and must undertake strategic initiatives to enhance operational efficiency and sustainable development. Lean manufacturing improves efficiency and minimizes waste; however, it necessitates alignment with strategic processes. This study investigated the relationship between systematic supervision and leadership management at Northern Cement Company in Iraq, utilizing data from 115 employees studied through several methodologies. Results indicate a strong positive association between data-driven monitoring and productivity improvement, particularly in efficiency and waste reduction. The study emphasizes the need for strategic thinking, intelligence, and alertness in facilitating lean success, and advocates for the enhancement of strategic controls and leadership competencies to ensure sustainable competitiveness.

Jena et al. [9] examined the implementation of Six Sigma in a cement facility in Odisha, India, with the objective of improving productivity. The plant's daily production rose from 3178 tons to 3425 tons, reflecting a 7.7% enhancement. In addition to productivity improvements, the study assesses environmental sustainability metrics, encompassing water and energy usage, emissions, and waste—all indicating favorable developments. The program realized an annual cost reduction of ₹10 crore, indicating robust economic feasibility. The research demonstrates that Six Sigma DMAIC may enhance both productivity and environmental performance in the cement sector concurrently.

Fabianova et al. [10] concentrated on enhancing material supply and handling via simulation methods to reduce loader inactivity. The primary aim is to optimize raw material acquisition and refine scheduling for material delivery and loader operations. A simulation model juxtaposes the current system with an optimal situation, demonstrating substantial enhancements. Loader downtime has decreased from 32.9% to 13.0% of net available time, while storage box utilization demonstrates enhanced supply efficiency. The updated schedule facilitates the delivery of greater volumes of gypsum within shorter timeframes while adhering to storage constraints, hence showcasing enhanced operational efficiency and resource management at the outdoor dump.

Salwin et al. [11] investigated the utilization of Value Stream Mapping (VSM) to enhance hand tool manufacturing processes within the construction sector. Value Stream Mapping (VSM) was employed to identify critical manufacturing tasks, gather value-stream data, and identify opportunities for enhancement.

The analysis covered financial results, KPIs, machine performance, energy usage, and OEE before and after optimization. Implementation of the enhancement led to a 9.4% increase in worker productivity, an 18% rise in OEE, and an improvement in machine availability from 70.3% to 85.2%. Additionally, the company achieved annual energy savings of 295,488 kWh (≈EUR 53,253), establishing a strong foundation for future process enhancement.

Improving plant efficiency in terms of OEE, ST, and DP is a great challenge in the present manufacturing paradigm. The present-day AI system may help with the same. Out of numerous LMTs used in cement plants, TPM, 5S, and Kaizen were used in this research to improve the productivity of the plant in terms of OEE, ST, and DP by applying an AI system.

2. Methodology

2.1. Lean Manufacturing Techniques (LMTs)

There are numerous LMTs, such as 5S, Kaizen, VSM, JIT, Kanban, Poka-Yoke (Error Proofing), TPM, Standardized Work, Root Cause Analysis, Cellular Manufacturing, and Heijunka (Production Leveling). The 5S, TPM, and Kaizen have been applied in this research.

The 5S system keeps the workplace clean, organized, and efficient. Unused tools and spare parts are removed from maintenance areas to reduce clutter. Conveyor belts, raw material bins, and tools are labeled and arranged properly for easy access.

Regular cleaning schedules are followed for areas such as the crusher, kiln, and mill to maintain cleanliness and order.

Kaizen focuses on making small, continuous improvements in daily operations. Operators and engineers work together on improvements such as reducing air leaks, improving fuel efficiency, and optimizing lubrication schedules.

TPM keeps machines in good working condition and prevents unexpected breakdowns. Operators carry out basic maintenance tasks such as cleaning, lubrication, and inspection.

Predictive maintenance techniques are used to monitor key equipment like the kiln, ball mill bearings, and compressors, helping to identify potential problems early.

2.2. Modeling Techniques

Response Surface Methodology (RSM) is a technique adopted to model and maximize/minimize processes where several factors affect a response. It fits experimental data using a suitable equation:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} {X_i}^2 + \sum_{i<j}^{k} \beta_{ij} X_i X_j + \varepsilon \quad (1)$$

Where Y is the predicted response, X_i are input variables, β are regression coefficients, and ε is random error. RSM helps identify optimal conditions and visualize variable interactions through contour and surface plots.

An Artificial Neural Network (ANN) is a nonlinear modeling technique that maps input variables to an output through interconnected neurons. The basic neuron output is expressed as:

$$Y = f\left(\sum_{i=1}^{n} w_i X_i + b\right) \quad (2)$$

Where X_i are inputs, w_i are edge value, b is bias, and f is some valuable function. ANNs learn by adjusting weights to minimize prediction error, making them suitable for complex, nonlinear process modeling and optimization.

2.3. Optimization using Genetic Algorithm (GA)

GA is a maximizing/minimizing technique encouraged by the nature-driven process evolution. It works by evolving a population of potential solutions through operations such as selection, crossover, and mutation to reach the optimal result. Each solution is represented as a chromosome, and its quality is measured by a fitness function f(x).

The general procedure follows:

$$x^{(t+1)} = Mutation(Crossover(Selection(x^t)))$$

Where x^t is the population at Generation T.

The objective is to find:

$$max/min \ f(x), \qquad x \in S$$

Where S is the search space, GA efficiently explores complex, nonlinear, and multi-modal spaces, making it suitable for engineering process optimization and parameter tuning. The integration of ANN with GA is highly suitable for the highly nonlinear and interactive nature of the problems and provides a robust framework that enhances prediction accuracy, convergence stability, and generalization capability.

3. Application of LMS in a Cement Plant

Out of numerous LMTs used in Cement Plant, TPM, 5S, and Kaizen were used in this research to improve the productivity of the plant in terms of OEE, ST, and DP. The prevailing TPM, 5S, and Kaizen events in percentage were taken as base data. It was found from the data that the existing average TPM, 5S, and Kaizen events in percentage are 70%, 63.33% and 6.69%, respectively. The corresponding average OEE, ST, and DP were found to be 69.96%, 135.60 Minutes, and 0.52%, respectively.

The TPM, 5S, and Kaizen events were improved in the cement plant. 5S was used to eliminate the unnecessary items. The " Red Tag Campaign" in workshops, control rooms, and stores was conducted. The workplace was organized to reduce wasted time in searching for tools, materials, or cleaning during setup. This improved the productivity; for example, technicians spend 30 minutes finding wrenches, belts, or measuring devices. After 5S, all tools are in labeled racks near the equipment, which saves 15–20 minutes per setup.

TPM shifted maintenance practices from reactive to proactive. Through autonomous maintenance, operators were trained to perform first-level maintenance such as cleaning, lubrication, and visual inspection of mills, conveyors, and packers. This minimized dependency on maintenance staff and reduced idle waiting time during setup. In the packing section, pre-shift inspection of bag chutes and air pressure eliminated last-minute adjustments, cutting setup time by 8–10 minutes. Small, employee-driven Kaizens were promoted to eliminate chronic process losses. Simple improvements—like preset pressure gauges for bag sizes, automatic lubrication systems, and optimized raw mill feeding—enhanced throughput and stability. A series of such initiatives collectively increased production output from 4700 to 5248 TPD**,** representing an 11.7% improvement**.**

The combined application of TPM, 5S, and Kaizen reduced the average setup time from 135.60 minutes to 98.9 minutes. Similarly, the OEE and DP also witnessed significant improvement.

These lean interventions enhanced process discipline, reduced idle losses, and improved equipment availability, thereby increasing overall plant efficiency.

Table 1 Below Shows the Effect on Productivity Before and After LMTs

Table 1. Productivity analysis by using LMTs

Performance	OEE %	Set up time	Defect %
Before	69.96	135.6	0.52
After	98.9	40.1	0.005

Sample data (by using Box–Behnken Design (BBD) of experiments) after improvement in productivity has been taken as shown below in Table 2, for modeling and optimization purposes.

Table 2. Sample data after improvement in productivity

SN	TPM % (X1)	5S % (X2)	Kaizen events (X3)	OEE %	Setup time (min)	Defect %
1	60	50	4	54.01	142.7	0.79
2	60	50	8	59	131.9	0.697
3	60	50	15	68.29	115	0.533
4	60	75	4	66.44	120.3	0.583
5	60	75	8	71.53	109.1	0.526
6	60	75	15	78.83	99.3	0.382
7	60	90	4	72.36	104.6	0.489
8	60	90	8	77.91	100	0.398
9	60	90	15	84.68	85.4	0.244
10	80	50	4	68.96	116.4	0.591
11	80	50	8	73.75	109.6	0.48
12	80	50	15	79.76	91.8	0.377
13	80	75	4	81.73	94.8	0.421
14	80	75	8	84.23	88.3	0.307
15	80	75	15	93.54	67.4	0.168
16	80	90	4	87.42	87.9	0.291
17	80	90	8	93.18	74.8	0.205
18	80	90	15	98.63	57.6	0.057
19	95	50	4	79.69	93.4	0.469
20	95	50	8	84.7	85.8	0.389
21	95	50	15	89.79	69	0.234
22	95	75	4	92.08	82	0.258
23	95	75	8	97.16	65.4	0.162
24	95	75	15	98.9	51.3	0.014
25	95	90	4	98.75	65.1	0.153
26	95	90	8	98.15	56	0.044
27	95	90	15	98.01	40.1	0.005

4. Results and Discussions

4.1. Results and Discussion for OEE

4.1.1. RSM for OEE

Equation 3 represents the second-order regression model developed for OEE using data from all 27 runs listed in Table 2. The ANOVA [12] results for this model are presented in Table 3. The model exhibits an F-value of 222.27, indicating that the quadratic model is statistically significant, with minimal likelihood that such a high F-value occurred due to random noise. The coefficient of determination (R^2) and adjusted R^2 data are 99.16% and 98.71%**,** respectively, demonstrating that a major portion of the variability in OEE is effectively explained by the model predictors, while only a negligible part is due to inherent or unexplained variability. The Standard Error (S) of 1.48 is relatively small, suggesting good model precision. Furthermore, the p-values for the overall model and its linear and quadratic terms are less than 0.05 (at a 95% confidence level), confirming that the model is statistically significant.

The concluding model for OEE is expressed as follows:

$$\text{OEE} = -70.4 + 1.446X_1 + 1.0848X_2 + 3.299X_3 - 0.00320X_1^2 - 0.00318{X_2}^2 - 0.0259{X_3}^2 - 0.00178X_1 X_2 - 0.01698X_1X_3 - 0.00762X_2X_3 \quad (3)$$

Table 3. Statistical evaluation of OEE through ANOVA

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	4392.65	488.07	222.27	0
Linear	3	4140.98	1380.33	628.61	0
X_1	1	2337.51	2337.51	1064.52	0
X_2	1	1300.31	1300.31	592.17	0
X_3	1	492.11	492.11	224.11	0
Square	3	16.95	5.65	2.57	0.088
X_1*X_1	1	5.51	5.51	2.51	0.132
X_2*X_2	1	8.35	8.35	3.8	0.068
X_3*X_3	1	3.09	3.09	1.41	0.252
2-Way Interaction	3	46.71	15.57	7.09	0.003
X_1*X_2	1	4.81	4.81	2.19	0.157
X_1*X_3	1	33.08	33.08	15.06	0.001
X_2*X_3	1	8.82	8.82	4.02	0.061
Error	17	37.33	2.2		
Total	26	4429.98			

Table 4. Optimized network parameters for OEE Computation

Weights to the hidden layer from the input layer	Bias to hidden layer	Weights to output layer	Bias to output layer
0.16, –0.552, 0.78, 0.52; 0.60, 0.079, 0.77, –0.052; 2.31, –0.63, –0.083, –0.103;	5.56; –19.55; 0.77;	–0.44, 0.72, 0.34	0.6787

4.1.2. ANN for OEE

Traditional modeling techniques such as linear regression often struggle to capture deep nonlinearity and variable interactions simultaneously. ANNs are universal function approximators and are well-suited for modeling complex nonlinear mappings without explicit assumptions about data distribution. After training, the optimized network parameters obtained from the network are utilized to construct the mathematical model for predicting the OEE. A network architecture comprising three neurons in the hidden layer was found to provide the most accurate and stable performance for OEE prediction. Accordingly, the ANN model can be mathematically represented as:

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

where x_i are input parameters, w_{1ji} and w_{2j} denote the connection weights of the input–hidden and hidden–output layers, b_{1j} and b_2 represent the Corresponding Biases, and f(·) is the Activation Function (AF). The Log Sigmoid AF (LSAF) and Linear f(·) (LAF) were found to be the most fit considering the Mean Squared Error (MSE) yardstick (Table 4).

4.1.3. Optimization for OEE

The Genetic Algorithm (GA) was implemented using a real-valued representation to maximize the nonlinear objective function OEE. A population size of 200 individuals was used to ensure adequate diversity in the search space.

The Arithmetic crossover operator, the exchange of genetic information between parent solutions, was carried out with a probability of 0.7**.** Gaussian mutation was applied on a per-gene basis with a rate of 0.2 and a Standard Deviation (σ\sigmaσ) equivalent to approximately 10% of the variable range to introduce small random variations and prevent premature convergence.

Elitism was incorporated to preserve the best-performing individuals across generations, while tournament selection was employed to choose parents for reproduction. The GA converged to the following optimal set of decision variables:

X_1= 93.1276, X_2=87.5376, X_3=14.0084

Corresponding to a maximum predicted objective value of OEE obtained is 99.97%.

The result demonstrates the effectiveness of the GA in identifying an optimal solution within the defined variable bounds while achieving the desired performance target.

4.2. Results and Discussions for Setup Time

4.2.1. RSM for Setup Time

Equation 5 presents the second-order regression model for ST, developed using data from 27 experimental runs. The ANOVA results (Table 5) show an F-value of 290.43, confirming the model's statistical significance. The R^2 (99.35%) and adjusted R^2 (99.01%) indicate excellent model fit, while the standard error suggests high precision. All p-values < 0.05 validate that both the linear and quadratic terms significantly influence ST.

The model for ST is expressed as follows:

$$\text{ST } 257.8 - 0.870\ X_1 - 1.044X_2 - 1.78X_3 - 0.003830X_1^2 - 0.00004{X_2}^2 - 0.010105{X_3}^2 + 0.00299X_1 X_2 - 0.010928X_1X_3 + 0.00167X_2X_3 \quad (5)$$

Table 5. Statistical evaluation of ST through ANOVA

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	16540.2	1837.8	290.43	0
Linear	3	16246.2	5415.39	855.79	0
X_1	1	8848.6	8848.59	1398.33	0
X_2	1	4435.6	4435.62	700.96	0
X_3	1	2892.2	2892.24	457.06	0
Square	3	6.4	2.14	0.34	0.798
X_1*X_1	1	5.9	5.94	0.94	0.346
X_2*X_2	1	0	0	0	0.988
X_3*X_3	1	0.5	0.47	0.07	0.788
2-Way Interaction	3	27.6	9.19	1.45	0.263
X_1*X_2	1	13.5	13.47	2.13	0.163
X_1*X_3	1	13.7	13.68	2.16	0.16
X_2*X_3	1	0.4	0.42	0.07	0.799
Error	17	107.6	6.33		
Total	26	16647.8			

Table 6. Optimized network parameters for ST computation

Weights to the hidden layer from the input layer	Bias to hidden layer	Weights to output layer	Bias to output layer
0.22, 11.23, 0.12, 0.32; 0.78, 0.99, 0.877, –0.342; 11.41, –0.73, –0.93, –0.53;	7.781; 7.55; 0.68;	0.89, 0.80, 0.55	0.8967

4.2.2. ANN for Setup Time

A Network Architecture comprising three Neurons in the Hidden Layer (LSAF) and LAF in the output layer was found to provide the most accurate and stable performance for ST prediction. The model in mathematical form is shown below:

$$ST = f\left(\sum_{j=1}^{3} w_{2j} f\left(\sum_{i=1}^{n} w_{1ji} x_i + b_{1j}\right) + b_2\right) \qquad (6)$$

4.2.3. Optimization for ST

To identify the optimal set of conditions that minimizes the response variable ST, a Genetic Algorithm (GA)–based optimization approach was employed. The process parameters TPM %, 5S% % and Kaizen events were selected as decision variables. The empirical relationship for the response ST, as depicted in equation 6, was taken as the objective function.

The objective of the study was to minimize ST subjected to the following variable bounds:

$60 \le X1 \le 95$,
$50 \le X2 \le 90$,
And
$4 \le X3 \le 15$

The population size was set to 100, and the algorithm was executed for 200 generations. The crossover and mutation probabilities were 0.9 and 0.05, respectively. A constraint-handling strategy was incorporated by using a large fitness penalty to ensure that the search remained within the feasible design space.

The optimization demonstrated smooth convergence, with the best fitness value improving progressively across generations until a steady state was achieved.

The optimal combination of parameters obtained through the GA was:
X_1= 92.14, X_2=88.02, X_3=14.
Corresponding to the minimized response value:
ST=39.99 Minutes

4.3. Results and Discussions for Defect Percentage (DP)

4.3.1. RSM for DP

Equation 7 presents the second-order regression model for DP, developed using data from 27 experimental runs. The ANOVA results (Table 7) show an F-value of 235.05, confirming the model's statistical significance. The R^2 (99.2%) and adjusted R^2 (98.78%) indicate excellent model fit, while the standard error (0.023) suggests high precision. All p-values < 0.05 validate that both the linear and quadratic terms significantly influence DP.

The final regression model for DP**,** after excluding non-significant terms, is expressed as follows:

$$\mathrm{DP} = 2.137 - 0.01413\,X_1 - - 0.01036X_2 - 0.03789X_3 - 0.000030\mathrm{X}_1^2 - 0.000020{X_2}^2 - 0.000391{X_3}^2 - 0.000005X_1\,X_2 - 0.000074X_1X_3 + 0.000058X_2X_3 \quad (7)$$

Table 7. Statistical evaluation of DP through ANOVA

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	1.1198	0.124422	235.05	0
Linear	3	1.0802	0.360066	680.22	0
X_1	1	0.45699	0.456992	863.33	0
X_2	1	0.3878	0.387799	732.61	0
X_3	1	0.22967	0.229673	433.89	0
Square	3	0.0015	0.000501	0.95	0.44
X_1*X_1	1	0.00047	0.000469	0.89	0.36
X_2*X_2	1	0.00033	0.000333	0.63	0.439
X_3*X_3	1	0.0007	0.000701	1.32	0.266
2-Way Interaction	3	0.00118	0.000393	0.74	0.541
X_1*X_2	1	0.00004	0.00004	0.08	0.786
X_1*X_3	1	0.00063	0.000625	1.18	0.292
X_2*X_3	1	0.00051	0.000513	0.97	0.339
Error	17	0.009	0.000529		
Total	26	1.1288			

Table 8. Optimized network parameters for DP computation

Weights to the hidden layer from the input layer	Bias to hidden layer	Weights to output layer	Bias to output layer
2.17, –0.0062, 0.009, 0.006; 0.080, 0.001, 0.034, –0.01; 0.40, –0.05, –0.022, –0.17;	0.050; –2.80; 0.07;	0.11, 0.42, 0.46	0.1256

4.3.2. ANN for DP

Similar to OEE and ST, a Network Architecture comprising three Neurons in the Hidden Layer (LSAF) and LAF in the output layer was found to provide the most accurate and stable performance for DP prediction. The model in mathematical form is shown below:

$$DP = f\left(\sum_{j=1}^{3} w_{2j} f\left(\sum_{i=1}^{n} w_{1ji}x_i + b_{1j}\right) + b_2\right) \quad (8)$$

Figures 1, 2 and 3 and illustrate a prediction accuracy assessment of the OEE, ST, and DP. It is evident that the predicted results from both the RSM and ANN models for OEE, ST, and DP closely match the corresponding real data. The Mean Squared Error (MSE) has been used as an indicator of model accuracy. The MSE values for the ANN model are 1.82×10^{-7}, 4.46×10^{-5}, and 6.64×10^{-6} for OEE, ST, and DP, respectively, indicating excellent predictive precision. Similarly, the RSM shows MSE values of 5.67×10^{-2}, 2.56×10^{-1}, and 7.83×10^{-2} for the same parameters. The comparatively lower MSE values of the ANN model demonstrate its superior accuracy and capability in capturing nonlinear relationships between process variables.

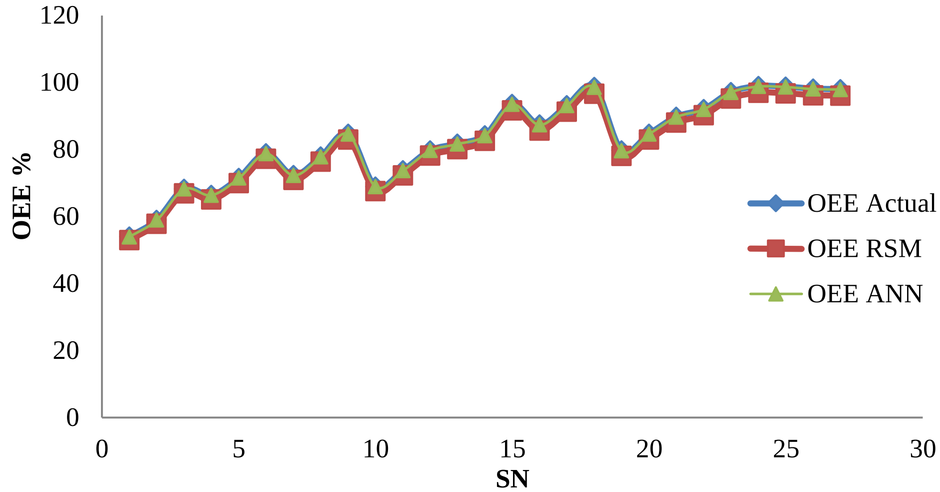

Fig. 1 Prediction accuracy assessment for DP for OEE

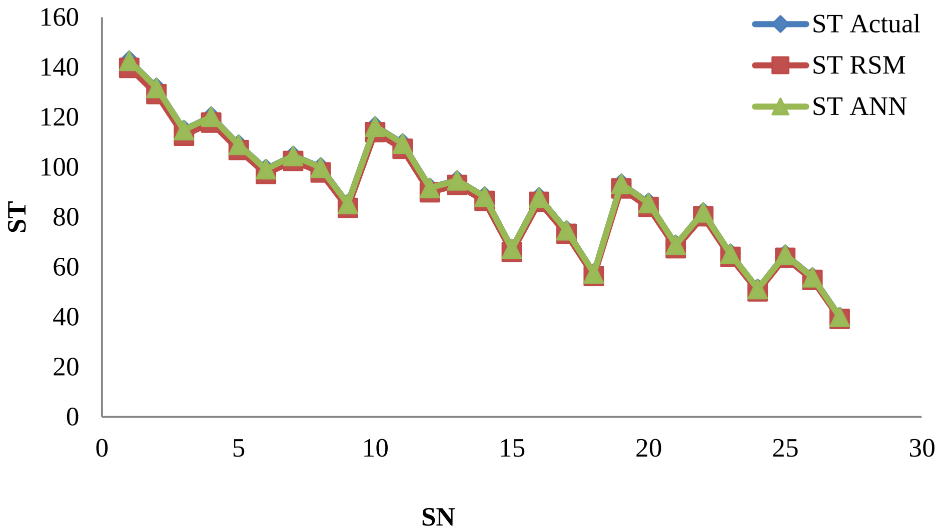

Fig. 2 Prediction accuracy assessment for ST

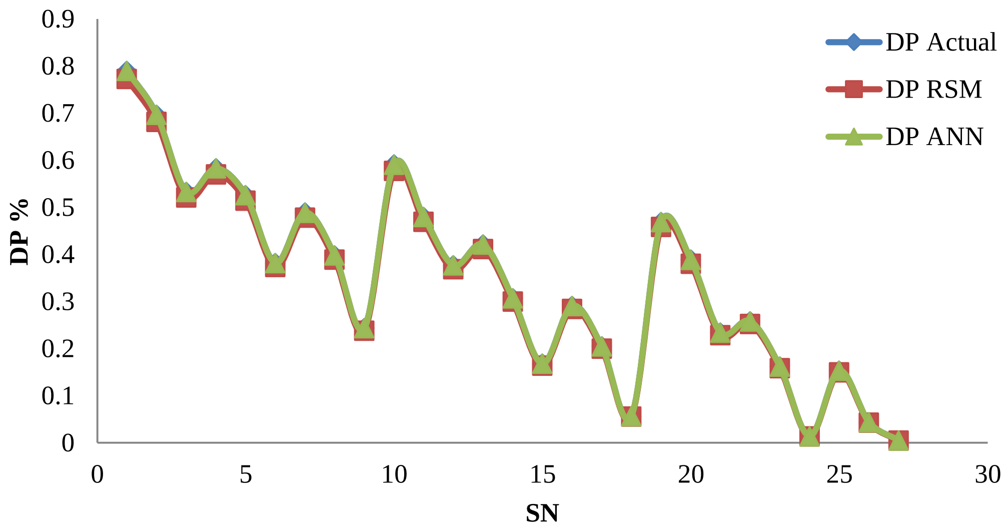

Fig. 3 Prediction accuracy assessment for DP

4.3.3. Optimization for DP

The Genetic Algorithm (GA) was applied to minimize the response variable DP, which represents the predicted process characteristic derived from the ANN model, as shown in equation 8. The objective of the study was to minimize DP subjected to the following variable bounds:

$60 \le X_1 \le 95$,
$50 \le X_2 \le 90$,
And
$4 \le X_3 \le 15$

The algorithm parameters included a population size of 100 and a maximum of 200 generations. The GA demonstrated progressive convergence, where the minimum fitness value continuously decreased until a stable minimum was obtained. The optimal parameter combination derived from the analysis was:

X_1= 90.21, X_2=85.93, X_3=14.72
Resulting in the minimized response:

DP=0.00498 %.

5. Discussion

The application of Lean Manufacturing Tools (LMTs) led to a substantial improvement in Overall Equipment Effectiveness (OEE) by 41.3%, along with significant productivity gains reflected by a 70% reduction in Setup Time (ST) and a 90% reduction in Defect Percentage (DP). Among the LMTs, Total Productive Maintenance (TPM) emerged as the most effective across all productivity parameters, followed by 5S. Advanced modeling showed that Artificial Neural Network (ANN) models outperformed Response Surface Methodology (RSM) in predicting productivity outcomes. Notably, an AI-driven approach using ANN and Genetic Algorithms has achieved these improvements more efficiently by automatically identifying optimal combinations of LMTs, predicting performance impacts in advance, and continuously optimizing process parameters with minimal human trial-and-error.

Table 9. Comparative analysis between the outcomes of the current study and existing designs

Performance	OEE %	Set up time	Defect %
Before	69.96	135.6	0.52
After Implementing LMPs	98.9	40.1	0.005
After Applying the ANN+GA Hybrid Approach	99.97	39.99	0.00498
% Improvement	42.89	70.51	99.04

6. Conclusion

The Lean Manufacturing Techniques (LMTs) such as TPM, 5S, and Kaizen have been applied in a cement plant in this research, and productivity parameters such as OEE, Setup Time (ST), and Defect Percentage (DP) have been evaluated. The conclusions are as follows:

1. There is considerable improvement in the OEE with the application of LMTs, as OEE has been found to be improved by 41.3%.
2. By the application of LMTs, the productivity in terms of ST and DP has also increased significantly, as there is a reduction of 70% and 90% in the ST and DP, respectively.
3. TPM has been identified as a common LMT that is most effective for all the productivity parameters in the present research, followed by 5S.
4. The ANN model for all the productivity parameters has been found to be superior to the RSM model in the present research.
5. An Artificial Intelligence-based approach by applying ANN and Genetic Algorithm has resulted in considerable enhancement in all the productivity parameters.

Funding Statement

This work was performed without funding from governmental organizations or research institutions**,** commercial, or charitable funding bodies.

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